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Housing Costs and Real Income Differences across Chinese Cities

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Abstract

We document variations in real income for high-skilled and low-skilled households across Chinese cities. Using comprehensive data on land parcel transactions and survey data for land development and household expenditure, we compute a city-specific housing cost index and we assess how it varies across locations. All three components of housing costs –unit land prices, land share in construction, and housing share in expenditure– decrease from the city centre to the periphery, increase with city population, and decrease with city land area, as predicted by theory. Overall, housing costs in China are high and vary a lot across locations. Income gains outweigh housing costs when moving from small to larger cities. However, in the largest cities, housing costs start dominating, especially for low-skilled households, illustrating a bell-shaped curve relationship between real income and city population in China.

Key words: Housing costs; income disparities; land use regulation; quality of life; city size; agglomeration economies; China.

JEL classification: O18, R21, R23, R31, R52, O53.

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1 Introduction

In sharp contrast to the tightly regulated expansion of cities of earlier decades, China has experienced an extremely rapid urbanisation process since the early 2000s. As of 2020, 63.9% of the Chinese population lived in urban areas, representing a 27.7 percentage point increase from 2000 and a 43-point surge from 1982. The shifting spatial distribution of China's population has been largely fuelled by rural-to-urban labor flows, with rural migrants constituting approximately two-thirds of the total migrant population in 2010.[1] However, the latest census data suggest a potential shift in this pattern, as urban-to-urban migration increased faster than rural-to-urban migration in the past ten years, to reach 82 million persons in 2020.[2]

How does real income vary when people move to cities of different sizes? Several recent studies have investigated the nominal productivity and income gains from locating in larger cities, and found them to be large in China as evidenced for instance by Combes et al. (2020). However, urban economics models predict that the cost of living, particularly the cost of housing, also increases with city size. This is an obvious fact in China, although it has not yet received a precise quantitative assessment.[3] In this paper, we assess whether and to what extent the increase of housing costs offsets nominal income gains from urbanisation. We explore how real income, defined as nominal income net of housing and commuting costs, varies based on various city characteristics such as population, land area and the share of rural migrants. Additionally, we investigate whether this differs among households of different skill levels.

[1] Population movements within China have been controlled for decades through the *Hukou* household registration system. Dating back to the late 1950s, this system has tied individuals to their place of birth and limited their access to social benefits and services outside their registered location. While the *Hukou* system has been effective in managing urbanization, it has also resulted in significant disparities between rural and urban areas. Since 1997, several steps have been taken at the central and the local levels to relax the *Hukou*-related constrains in order to address these disparities and promote greater labor mobility. Initially, the focus was on skilled workers from rural areas and other cities, with certain prefectures implementing targeted reforms (Fan, 2019). Starting from 2014, small and medium-sized cities (with populations of less than 1 million inhabitants) were mandated to progressively or completely eliminate *Hukou* restrictions.

[2] Figures from the 7th National Population Census of China (2020) are available at `https://www.stats.gov.cn/sj/pcsj/rkpc/d7c/202303/P020230301403217959330.pdf`, retrieved on January 18, 2024.

[3] The Chinese real estate boom is documented by Fang et al. (2016) and Glaeser et al. (2017). From 2007 to 2014, Chinese official statistics highlight a doubling of housing prices, with significant disparities between cities.

Our quantitative framework builds on recent developments in the urban economics literature. We first quantify urban housing costs and we assess how they vary between cities. For that, we compile data on the universe of individual land parcel transactions within China and provide insights into the variations in land prices within and between cities. We use complementary individual surveys on land development and housing expenditure to similarly assess how the share of land used for housing production and the share of housing in households' expenditure vary across locations. Finally, we combine the three components –unit land prices, land share in construction and housing share in expenditure– to quantify how the elasticity of housing plus commuting costs with respect to population varies with the city population, land area, and share of rural migrants. This assessment is conducted separately for high- and low-skilled households.

We find that unit land prices, land share in construction and housing share in expenditure all decrease from the centre to the periphery of cities, increase with the city's population size, and decrease with the city's land area, as predicted by urban economics theory. Conversely, they are not significantly affected by the presence of rural migrants. Overall, housing costs in China's urban areas are high, and they vary a lot across locations. Our estimates show that the population elasticity of housing plus commuting costs varies across cities in a magnitude comparable to that observed in some developed countries, the US, Germany and France for instance. It ranges from 0.027-0.029 for a city with 500,000 inhabitants up to 0.255-0.275 for a city of the size of Shanghai, and it is always higher for low-skilled households. Housing costs exhibit a strongly convex pattern, notably for low-skilled households. They increase by 39.3% and 36.4% for low-skilled and high-skilled households respectively when moving from the lowest to the highest housing cost city. Importantly, less stringent land use regulations –especially the possibility for cities to expand their fringe– reduce the elasticity of housing costs by 38% for an average-sized city and by up to 53% for a city like Shanghai.

Comparing these variations with those in nominal income, we then show that the income-net-of-housing-and-commuting-costs implications of moving to larger cities also vary across cities of different sizes and between low-skilled and high-skilled households. These implications also depend on whether city land area expansion and the presence of rural migrants are accounted for. First, when only population impacts nominal income and housing costs, we find an almost symmetrical bell-shaped curve, for both high- and low-skilled households. In cities with up to 2.6 million inhabitants, where approximately half of the Chinese population lives, nominal income increases faster than housing costs, resulting in an increase in real income of about 8.7%. However, in cities with over 3 million inhabitants, nominal income gains lag behind housing costs, leading to a gradual decline in real income of up to 10.5% for high-skilled households and 12.6% for low-skilled households in Shanghai compared to the city with the highest real income. Second, when the roles of both population and land area are considered, the declining part of the real income curve substantially diminishes, albeit slightly less for low-skilled households than for high-skilled ones. Moving to very large cities like Beijing, Chongqing or Shanghai remains less advantageous. In these cities, real income is 2.1% to 2.8% lower for high-skilled households and 8% to 9.2% lower for low-skilled households compared to the city with the highest real income. Finally, accounting for the role of rural migrants amplifies the benefits of larger cities, especially for high-skilled households. It makes real income monotonously increase with population for both high- and low-skilled households, and even more so for the former. In Beijing, Chongqing, and Shanghai, high-skilled households typically enjoy real incomes about 36-38% higher than those in the average city, while low-skilled households have a more concave real income profile, which is 10% higher in the largest cities compared to the average city.

The importance of land and housing markets for the overall Chinese economy has only recently been acknowledged. For instance, Rogoff and Yang (2023) stress that the existing literature has overlooked the benefits but also the risks that these markets exert on China's long-term development. Thanks to newly accessible data, a series of articles has started to assess the determinants of the dynamics of Chinese land and housing markets, particularly their booms and busts (Fang et al., 2016; Glaeser et al., 2017; Henderson et al., 2022; Rogoff and Yang, 2023). We contribute to the understanding of these markets by shading a specific light that focuses on the spatial dimension, through the cross-section of cities across the entire Chinese territory, and on the specific role played by cities' characteristics on land and housing markets disparities.

A distinctive feature of our work is to adopt an urban economics theory perspective to assess how much space, and more broadly, location within a global economy, contributes to overall inequality between households. In the context of the US, Moretti (2013) stresses the importance of accounting for the role of the local cost of living, particularly housing costs, when assessing income inequality and its evolution over time, across households that not only differ in skills and education levels, but also, importantly, live in cities with different characteristics. Moretti (2013) emphasizes that the size of a city significantly impacts the price index faced by households, which therefore must be considered for meaningful comparisons of real, rather than nominal, income across individuals. Subsequent papers have expanded on Moretti's contribution, increasingly building on urban economics models (Diamond, 2016; Diamond and Gaubert, 2022; Duranton and Puga, 2023; Couture et al., 2023). However, these assessments have primarily focused on the US economy, occasionally extending to countries like Germany or the UK (Ahlfeldt et al., 2021; Overman and Xu, 2022; Dustmann et al., 2022), but have not explored emerging countries, a gap we address here.

Importantly, this literature echoes an earlier one by Rosen (1979) and Roback (1982), which assesses the quality of life in a location as the inverse of real income, an assumption that holds true when households freely choose where to locate.[4] Rosen-Roback's framework, or its extension to migration choices, has become a cornerstone in quantitative spatial economics models (see Redding and Rossi-Hansberg, 2017, for a review). We also adopt a Rosen-Roback's perspective although we make no attempt here to quantify the value of specific local amenities.

Compared to both the literature on real income and on the quality of life, our study, apart from its focus on China, also stands out by using individual data. This approach allows us not only to precisely control for individual characteristics (of land parcels and households) and their potentially non-random distribution across locations, but also to control for location simultaneously at two distinct levels that play different roles in spatial inequality: the neighborhood within the city and the city itself. Although not feasible in studies using data already averaged at the city level, as in most of the previously cited articles, Albouy and Lue (2015), Combes et al. (2019), and Ahlfeldt et al. (2021) have demonstrated the necessity of this approach from a theoretical perspective. One must control for the location within the city, and in particular account for commuting costs, in order to obtain consistent estimates of the impact of city characteristics, such as their size, on the cost of living encompassing both housing and commuting costs. For this purpose, we adopt the two-step empirical strategy proposed by Combes et al. (2019), which nets out the role of the within city location in a first step.

Our study also directly relates to the literature that estimates agglomeration gains for

[4] Albouy (2008) and Albouy (2016) have revisited these approaches for both the US and Canada.

China. Au and Henderson (2006) were among the first to quantify the role of city size on productivity in China. They notably highlighted the potential bell-shaped impact of city size on firms' productivity due to declining returns to agglomeration during the 1990s –a conclusion that aligns with our findings, although here in the context of households' real income in the present time. Subsequent literature, whether focusing on nominal income through reduced-form approaches or adopting a more theory-grounded stance[5], has largely overlooked the role of differences in land and housing costs, partly because of the absence of relevant and consistent data. We contribute to this literature by explicitly taking into account housing and commuting costs that we compare to nominal income gains in cities with different characteristics, estimated in an earlier work (Combes et al., 2020). This approach allows us to quantify the real income gains associated with locating in larger cities, i.e. nominal income gains adjusted for housing and commuting costs.

Last, though somewhat more tangentially, our article also contributes to a growing body of literature on spatial misallocation (Hsieh and Moretti, 2019; Ngai et al., 2019). This research explores the role played by land use regulation and mobility barriers in the allocation of production factors across space. More broadly, there is a renewed interest in the role of land use regulation and its continued use by local authorities worldwide, as discussed by Glaeser and Gyourko (2018). In China too, large cities like Beijing and Shanghai have implemented stringent land use regulations and internal migration restrictions, potentially impeding the efficient spatial allocation of workers. Our paper provides evidence that a specific aspect of land use regulation –the possibility for the urban fringe to expand– helps mitigate the impact of population concentration on housing prices, resulting in larger real gains for non-landowning workers. These findings highlight the importance of considering the role of land use policies in spatial misallocation, and more broadly, spatial inequality.

The rest of the paper is organised as follows. In section 2, we describe the conceptual framework and our empirical strategy. Section 3 introduces the data and Section 4 provides a descriptive analysis of the spatial distribution of unit land prices in China, both within and between cities. In Section 5, we estimate the impact of city characteristics on the three key components of housing costs, and we study the variations of the population elasticity of housing plus commuting costs. Section 6 presents the predictions of real income disparities

[5] See, for instance, evaluations of the impact of transport infrastructure on regional disparities and city growth as in Faber (2014) and Baum-Snow et al. (2017).

across Chinese cities. Section 7 discusses various robustness checks. Section 8 concludes.

2 Conceptual framework

2.1 Theoretical background

Our empirical strategy is embodied in the following theoretical framework, which clarifies the interpretation of the estimated parameters and discusses various estimation issues. This framework closely aligns with Combes et al. (2019). Individuals are assumed to choose the city c in which they work and, within city c, the neighbourhood/district d in which they live and from which they commute, at a cost, to their workplace, a location named the central business district (CBD) where they earn an income W_c. In a framework à la Roback (1982), the utility of household i of type k (e.g. low- or high-skilled) in city c, $U_{i,c}$, is a function of their consumption of housing, h_i, and a composite good, x_i, of the city's amenities (such as climate, health, leisure, or culture) possibly specific to each household type, A_c^k, and of an idiosyncratic preference for the city, $\epsilon_{i,c}$. One assumes that

$$U_{i,c} = v\left(h_i, x_i\right)\, A_c^{k(i)}\, \epsilon_{i,c}, \tag{1}$$

where $v(.,.)$ is increasing in both arguments and strictly quasi-concave.

Beyond idiosyncratic preferences, moving to a larger city typically induces nominal income gains, thanks to the presence of agglomeration economies in production, but also urban costs, due to the increase in the cost of living, and changes in urban amenities. This paper focuses on the between-city disparities in the monetary part of the utility, denoted V_c^k, which we refer to as the real income of type-k agents, i.e. the value of $v\left(h_i, x_i\right)$ once maximised under budget constraint. Our purpose is to assess how real income changes along with some characteristics of the cities, their size among others.[6]

As the literature shows, to properly assess between-city disparities in the cost of living, within-city variations in housing prices and commuting costs must be properly accounted for. This can be easily grasped using an Alonso-Muth framework where, in equilibrium, housing markets ensure that all agents of a particular type k derive the same level of utility

[6] Note that lower values can reflect the presence of better amenities in the city, as proposed by the 'quality of life' literature (Albouy, 2008). We do not intend to evaluate this dimension here.

across all locations within a city (see Fujita and Thisse (2013)). Hence, locations with higher commuting costs exhibit lower housing prices while maintaining the same level of indirect utility. As a consequence, utility can be assessed at any specific location, which explains why the real income V_c^k above does not depend on d, the district chosen by the household. In particular, we can measure utility at the CBD, where commuting costs are the lowest and the unit housing price, denoted P_c^k, is the highest.

In line with urban economics models and empirical studies showing that goods other than housing vary less across cities (see for instance Handbury, 2021), but also considering that such data for China, as for many countries, is unavailable, we assume all goods except housing to be perfectly tradable, resulting in identical prices across locations. As we assess urban costs through housing prices at the CBD, where they are the highest in the city, these costs encompass not only housing costs but also the extra commuting costs incurred in the city beyond their minimal value at the CBD. We further set this minimal value to zero, meaning that any potential commuting costs at the CBD are considered part of the city's amenities and enter utility through A_c^k. Under these assumptions and using basic consumer theory, Combes et al. (2019) show that the elasticity of real income for type-k agents with respect to the city population, Pop_c, denoted $\epsilon_c^{V,k}$, is equal to the difference between the elasticity of nominal income, $\epsilon_c^{W,k}$, and the elasticity of urban plus commuting costs, $\epsilon_c^{C,k}$:

$$\epsilon_c^{V,k} \equiv \frac{\partial \log V_c^k}{\partial \log Pop_c} = \epsilon_c^{W,k} - \epsilon_c^{C,k}, \tag{2}$$

where urban costs correspond to the expenditure compensation needed to keep utility constant when relocating to a larger city. The elasticity of urban costs is itself equal to the product of the share of housing in expenditures, γ_c^k, and the elasticity of unit housing price

$$\epsilon_c^{C,k} = \gamma_c^k \frac{\partial \log P_c^k}{\partial \log Pop_c}. \tag{3}$$

In the absence of housing price data, but with access to all transactions of land parcels intended for housing purpose, we further relate unit housing prices at the CBD, P_c^k, to unit land prices at this location, R_c, according to:

$$P_c^k = (R_c)^{\beta_c} \tag{4}$$

where β_c is the share of land in the housing production function assuming a Cobb-Douglas technology.[7] As we lack information about the individuals who will occupy the housing units constructed on the land parcel, specifically their skill type k, neither R_c nor β_c depends on k. Therefore, we estimate unit housing prices for the average Chinese household (with local skills composition controlled for at the district level in estimations), although we are able to estimate type-k agents' specific parameters for nominal income and for the housing budget share. Overall, we have

$$\epsilon_c^{C,k} = \beta_c \, \gamma_c^k \, \frac{\partial \log R_c}{\partial \log Pop_c}. \tag{5}$$

To assess how real income varies across cities, we start by separately evaluating how each of the three components that enter the urban costs elasticity, the unit land price (R_c), the land share in housing production (β_c), and the housing share in expenditure (γ_c^k), depends on the characteristics of cities, most importantly their population, area, and share of rural migrants. This is the first contribution of the paper. The second contribution is to combine these three sets of estimations according to equation (5) to evaluate how the urban costs elasticity varies across cities. The third contribution is to compare the elasticity of urban costs to the income elasticity, and integrate them with respect to city size in order to assess whether moving to larger cities induces real income gains, and if so, by how much. Since various quantitative assessments for the income elasticity are available in the empirical literature on agglomeration gains in China, we do not present any new estimates here. Instead, we rely on those provided by Combes et al. (2020), whose two-step methodology is fully consistent with the present approach for the three components of urban costs, enabling us to meaningfully compare them.

On the empirical side, we need to address three key issues: i) the presence of heterogeneity among both households and land parcels, which may not be randomly distributed across locations; ii) the role of within-city differences in commuting costs, land supply factors and consumption amenities; and iii) the potential reverse causality arising from endogenous location choices, wherein local income, land price, and expenditure shares influence city characteristics. The following section outlines our approach to address these concerns.

[7] Data limitation for China prevents us from estimating a more sophisticated production function for housing. Hence, we stick to the assumptions of Combes et al. (2019). Combes et al. (2021) show that a Cobb-Douglas specification provides an almost perfect fit on French individual housing production data.

2.2 Empirical specifications

In line with the necessity to account for within-city location choices discussed in the previous section, we follow Combes et al. (2019) and adopt a two-step procedure to estimate the impact of city characteristics on each of the three components entering urban housing costs. In the first step, we regress the variable of interest at the micro level (the parcel for unit prices and land share, and the household for housing share) on a city fixed effect and on control variables that account for specific characteristics of the parcel, household and/or neighbourhood. These control variables are chosen so that the city fixed effect represents the (logarithm of the) dependent variable of a representative parcel or individual located in a neighbourhood with average amenities and commuting costs equal to those at the city centre. In the second step, we regress the city fixed effect on relevant city-level characteristics. As detailed below, our main variables of interest are the population and area of the city, and the presence of rural migrants, although we also consider income for instance, as an extra source of local demand difference.

Starting with land prices, the first step is specified as follows:

$$\log r_p = \log R_{c(p)} + \delta^R_{c(p)} \log dis_p + X^P_p \, \lambda^R + X^D_{d(p)} \, \varphi^R + \varepsilon_p \tag{6}$$

where r_p is the price per square meter of land parcel p located in district $d(p)$ of city $c(p)$, $\log R_c$ is a fixed effect for city c and ε_p a random component. Superscript R on the estimated parameters refers to the dependent variable we consider, unit land prices ('rent') here, and superscripts in control variables correspond to the level of observation, P and D for parcels and districts respectively.

The characteristics of the parcel, X^P_p, include the parcel's surface area and its square, as well as the auction type used to sell it. These controls are introduced to capture intrinsic differences in land parcels' characteristics across locations, most importantly their size. Moreover, introducing the auction type can capture the role of some unobservable parcel's characteristics, in addition to controlling for different types of markets exhibiting varying degrees of competition. Combes et al. (2019) also suggest to control for exogenous land supply factors and the easiness to build, which we do by introducing in $X^D_{d(p)}$ the share of watered area, the mean slope and the steepness of terrain in the district, as in Saiz (2010). As mentioned above, we cannot estimate unit prices for each type-k household separately, and we can only control for the share of high school/college graduates and the share of university graduates at the district level. By doing so, we also control for potential spatial income segregation across neighbourhoods within cities.

Less standard, and as discussed above, in order to make meaningful comparisons across cities, we need to control for the access to jobs and obtain a price index for the neighbourhood where commuting costs are the lowest, the CBD. This is the role of the distance to the city centre variable dis_p. Within an Alonso-Muth model, it would fully capture the impact of commuting costs on unit housing and land prices if jobs in Chinese cities were mono-centrically distributed, with a declining job density from the centre to the periphery. This is obviously not fully the case in reality, but we provide evidence that it holds to a large extent in China. We also provide several robustness checks that consider variants for the definition of the city centre, including the presence of secondary centres and more sophisticated functional forms for the impact of distance (see Appendix C.1). Finally, the Alonso-Muth condition states that the land prices gradient should be proportional to the marginal commuting cost in the city. As it depends on the quality of the city transport infrastructure and on the degree of transport congestion in the city, this marginal cost probably varies across cities. To account for that, the effect of distance is made specific to each city by interacting it with another city fixed effect, δ_c^R.

A related concern regards the access to consumption amenities, which can also vary between neighborhoods and is reflected in local housing prices (Brueckner et al., 1999). To compute unit prices for a neighbourhood that would benefit from the average level of amenities in the city, we use a number of local consumption amenities (schools, hospitals, parks, rail stations) as control variables, $X_{d(p)}^D$, which we compute in a radius of 2 kilometres around the parcel.

To capture the potentially non-random distribution of neighbourhood variables within the city only, supply factors, education and amenities within cities, all these characteristics are centred with respect to their city mean, so that the city fixed effect still fully captures their between-city differences.

The specification for the second step is given by:

$$\widehat{\log R_c} = \alpha_1^R \log pop_c + \alpha_2^R (\log pop_c)^2 + \eta_1^R \log area_c + \eta_2^R (\log area_c)^2 + \rho^R \log mig_c + \mu^R \log w_c + X_c^C \psi^R + \kappa^R + \nu_c \quad (7)$$

where the city fixed effect estimated in the first step, $\widehat{\log R_c}$, is regressed on our main variables of interest, city population (pop_c), land area ($area_c$) and migrant share (mig_c), as well as on average income (w_c) and additional city controls (X_c^C). κ^R is a constant and ν_c a random component. The city controls, X_c^C, include the same supply factors and education as in the first step, but computed at the city level.[8] This enables us to obtain the unit price for a representative parcel bought by a household with average education. To further control for supply factors, additional land use variables only available at the city level are also introduced. They include the city share of residential, industrial, and commercial land uses in the built-up stock, as well as a dummy for coastal cities.[9] Finally, following Combes et al. (2019), the city past population growth is used as an additional control because it can shape expectations about future housing price increase and therefore affect current land prices beyond the impact of the city's current size, income, and migrant share. It can also control for potential discrepancies between land prices, which are available in the data, and land rents, which are more consistent from a theoretical point of view.

Since our land price dataset covers the period from 2007 to 2019, we pool all years together for the estimation. Time subscripts t are omitted above to ease the reading. Yet, in the first step, city-year fixed effects are included, and the second step pools together all the years and includes time fixed effects. While some of the control variables are either time-invariant or are not separately available at different dates, our main city variables of interest in the second step vary over time. Notably, as detailed in Appendix A, land area is a time-varying variable here because we use the official time-varying definition of cities.

The elasticities of unit land prices with respect to population and land area, ϵ^{RP} and ϵ^{RA}

[8] In this second step, amenity variables are not introduced. Indeed, as our purpose is to isolate the role of real income within the indirect utility, we do not want to control for the average provision of amenities at the city level that separately enters utility (see term A_c^k in equation (1)). In the first step, amenities only control for between-neighbourhood differences within city but not for their average effect at the city level, as they are centred with respect to the city average.

[9] Tan et al. (2020) convincingly argue that land use regulation largely differs between coastal cities and other cities in China.

respectively, are therefore given by:

$$\epsilon_c^{RP} \;=\; \alpha_1^R + 2\,\alpha_2^R \,\log pop_c \quad \text{and} \quad \epsilon_c^{RA} \;=\; \eta_1^R + 2\,\eta_2^R \,\log area_c. \tag{8}$$

ϵ_c^{RP} measures the impact on land prices of increasing the population of the city, a housing demand effect, while simultaneously keeping the city fringe (therefore land area, or the land supply) as well as average income and the share of rural migrants constant. ϵ^{RP} is expected to be positive. Conversely, the impact of increasing the spatial extent of the city (a land supply effect) at given demand (population, income and rural migrants, but also population growth typically), ϵ^{RA}, is expected to be negative. The presence of richer people on average, at given other city characteristics, should also increase the unit price (as captured by a positive μ^R) because richer people have larger housing consumption. Importantly, this income effect is also at given average education level in the city (as it is controlled for in the specification). Education may capture different preferences for housing across education levels. Finally, the role of rural migrants, ρ^R, which we introduce also to match what is done on the income side (Combes et al., 2020), is specific to the Chinese context. On the one hand, there are claims that migrants put pressure on local housing markets, which would increase land price and result in a positive ρ^R. On the other hand, since the overall population is controlled for in the specification, the migrant variable captures here a composition effect at given population and nominal income. As migrants are poorer and tend to live in cheaper housing units of lower quality (Wang and Chen, 2019), a negative ρ^R could be obtained.

Turning to the estimation of the determinants of the share of land in the housing production function, we follow a similar two-step procedure and estimate:

$$\begin{aligned} b_p \;&=\; \beta_{c(p)} + \;\delta^B \log dis_p + X_p^P\,\varphi^B + X_{d(p)}^D\,\varphi^B + \zeta_p \\ \widehat{\beta}_c \;&= \alpha^B \log pop_c + \eta^B \log area_c + \rho^B \log mig_c + \mu^B \log w_c + X_c^C\,\psi^B + \kappa^B + \mu_c\,, \end{aligned} \tag{9}$$

where b_p is the land share in housing production on parcel p, from which we can get the land share β_c for a representative parcel in the city that enters $\epsilon_c^{C,k}$, captured by a city fixed effect. The control variables are the same as those defined in equations (6) and (7). κ^B is a constant and ζ_p and μ_c are random components. Superscripts P, D and C correspond to the level of observation, for parcel, district and city respectively. Expected signs for city characteristics are the same as for land prices since, assuming that non-land input prices in the housing production do not vary much across space compared to land prices, and that the markets for land developers are competitive, housing positive demand (supply, respectively) effects translate into an increase (decrease, respectively) of the land share in the housing production.

Finally, we estimate the housing budget share separately for type-k (high- and low-skilled) household heads, using the same two-step procedure.[10] Let γ_c^k be a city c fixed effect corresponding to the household budget share parameter that enters $\epsilon_c^{C,k}$is. We assume that the budget share g_h^k of household h located in district $d(h)$ in city $c(h)$ is given by:

$$\begin{aligned} g_h^k &= \gamma_{c(h)}^k + X_h^H \lambda^{G,k} + \delta^G \log dis_{d(h)} + \mu^{G,k} \log w_h + X_{d(h)}^D \varphi^{G,k} + \sigma_h \\ \widehat{\gamma_c^k} &= \alpha^{G,k} \log pop_c + \eta^{G,k} \log area_c + \rho^{G,k} \log mig_c + X_{c(i)}^C \psi^{G,k} + \kappa^{G,k} + \phi_c \end{aligned} \tag{10}$$

where the labelling of variables is the same as in (9). Following again Combes et al. (2019), the housing budget share is assumed to vary with location and household characteristics, including not only those that may shape their housing preferences (age, education, home ownership, family structure) but also the household's income, w_h.[11] The same district-level variables, including distance to the centre, are introduced, except for those directly related to land supply factors that have no obvious influence on preferences. City population and area are expected to have an effect of the same sign as for land prices, positive and negative respectively. Finally, to match what is assumed for land price, land share and income, we also control for the city migrant share.

2.3 Estimation issues

A first concern in assessing the role of location on individual outcomes is the potential non-random spatial sorting of individuals based on characteristics that directly affect the outcome. For instance, a large literature shows that failing to properly control for individual skills may lead to overestimate agglomeration gains by a factor of 2 (Combes and Gobillon, 2015). To address this issue, we use individual data and control for the characteristics of the parcels in the estimation of land prices and of the land share in housing production, and

[10] We consider households rather than individuals as this is the level at which housing decisions are usually made.

[11] This accounts for possibly non-homothetic preferences. Our household-level data allow us to directly consider the role of each household income rather than relying solely on the city average, which is therefore removed from the estimation of the second step.

for households' characteristics in the estimation of the housing expenditure share. While concerns may still arise if sorting on unobserved characteristics occurs, the use of individual fixed effects for instance is rare in the literature on housing costs, mostly because of the scarcity of repeated sales and other biases associated with them.

Another major concern in estimating Equation (7) (and similarly, Equations (9) and (10)), to which the literature has paid most of its attention, is the endogeneity of local characteristics, mostly city size that reflects in the city population and area variables, and the share of rural migrants. Some of the control variables can also be affected, albeit to a lesser extent.

Endogeneity may arise from missing local variables that affect both population and prices, or from reverse causality, as high housing and land prices can deter households from migrating to the city. For instance, a positive shock to the productivity of firms located in the city can simultaneously boost local land prices, since land is an input used by firms, and attract workers because of the resulting income shock, thereby increasing the population (and area in turn). This process tends to generate an upward bias in estimating the population impact. Conversely, reverse causality from households choosing to locate where housing prices are low would induce a downward bias. To address these concerns, we rely on standard instrumental variable tools proposed by the literature to assess whether large biases can be expected, as the primary purpose of the present article is not to specifically contribute to this dimension. Section 5 presents OLS estimation results, while Section 7 reports various estimations where population, area and migrant share are instrumented. IV estimations confirm the literature's findings that endogeneity biases do not seem to be of primary concern, and that they do not affect our conclusions, only slightly reinforcing the trends we document.

Three sets of instruments are used. The first set is inspired by Roback (1982)'s model where exogenous amenities determine population, and in turn area, but do not directly determine land prices. In the spirit of the literature on urban growth, we construct three proxies for collective natural amenities: a city-level count of "AAAAA (5A)" scenic spots, a count of starred hotels and a climate indicator on sunshine duration in January (over the period 1960-2010).[12] These three instruments isolate the variation in city population driven

[12] 5A is awarded to the most important and best-maintained tourist attractions in China by the Chinese Ministry of Culture and Tourism. As of 2020, there are 279 tourist attractions listed as 5A. To determine the number of starred hotels in each city, we rely on 2011 POI data (see Appendix A). The sunshine duration data

by amenities.

The second set of instruments follows a long tradition in the urban literature since at least Ciccone and Hall (1996), and consists of using long lags of city population and land area. These historical values are usually relevant as the hierarchy of cities is pretty stable even in the very long run, but arguably orthogonal to the supply and demand of housing shocks today. We use the 1982 and 1990 National Population Censuses of China to construct instrumental variables measuring city population and land area for these two census years. Given the context of China, historical variables from 1982 and 1990 are deemed to be sufficiently exogenous as the implementation of market reforms, particularly with regard to land and housing markets, and the acceleration of economic changes occurred mainly after the mid-1990s. Following Au and Henderson (2006), we also use the historical rural population of provincial or prefecture-level cities, measured in 1990, as it is the base for much of migration into nearby cities.[13]

Third, to more specifically address the endogeneity of the city migrant share, we use past migration flows predicted by Combes et al. (2020), who use a gravity model based on the distance between migration origin and destination and apply it to historical data from the 1995 National One Percent Sample Population Survey and from the 2000 National Population Census. We use this variable as an additional instrument when simultaneously instrumenting population, area and migrants. This instrument is motivated by the idea that migration patterns are relatively stable over time and the role of distance in particular is present at any period, but, reversely, the distance predicted value of migrant inflows does not drive the current demand and supply of housing. Lagging in time further reinforces the exogeneity condition, with the same intuition as for historical instruments.

3 Data

Implementing the regressions described in Section 2.2 requires measures for land prices, land share in housing production, and housing expenditure share. Data sources for these variables

is obtained from the Urban Meteorological Data maintained by the China Meteorological Administration.

[13]As documented in Cheng and Duan (2021), migration flows to cities were minimal during the 1980s and 1990s, but started to accelerate towards the late 1990s, coinciding with the relaxation of the stringent constraints of the *Hukou* system initiated in 1997.

are briefly described below, while Appendix A provides a full description of these sources and additional city-level data used in the estimations. Our analysis focuses on 4 provincial-level cities (Beijing, Shanghai, Chongqing, and Tianjin) and 250 prefecture-level cities, gathering data for the core city (*shixiaqu*) or city proper only, the urban part of prefecture-cities. City centres are defined as the brightest cell(s) in each city identified with nighttime light data.

Land prices are extracted from the Land Transaction Monitoring System website, which records all primary land market transactions in China from 2007 to 2019, totaling 2,233,917 observations. We include only transactions with market-mediated methods in core cities, resulting in 66,973 residential land transaction records after data cleaning and geo-coding. A robustness check in Appendix C.1 considers all kinds of residential land transactions involving 190,042 observations.

Data on residential development projects (RDPs) with new properties for sale between 2010 and 2022 are sourced from the two largest online real estate agencies in China, Anjuke and Lianjia. RDPs are matched to land parcels using geo-coded information, resulting in 47,421 matched pairs in 146 cities. The land cost share is calculated as the ratio of the parcel's unit price to the RDP's average housing price multiplied by its floor area ratio.

Finally, the Chinese Household Income Project (CHIP) survey data from 2007, 2013, and 2018 provide information on income, expenditure, and composition for urban households. The sample includes 6,595 households across 66 representative cities in 2007, 3,721 households across 98 cities in 2013, and 5,329 households across 88 cities in 2018. The housing expenditure share is computed using imputed rents for homeowners and actual rental payments for renters.

An obvious limitation of the data on land and housing shares is that the set of cities is smaller than the set covered by the comprehensive land price data. However, given the available data sources, this is the best that can currently be done for China. Additionally, there is no reason to believe that the city sample is biased in any particular way, such as in terms of size. In particular, the CHIP data sample is specifically chosen to be representative. Despite this limitation, our approach improves on the usual practice, as the literature often relies on even stronger assumptions, typically that these shares are constant across cities (Albouy, 2008; Moretti, 2013).[14]

[14] Although Combes et al. (2019) do not make this assumption, their estimation of the housing expenditure

4 Within- and between-city land prices disparities

Table 1 reports descriptive statistics for our variables of interest regarding city size, land prices, land share, and housing expenditure shares. The average parcel area for residential land is close to 49,000 square meter and it sells for an average of US$675 per square metre.[15] The average land share in housing production is 32%, and households spend on average 25% of their monthly expenditure on housing (with only slight differences between high-skilled and low-skilled households).[16] The average land share in our sample aligns with the levels found for Western countries, including Germany (0.32), the US (0.36), France (0.39), and the UK (0.54) (Knoll et al., 2017). Similarly, the average housing expenditure share is comparable to that of the US (0.23-0.32), France (0.31), the UK (0.15-0.31), and Germany (0.25-0.33) (Ahlfeldt et al., 2015; Combes et al., 2019; Ahlfeldt and Pietrostefani, 2019; Ahlfeldt et al., 2021; Overman and Xu, 2022).

Beyond the average, Table 1 also highlights large disparities between cities. Land prices vary by a factor of 25, ranging from a low of US$64 per square meter in a city at the first decile to a high of US$1,543 per square meter in a city at the ninth decile. Similarly, the land share in housing production for a residential development project in the third quartile is approximately 65% larger than in the first quartile. Finally, high-skilled (low-skilled) households in the first decile spend 9% (12%) of their monthly expenditure on housing, while those in the ninth decile spend about 40 percentage points more.

As detailed in Section 2, within-city variations must be controlled to properly assess between-city differences. Although these variations are not our primary focus, documenting land price variations within cities provides valuable insights into urban development in China. Figure 1 plots the logarithm of unit land prices against the logarithm of the distance between a land parcel's centroid and the barycentre of its city for 4 representative cities separately: Shanghai, the most populated city in China; Lanzhou, a province capital city in

share is constrained to a one-step specification due to the limited number of cities in their dataset compared to their land parcel transaction data.

[15] As documented by Tan et al. (2020), condominium units prevail in urban China, and RDPs typically provide housing for more than 500 households. This explains the large average parcel area compared to countries like France where individual houses are common.

[16] Using information on the level of education of the household head from the CHIP surveys, we classify registered urban households as high-skilled households if the household head has at least 12 years of education and as low-skilled households otherwise.

Table 1: Descriptive statistics

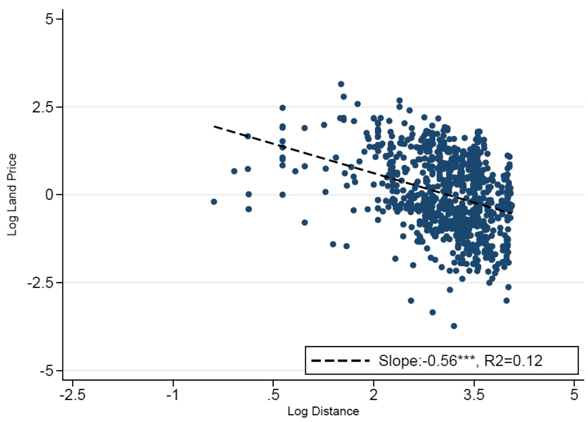
Variable	Mean	St.Error	1^{st} decile	1^{st} quartile	Median	3^{rd} quartile	9^{th} decile
Panel A. City characteristics (254 cities, 3,209 obs.)							
Population (city proper, '000)	1,969	2,950	506	694	1,130	1,929	3,604
Land area (city proper, km^2)	2,587	3,806	490	1,020	1,850	2,951	4,767
Number of districts per city	5	4	2	3	4	6	11
Panel B. Residential land characteristics (254 cities, 66,973 obs.)							
Price (US$/$m^2$)	675	1,136	64	136	310	722	1,543
Parcel area (m^2)	48,966	62,827	3,334	11,147	32,475	67,688	113,499
Panel C. Land share in housing production (146 cities, 47,421 obs.)							
Overall	.32	.11	.19	.23	.3	.38	.47
Panel D. Household housing expenditure share (137 cities, 15,645 obs.)							
Overall	.25	.21	.04	.1	.2	.34	.51
High-skilled households	.24	.21	.04	.09	.19	.33	.5
Low-skilled households	.26	.21	.05	.12	.21	.35	.51

Notes: Data pooled over all available years. Prices in current US$. High-skilled households are households whose head has at least 12 years of education.

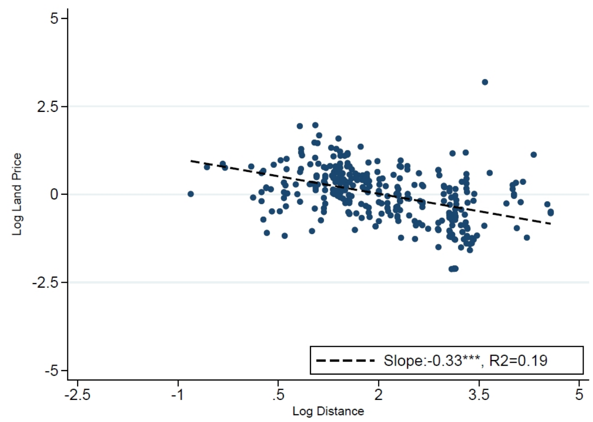
the Northwest close to the sample average population with 2.15 million inhabitants; Yichun, a city in Central China just below the median with 1.19 million inhabitants; and Huaihua, a city in Southwestern China at the first decile, with a population of 0.56 million people. Two patterns emerge from Figure 1. First, all four plots display a monocentric pattern with a city-specific gradient. This is consistent with the monocentric city model and the Alonso-Muth condition, where land price gradients match the marginal cost of commuting to jobs that are more abundant near the centre. Second, the distance gradient is steeper in more densely populated cities, possibly due to transport congestion. These two findings align with observations for developed countries, as documented by Combes et al. (2019) for France, Ahlfeldt et al. (2015) for Germany, and Albouy et al. (2018) for the US.

To visualize the distribution of the price-distance gradients across all cities, Figure 2 plots the estimated price-distance gradient for each city in ascending order, highlighting the ranks of the four representative cities. Panel (a) includes no control variables, while Panel (b) depicts the distribution of the estimated gradients conditional on all parcel and local controls introduced in equation (6). The figure reveals a robust pattern, with only slightly lower distance gradients in absolute value when controls are introduced. Shenzhen, in Guangdong province, ranks first with a price-distance gradient of around -0.9 (bottom-left of the graph), which is very close to the estimates for Paris (around -1) in Combes et al.

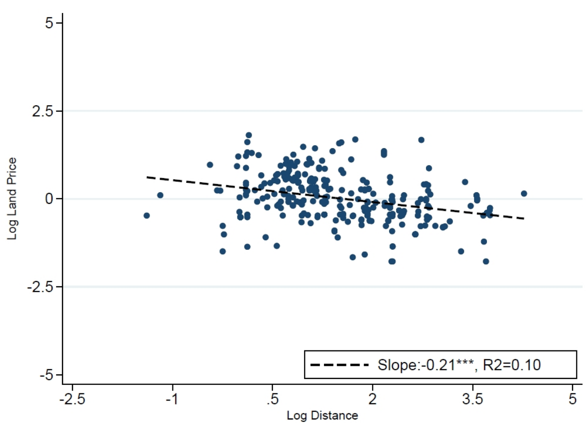
Figure 1: Residential land prices per square metre and distance to the centre for four cities



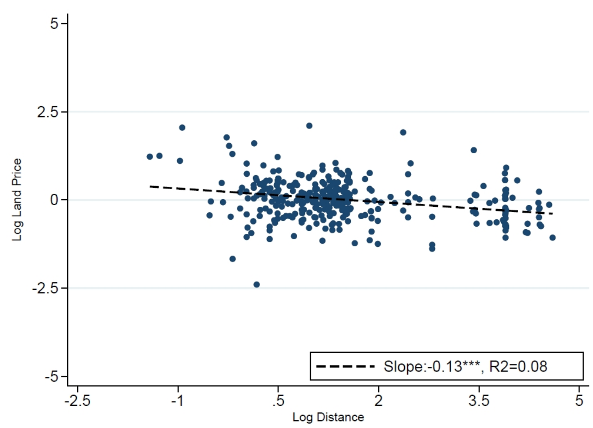
Panel (a): Shanghai



Panel (b): Lanzhou



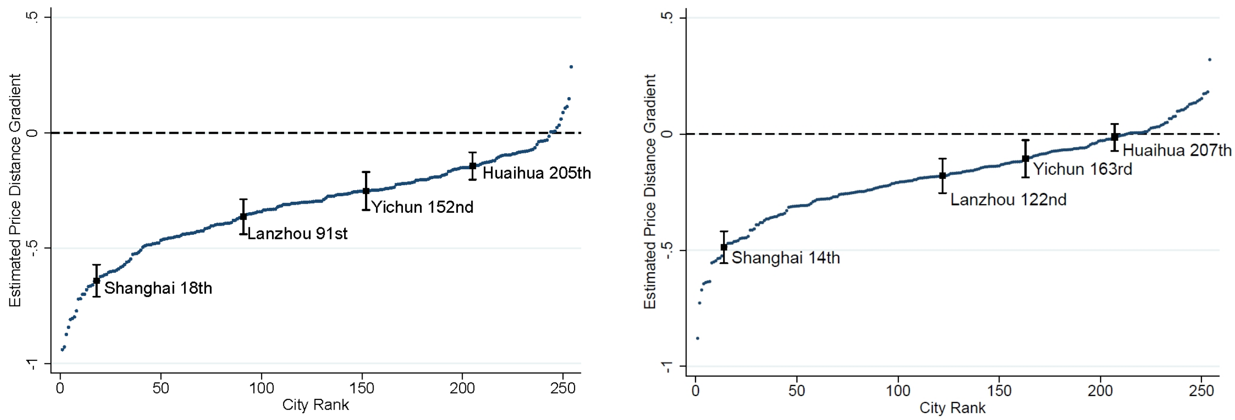
Panel (c): Yichun



Panel (d): Huaihua

Notes: Panels (a) to (d) plot the land price-distance gradient for 4 representative cities, namely Shanghai, Lanzhou, Yichun, and Huaihua. The logarithm of the distance between the land parcel and the city center is shown on the horizontal axis, while the vertical axis represents the residualized logarithm of the land transaction prices de-trended with respect to city-year fixed effect. Each sub-figure also features a dashed line corresponding to a linear fit, and its coefficient and R^2 are reported in the right-bottom corner.

Figure 2: Residential land price-distance gradient for all Chinese cities



Panel (a): All cities (without controls)

Panel (b): All cities (with controls)

Notes: Panel (a) provides an overview of the land price-distance gradient for all Chinese cities by plotting the estimated gradient against the city's rank in ascending order. Panel (b) duplicates panel (a) with a full set of control variables when calculating the residualized logarithm of the land transaction prices.

(2019) or for Chicago (-0.84) in Ahlfeldt and McMillen (2018). At the other end of the distribution, still with all controls, 11 relatively small cities display a positive price-distance gradient, with only two showing a gradient significantly different from zero. Out of the 254 cities, 208 exhibit significantly negative gradients.

To further document the within-city land price variation, we use the first-step estimation for the price of residential land parcels as specified in equation (6). As described in Section 2.2, Equation (6) estimates an individual land price equation that controls for the distance to the city center, with fixed effects representing land prices at the centre. It also includes controls for parcel characteristics, geography and geology, education and consumption amenities. Table 2 presents various quantiles of the distribution of the city fixed effects (with the mean normalized to zero) and of the log distance effect, along with the R^2 for specifications that vary in the number of controls.

Column 1 includes only parcel characteristics, such as the log parcel area, its square, and a dummy for the land parcel transaction type. With only 2% of the variance explained, the explanatory power of the parcel characteristics is much lower than in developed countries (e.g., 48% in France (Combes et al., 2019)). A primary factor contributing to this low explanatory power is the homogeneity of residential land parcels in our restricted sample, especially in terms of their size. The standard deviation of the parcel size is only 1.5 times the mean, indicating notable consistency.[17] Column 2 excludes parcel characteristics and includes only city-year fixed effects, which explain 46.9% of the variance of residential unit land prices. This emphasises the importance of location at the macro-geographical level, between cities. Column 3 extends the specification by adding a city-specific distance effect. The larger R^2 at 56.4% confirms that land prices also vary a lot within cities, declining regularly from the centre to the periphery. The substantial variation in gradients between cities observed in Figure 2 is also confirmed, as the gradient at the first quartile is 6 times larger than at the third quartile when all controls are included.

Table 2: Summary statistics from parcel land prices estimates (first step)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
City effect								
Bottom 5%		-1.047	-1.566	-1.523	-1.513	-1.514	-1.459	-1.415
1^{st} quartile		-.451	-.644	-.678	-.664	-.649	-.635	-.612
Median		-.068	-.221	-.206	-.21	-.201	-.181	-.173
3^{rd} quartile		.378	.457	.497	.488	.443	.446	.425
Top 5%		1.228	2.271	2.336	2.352	2.326	2.251	2.208
Log distance effect								
Bottom 5%			-.7	-.691	-.677	-.645	-.607	-.551
1^{st} quartile			-.448	-.433	-.431	-.387	-.331	-.284
Median			-.28	-.271	-.274	-.255	-.193	-.166
3^{rd} quartile			-.164	-.165	-.159	-.133	-.078	-.047
Top 5%			.008	.032	.032	.055	.093	.132
Observations	66,973	66,973	66,973	66,973	66,973	66,973	66,973	66,973
R^2	0.020	0.469	0.564	0.573	0.574	0.576	0.579	0.583
Controls								
Parcel charac.	Y			Y	Y	Y	Y	Y
Geography and geology					Y			Y
Education						Y		Y
Consumption amenities							Y	Y

Notes: All columns perform OLS regressions using Equation (6). All reported R^2 are within-year. The urban area effects are averaged over time weighting each year by its number of observations. Land parcel characteristics include log parcel size, its square, and the transaction method (English auction, two-stage auction, or bilateral agreement). Geography and geology characteristics consist of the district-level standard deviation of elevation, share of water body, and mean slope. Education variables include the district-level share of high school/college degrees and share of university degrees in the working-age population. Accessibility to consumption amenities is measured by the number of each kind of amenity (schools, hospitals, public parks, and public transportation facilities) within a 2–km radius surrounding a parcel. All district- and neighborhood-level controls are centered relative to their city mean.

Column 4 adds parcel characteristics to location effects, while columns 5, 6 and 7 enrich the specification with the household, land supply, and geography controls. Column 8 includes

[17] When the full sample is used, which includes non-market-based transactions, parcel characteristics become more important, accounting for over 30% of the variations in land prices (see Appendix Table A1).

all parcel and local variables. The controls have a limited impact, partly because distance to the center is controlled for and many variables correlate with it, as expected from theory. The estimates for city effects and distance effects remain very stable across specifications. Specifically, the pairwise correlation between the city effects estimated in columns 3-8 is strong (0.9 or above), and a similar pattern holds for distance effects (0.98 or above).[18]

Finally, the first lines in Table 2 shed light on between-city disparities in city fixed effects (i.e., land prices at the city center) and reveals distinct patterns. Notably, cities at the first quartile and the median of fixed effects show a negative gap in land prices of 46% and 16%, respectively, compared to cities at the mean (with a 76% gap for cities at the bottom 5%). Conversely, cities at the third quartile exhibit higher unit land prices at the city center, 53% above the average city (810% for the top 5%).

5 City determinants of housing costs

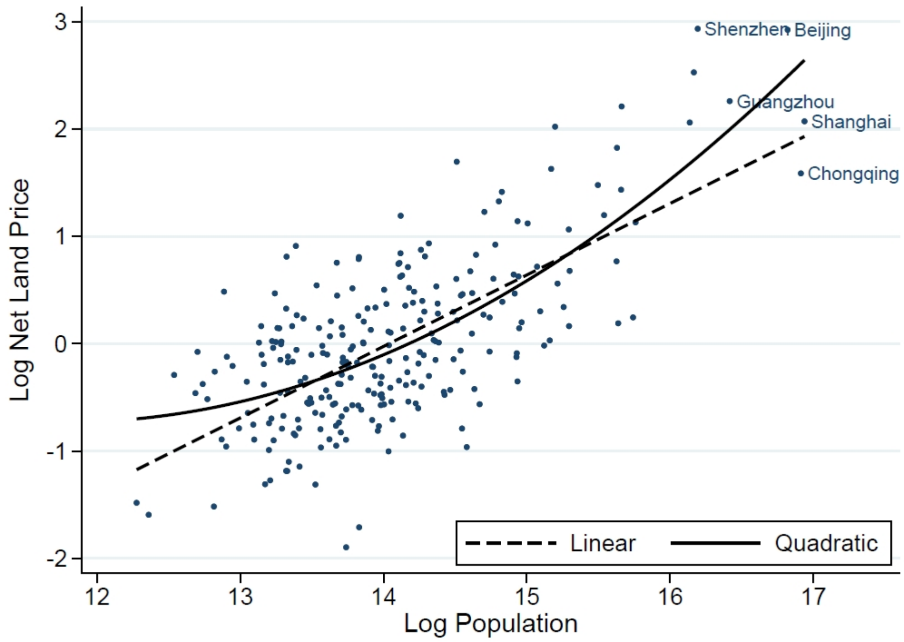
5.1 Land prices, land share and housing share

As detailed in Section 2.2, we employ a two-step procedure. Table 3 summarizes the second-step OLS estimation. First-step estimations and robustness checks including IV are presented in section 7 and Appendices C and D, respectively. To complement the estimation results, Table 4 illustrates how the population elasticity of land prices at the city center (Panel A), the share of land in housing production (Panel B) and the share of housing in household expenditure (Panel C) vary for four hypothetical cities of different population size. We consider two scenarios for each panel: one that does not allow the city fringe to adjust, i.e., where the city land area is fixed, and another that permits such an adjustment.

Residential unit land prices As a preliminary visualization, Figure 3 plots the logarithm of the unit land price at the city center, net of all control variables except population, against the logarithm of city population. A very strong positive correlation emerges. Whereas both linear and quadratic models yield similar predictions for cities with a population below 3.2 million inhabitants, the largest cities like Beijing or Shenzhen display unit land prices well

[18]These robust estimates are important because we use these fixed effects as the dependent variables in the second step. Further robustness checks are provided in Appendix C.1.

Figure 3: Net log unit land prices vs log city population



Notes: The logarithm of the city population is depicted on the horizontal axis, while the vertical axis represents the residual of the second step incorporating all controls in both steps (column 8, Table 2), plus the estimated effect of the city population. The dashed and solid lines correspond to linear and quadratic fits, respectively. Mean prices across cities are normalized to zero.

above the linear prediction, reflecting a stronger response of land prices to population. This convex pattern is consistent with standard urban economics predictions of increasing land congestion in larger cities.

Column 1 of Table 3 presents the pooled cross-section land price estimation of Equation (7). The point estimates for population and its square confirm the non-linear relationship observed in Figure 3. Using these estimates, Panel A of Table 4 illustrates how the estimated population elasticity of unit land prices, defined in Equation (8), varies with city size when city land area is fixed. The elasticity spans from 0.335 for a small city of 500,000 inhabitants (1^{st} decile of population) to 0.559 for a city with 1 million inhabitants (approximately the median), 0.782 for a city with 2 million inhabitants (approximately the mean), and 1.582 for a mega-city of 24 million inhabitants like Shanghai. Hence, at given land area, average income and migrant share, the city population drives unit land prices up, with this effect becoming more pronounced as the city size increases. For instance, a 10% population increase in the four hypothetical cities would raise unit land prices by 3.4%, 5.6%, 7.9%, and 16.4%, respectively.

Similarly, we compute the land area elasticity of unit land prices, as defined in Equation (8). It varies from -0.08 for a small city with an area of 500 km^2 (1^{st} decile) to -0.255 for a city covering 2,000 km^2 (approximately the median), -0.306 for a city covering 3,000 km^2 (approximately the mean), and -0.632 for the largest city with an area of roughly 40,000 km^2. The negative impact of land area reflects the role of increasing land supply at given demand, which also presents a convex shape.

Letting the city fringe expand when population increases mitigates the rise in unit land prices, as shown in column 2 of Table 3 where land area is not controlled for.[19] This finding is consistent with the monocentric city model's prediction, as land supply can now adjust in response to a larger population. The corresponding population elasticities of unit land prices are displayed in Panel A of Table 4 under 'Allowing for land area expansion'. For a small city, the population elasticity is slightly higher than without area expansion, at 0.374, primarily because of a minor change in convexity. However, for other cities, population elasticities are smaller, at 0.503 for a median-sized city, 0.632 for an average-sized city, and 1.094 for a mega-city, representing a 30% reduction thanks to land area adjustment.

Interestingly, the estimated population elasticity of unit land prices in China is close to that of France, while the land area elasticity is much lower (Combes et al., 2019). Land use regulation seems to be less stringent in urban China, resulting in a less sensitive response of land prices to horizontal expansion (Tan et al., 2020), although the sensitivity remains relatively high for the largest cities. A plausible explanation also lies in the role of local politicians in China. As argued by Wang et al. (2020), Chinese city leaders have strong promotion incentives to expand cities.

Last, holding city population and land area constant, the income elasticity of land prices is significantly positive. This corresponds to a demand effect wherein richer residents have larger housing consumption. The coefficient on the migrant share is positive but not statistically different from zero. This is not surprising since the overall population is controlled for, and migrants may impact land prices through two opposite channels as highlighted in Section 2.2.

[19]In the context of China, the land area of a city changed over time, as observed during our study period from 2007 to 2019. For example, Beijing incorporated two counties in 2015, Miyun (2,229.5 km^2) and Yanqing (1,994.9 km^2).

Table 3: City determinants of unit land price, land share, and housing expenditure share

Dep. Variable	Land Price		Land Share		Housing Share High-skilled		Housing Share Low-skilled	
Allowing for urban expansion		Y		Y		Y		Y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log population	-3.890^a	-2.067^c	0.020^a	0.010^b	0.034^a	0.038^a	0.036^a	0.039^a
	(1.061)	(1.100)	(0.006)	(0.005)	(0.009)	(0.008)	(0.010)	(0.010)
Log population sq.	0.161^a	0.093^b						
	(0.037)	(0.038)						
Log land area	0.703^a		-0.013^a		0.010		0.007	
	(0.227)		(0.005)		(0.010)		(0.007)	
Log land area sq.	-0.063^a							
	(0.016)							
Log income	0.592^a	0.523^a	0.055^b	0.048^b	-0.043^a	-0.043^a	-0.046^a	-0.046^a
	(0.158)	(0.169)	(0.021)	(0.022)	(0.006)	(0.006)	(0.007)	(0.007)
Log migrant share	0.293	0.382	0.029	0.036	0.069	0.064	0.086	0.086
	(0.249)	(0.264)	(0.023)	(0.024)	(0.051)	(0.049)	(0.063)	(0.062)
Observations	3,209	3,209	1,223	1,223	246	246	246	246
R^2	0.64	0.62	0.30	0.29	0.31	0.30	0.24	0.24
Controls								
Past population growth	Y	Y	Y	Y	Y	Y	Y	Y
Education variables	Y	Y	Y	Y				
Geography and geology variables	Y	Y	Y	Y	Y	Y	Y	Y
Land use variables	Y	Y	Y	Y	Y	Y	Y	Y

Notes: OLS estimates. The dependent variable is a city-year fixed effect estimated in the first step, corresponding to equations (6) for columns 1-2, (9) for columns 3-4, and (10) for columns 5-8. The coefficient for income reported in columns 5-8 is estimated in the first step, see equation (10). Estimation results for both steps are detailed in Section 7. Even columns allow for city fringe expansion by excluding land area. City-level controls include past annualised population growth during 1990-2005, education variables (share of high school/college degrees and share of university degrees), geography and geology variables (standard deviation of elevation, share of waterbody, and mean slope), and land use variables (share of residence-, production-, commerce-use land in stock within urban built-up area, and dummy for coastal province).

Land share in housing production Column 3 of Table 3 reports estimates of the city determinants of the land share in housing production, as specified in Equation (9). As quadratic terms for population and land area are not significant when added to the specification, we prefer to use a linear specification rather than one with non-significant quadratic terms when computing housing costs in Section 5.2. The semi-elasticity of the land share in housing production at the city center with respect to population is estimated at 0.02. This is consistent with standard urban economics models where the share of land in housing production increases with urban development (Fujita and Thisse, 2013). Moreover, more populated cities with an expensive housing market tend to be more regulated and have less elastic housing supply, resulting a higher land share in housing production (Glaeser and Gyourko, 2018). As reported in column 4, allowing for urban expansion lowers the population elasticity of land share to 0.01. At a given population, the positive and significant effect of income also reflects a positive housing demand effect on the land share, while the statistically significant negative coefficient for land area captures a positive supply effect. Finally, the share of migrants plays no significant role in explaining the cross-section variations of the land share in housing production.

Next, we quantify how much larger the share of land in housing production is in larger cities. We first compute the land share in housing production at the city center for the average city in the RDP dataset, denoted β_m, using the estimation from the first step. For the average city with a population, pop_m, at 3.94 million, $\beta_m = 0.33$. This corresponds to the scenario with land expansion. If land expansion is not allowed, we can use the difference in population elasticities between columns (3) and (4) in Table 3 to compute the average land area share, yielding $\beta_m = 0.48$. Then, the land share of housing production in a city with population pop_c can be predicted, all other things equal, as follows:

$$\beta_c = \beta_m + \alpha^B (\log pop_c/pop_m) \tag{11}$$

where $\alpha^B = 0.02$ and $\alpha^B = 0.01$ are the marginal effect of population when controlling or not for land area (Equation 9 and Table 3).

As reported in Panel B of Table 4, the land share in housing production when city area expansion is not allowed equals 0.44, 0.45, 0.47 and 0.52 for cities with 500,000, 1 million, 2 million and 24 million inhabitants, respectively. When the city fringe can expand, these values decrease to 0.31, 0.32, 0.32 and 0.35, respectively. The estimated average value when allowing for city expansion is consistent with the mean land share of 0.31 for 30 major Chinese cities calculated by Tan et al. (2020). This is also comparable in magnitude to estimates for France, where it ranges from 0.35 in the smallest cities to 0.46 in Paris (Combes et al., 2021), particularly considering that land area adjusts less there.

Housing expenditure share Table 3 present the results of semi-elasticity estimations for the household housing budget share (of)Equation (10)), separately for the sub-samples of high-skilled households (columns 5 and 6) and low-skilled households (columns 7 and 8). The estimates suggest a semi-elasticity of housing expenditure share with respect to population of 0.034 for high-skilled households and 0.036 for low-skilled households.[20] City land area and the share of migrants play no significant role in explaining the housing expenditure share across cities. Conversely, household income, controlled for in the first step, exhibits a significantly negative impact. This aligns with non-homothetic preferences for housing, as commonly found in empirical studies (Combes et al., 2019; Dustmann et al., 2022).

Let γ_m^k denote the share of housing expenditure at the city center for the average city of the sample of type-k households, computed from the first step. It equals 0.24 for high-skilled households and 0.26 for low-skilled households. As land area does not significantly impact the housing budget share, it takes the same value regardless of whether land area expansion is allowed. These estimates are very close to the national average of 0.24 in 2021, as reported by the National Bureau of Statistics of China, which, however, does not control for any effect.[21] Then, we can compute the housing expenditure share for each type of household in any city with population pop_c as:

$$\gamma_c^k = \gamma_m^k + \alpha^{C,k} \left(\log pop_c / pop_m\right) \tag{12}$$

where $\alpha^{C,k}$ is the marginal effect of population (Equation 10, columns 5 and 7 in Table 3).

As shown in Panel C of Table 4, the housing expenditure share in cities with 500,000, 1 million, 2 million and 24 million inhabitants is 0.18, 0.20, 0.23, and 0.31 for high-skilled households and 0.20, 0.22, 0.25, and 0.34 for low-skilled households. The slightly higher share estimated for low-skilled households is consistent with a stronger preference of these households for housing, possibly due to different family structure, and it should not reflect any income effect as income is controlled at the household level.

5.2 Population elasticity of housing costs

Panel D of Table 4 reports the population elasticity of housing costs defined in Equation (5) and computed by multiplying the values provided in Panels A, B, and C. As expected, the elasticity of housing costs increases with city population, given that all three components of housing costs increase. A 1% increase in population results in housing costs rising about 10 times more for a mega-city than for a small city (the elasticity changes from 0.027 to 0.255).

[20] As for land share in housing production, quadratic effects for population and area are ignored here as they are not significant when included.

[21] http://www.stats.gov.cn/english/PressRelease/202201/t20220118_1826649.html

Doubling population from 500,000 to 1 million nearly doubles the population elasticity of housing costs (from 0.027 to 0.052), and when population doubles from 1 to 2 million, the elasticity further increases by 60% (0.052 to 0.083).

Table 4: Population elasticity of housing cost

Population	Small city 500,000	Median city 1 million	Average city 2 million	Mega-city Shanghai
Panel A. Population elasticity of unit land prices				
Not allowing for city area expansion	0.335	0.559	0.782	1.582
Allowing for city area expansion	0.374	0.503	0.632	1.094
Panel B. Land share in housing production				
Not allowing for city area expansion	0.440	0.454	0.467	0.517
Allowing for city area expansion	0.309	0.316	0.323	0.348
Panel C. Share of housing in households' expenditure				
High-skilled workers				
Not allowing for city area expansion	0.180	0.204	0.228	0.312
Allowing for city area expansion	0.180	0.204	0.228	0.312
Low-skilled workers				
Not allowing for city area expansion	0.197	0.222	0.247	0.336
Allowing for city area expansion	0.197	0.222	0.247	0.336
Panel D. Population elasticity of overall housing costs				
High-skilled workers				
Not allowing for city area expansion	0.027	0.052	0.083	0.255
Allowing for city area expansion	0.021	0.032	0.047	0.119
Low-skilled workers				
Not allowing for city area expansion	0.029	0.056	0.090	0.275
Allowing for city area expansion	0.023	0.035	0.050	0.128

Notes: In row 1 of Panel A, the estimates of the unit land price population elasticity are marginal effects calculated from Table 3, column 1. In row 2, we use estimates that do not include city land area as a control (Table 3, column 2). Panel B uses the estimate from columns 3 and 4 of Table 3, and Panel C uses the estimates from columns 5-8 of Table 3. Panel D reports the housing cost elasticity obtained by multiplying the housing expenditure share, the land share in housing production, and the population elasticity of land prices, as defined in Equation (5).

When the adjustment of the city fringe is allowed, the elasticity of housing costs with respect to city population drops by 53% for the largest cities, and by 43%, 38% and 21% for cities with 2 million, 1 million and 500,000 inhabitants, respectively. Therefore, letting the fringe adjust or not when the city population expands is an important decision for policymakers regarding its impact on housing costs, especially for the largest cities.

The population elasticity of housing costs also varies slightly between low- and high-skilled households. Housing costs increase slightly less (by approximately 10%) in response to a city population increase for high-skilled households, thanks to their lower housing expenditure share.

6 Real income gains from moving to larger cities

The preceding section has shown that housing costs increase in a convex way when cities get larger. However, the spatial concentration of economic activities also triggers productivity gains that translate into nominal income gains. In this section, we shift our focus to the balance between these two countervailing effects for household utility. Do households experience an increase in real income when they move to larger cities, and does this differ for low- and high-skilled households?

6.1 Population elasticity of nominal income and real income

To answer these questions, we begin by calculating the population elasticity of nominal income, $\epsilon_c^{W,k}$ in Equation (2), for high- and low-skilled households separately, using the values estimated by Combes et al. (2020).[22] We aim to compare the population elasticity of income with and without controlling for land area, as for the housing elasticity estimations. We also want to control or not for the presence of migrants, as they now play a significant role on income. Since we do not have income estimations that do not control for area or migrants, we evaluate the population elasticity allowing for land area expansion using the following procedure. First, we regress the logarithm of land area on the logarithm of population, using the same controls as in housing estimations. We then multiply this population elasticity of land area by the land area elasticity in the income estimation. Finally, we add this product

[22] Table 2 Panel (b), columns (1) and (4) for high- and low-skilled workers respectively. Since the specifications are in logarithm, the coefficient for land area in the income specification is obtained as the difference between the coefficient for land area and the coefficient for density in the original estimations. This coefficient is not significantly different from zero for low-skilled households. Moreover, the migrant variable is measured as the ratio of the number of migrants to the number of low-skilled workers, rather than to the total population as in housing cost estimations. Acknowledging a slight abuse of notation, we retain the same variable label despite a different denominator. Last, the income estimations use employment rather than population (density). Given the very high correlation between population and employment across cities, the elasticities of income with respect to these two variables are typically very similar, as documented in the literature (Combes and Gobillon, 2015). Therefore, we use the population variable for employment in our computations as there is no way to simply compute employment for each year with the precise city definition we use.

to the population elasticity. We use a similar procedure to obtain a population elasticity that does not control for the share of migrants.

As shown in Panel A of Table 5, the population elasticity of nominal income is slightly higher for high-skilled households (0.066) than for low-skilled households (0.064), and it does not vary across the four hypothetical cities because of the linear nominal wage estimation equation in Combes et al. (2020). If we allow for the adjustment of the city fringe, the elasticity increases by 48.5% (to 0.098) for high-skilled households but remains unchanged for low-skilled households, as land area does not bring them any additional gains. Finally, if we also allow for an increase in the migrant share, the population elasticity of nominal wage rises to 0.244 for high-skilled households and to 0.149 for low-skilled households who also benefit, although to a lesser extent, from migrant workers.

Table 5: Population elasticity of nominal income and real income

Population	Small city 500,000	Median city 1 million	Average city 2 million	Mega-city Shanghai
Panel A. Population elasticity of nominal income				
High-skilled workers				
Allowing for neither city area nor migrant share changes	0.066	0.066	0.066	0.066
Allowing for city area but not migrant share changes	0.098	0.098	0.098	0.098
Allowing for both city area and migrant share changes	0.244	0.244	0.244	0.244
Low-skilled workers				
Allowing for neither city area nor migrant share changes	0.064	0.064	0.064	0.064
Allowing for city area but not migrant share changes	0.064	0.064	0.064	0.064
Allowing for both city area and migrant share changes	0.149	0.149	0.149	0.149
Panel B. Population elasticity of real income				
High-skilled workers				
Allowing for neither city area nor migrant share changes	0.039	0.014	-0.017	-0.189
Allowing for city area but not migrant share changes	0.077	0.066	0.051	-0.021
Allowing for both city area and migrant share changes	0.223	0.212	0.197	0.125
Low-skilled workers				
Allowing for neither city area nor migrant share changes	0.035	0.008	-0.026	-0.211
Allowing for city area but not migrant share changes	0.041	0.029	0.014	-0.064
Allowing for both city area and migrant share changes	0.126	0.114	0.099	0.021

Notes: In rows 1 and 4 of Panel A, the estimates of the nominal income elasticity for high- and low-skilled households are marginal effects calculated from Combes et al. (2020). In rows 2 and 5, we add the effect of land area changes. In rows 3 and 6, we use also adds the role of changes in the migrant share. Panel B reports the population elasticity of real income, defined as the difference between the population elasticity of nominal income and housing costs, as specified in Equation (2).

We then assess how the population elasticity of real income –defined as the difference between the nominal income elasticity and the housing cost elasticity in Equation (2)– varies across cities (Panel B of Table 5). While the elasticity of real income for both high-skilled and low-skilled households is positive in small and median-sized cities, it turns negative in average-sized cities and mega-cities when neither land area nor the migrant share change (rows 1 and 4). In essence, this means that while nominal income tends to increase faster than housing costs in smaller cities, the trend reverses in larger cities. Allowing for city land area adjustment significantly increases the elasticity of real income for both high- and low-skilled households. For high-skilled households, it increases by 97.4% in small cities, by 371.4% in median-sized cities. It turns positive in average-sized cities with a three times higher absolute value, and decline by 88.9%, even if remaining negative for Shanghai (row 2). The pattern for low-skilled households is similar, albeit with smaller percentage increases (row 5). If we further allow for an increase in the migrant share, the elasticity of real income becomes positive, and pretty large for both high- and low-skilled households for all four hypothetical cities (rows 3 and 6) even of remaining smaller the larger the city.

6.2 Predicted real income across cities

Integrating the estimated population elasticity of nominal income, housing costs, and by difference, real income, this section presents real income disparities across Chinese cities, separately for high-skilled and low-skilled households. To better understand the specific role of each city characteristics, we start by presenting the role of population only in Panels (a) and (b) of the figures, assuming that cities otherwise have the average land area and migrant share (and other controls). Next, the simultaneous roles of population and area are presented in Panels (c) and (d), assuming that cities have the same migrant share and controls. Finally, the roles of all three variables are taken into account in Panels (e) and (f).

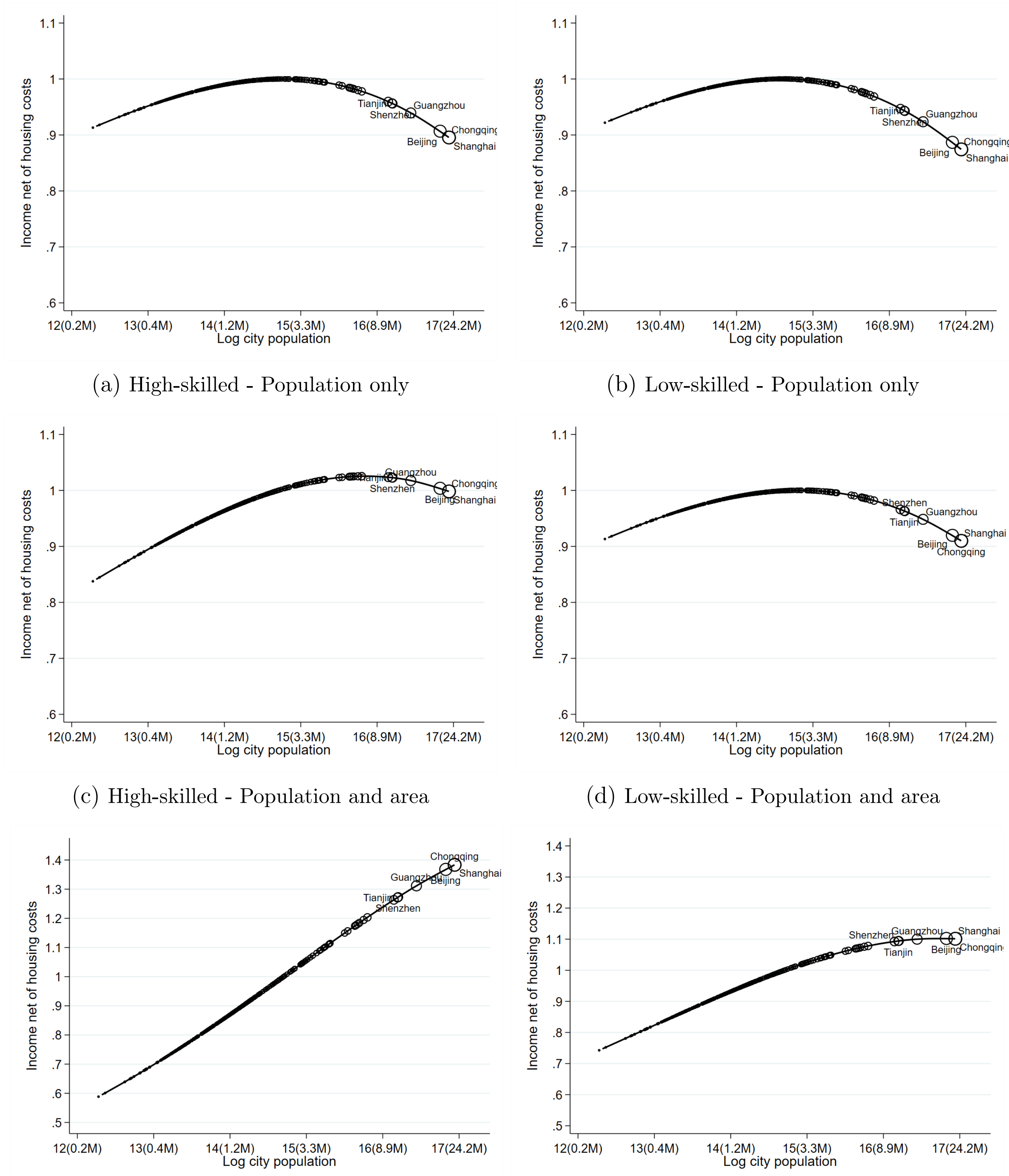
We first plot separately the predictions for housing costs and nominal income, which is presented in Appendix B, Figures A1 and A2, respectively. In Figures A1 Panels (a) and (b), housing costs exhibit a strongly convex pattern, which is due to the convexity of unit land prices, further raised to the power of the product of almost linear impacts of population for the land and housing expenditure shares. While a large quadratic term is necessary to match the housing costs of the largest cities, it is too strong to accurately fit the housing costs of the smallest cities. Additionally, housing costs appear to be slightly more convex for low-skilled households. For instance, housing costs increases by 38.6% (42.4%) for high-skilled (low-skilled) households when moving from the lowest housing cost city to the city where it is the highest. This increase is slightly less large if city land area expansion is considered: the housing costs rise by 32.4% (35.5%) for high-skilled (low-skilled) households in the same scenario (Panels c and d).

Nominal income predictions presented in Figure A2 Panels (a) and (b), increases almost linearly with the (log) city population. As documented by Combes et al. (2020), nominal income gains from locating in larger cities in China are higher than in Western countries. For instance, nominal income rises by 35.9% for high-skilled households and by 35% for low-skilled households when moving from the city with the lowest income to the one with the highest. This increase is magnified when accounting for city land area expansion (Panels c and d), particularly for high-skilled households, and it becomes even more pronounced when allowing for an increase in the migrant share as nominal income rises by 211.3% for high-skilled households and by 100.9% for low-skilled households in the same scenario (Panels e and f).

The predictions for real income with respect to city population are depicted in Figure 4. When only population impacts nominal income and the housing costs, as in Panels (a) and (b), an almost symmetrical bell-shaped curve emerges for both high- and low-skilled households. The maximum is reached for a city with 2.6 million inhabitants, where the predicted real income closely aligns with that of the average city with 2 million inhabitants, the curve being pretty flat between 1.2 and 4.5 million inhabitants. In cities with up to 2.6 million inhabitants, where about half of the Chinese population lives, nominal income increases faster than housing costs, resulting in a 8.7% increase in real income for both high-skilled and low-skilled households. However, for cities exceeding 3 million inhabitants, nominal income growth lags behind the housing costs, leading to a gradual decline in real income. For high-skilled households, the lowest value is reached in Shanghai, where real income falls 10.4% below that of the average city with 2 million inhabitants (and 10.5% below the city with the highest real income). For low-skilled households, regional disparities in real income are slightly more pronounced: in Shanghai, real income is 12.6% lower than both the average city and the city with the highest real income.

Panels (a) and (b) illustrate the worst-case scenario for larger cities as the prediction does not take into account the positive impact of land area and migrants on nominal income, nor

Figure 4: Predicted real income across Chinese cities



(a) High-skilled - Population only

(b) Low-skilled - Population only

(c) High-skilled - Population and area

(d) Low-skilled - Population and area

(e) High-skilled - Population, area and migration

(f) Low-skilled - Population, area and migration

Notes: This figure displays the predicted real income corresponding to the integral of equation (2) for high-skilled households (Panels a, c, and e) and low-skilled households (Panels b, d, and f), respectively. In Panels (a) and (b), only the role of city population is considered, in Panels (c) and (d) the impact of land area is additionally considered, and the role of all three variables is considered in Panels (e) and (f). Each black circle symbolizes a representative household in one of the 254 cities, and the solid line depicts a spline fit.

the negative impact of land area on housing costs. When considering the impact of a larger land area, as shown in Panels (c) and (d), the declining part of the real income curve substantially diminishes for both types of households, which strongly confirms the critical role of land supply in spatial inequality in real income. For high-skilled households, real income in Tianjin, Shenzhen and Guangzhou is nearly on par with the city with the highest real income, while in Beijing, Chongqing and Shanghai, it is lower by 2.1%, 2.7%, and 2.8%, respectively. Regarding low-skilled households, real income is lower than in the city with the highest real income by 3.7% in Shenzhen and Tianjin, while Guangzhou and Beijing experience a larger deficit of 5.2% and 8%, respectively. In large cities that offer the lowest real income, namely Shanghai and Chongqing, real income is 9.2% lower compared to the the city with the highest real income. Overall, moving to larger cities is less advantageous for low-skilled households, primarily because they benefit less from agglomeration economies associated with the expansion of city land areas and experience smaller increases in nominal income, and because their housing costs increase more.

Further taking into account the role of rural migrants, as shown in Panels (e) and (f), accentuates the steepness of the real-income profile for high-skilled households, and makes it less concave for low-skilled households. The presence of migrants amplifies the benefits of larger cities for high-skilled households, both in absolute terms and relative to low-skilled households. As the literature shows (Combes et al., 2020), high-skilled households benefit from a strong positive externality from the presence of migrants, without a corresponding increase in housing costs. In contrast, this effect is less pronounced for low-skilled households as they are more substitute to migrants in the production sector. Nevertheless, for both types of households, moving to a larger city never decreases real income when migration is accounted for. In Tianjin, Shenzhen, Guangzhou, Beijing, Chongqing and Shanghai, high-skilled households typically enjoy real incomes that are 27.1%, 27.3%, 31.1%, 36.8%, 38.3% and 38.4% higher than those in the average city, respectively. Low-skilled households exhibit less pronounced real income advantages, of approximately 10% in the largest 6 cities.

The figures presented above are predictions for a representative household living in a representative dwelling rather than the actual average real income in each city. They ignore all factors other than population, land area and the presence of migrants, assuming that each city responds to changes in these variables as the average city. Nevertheless, these findings illustrate the important role of these three city characteristics in shaping real income across cities, and how this impact varies for households of different types. They also offer insights into China's massive internal migration, which increasingly takes place between cities rather than just from rural areas, and into the different location choices made by households with different education levels. This could result in a spatial sorting of households along their skills, similar to the trend observed in Western countries where high-skilled households disproportionately concentrate in the largest cities.

7 Robustness checks and extensions

In this section, we provide various robustness checks for each of the three key parameters that enter the housing cost elasticity. First, we present variants of the estimates using alternative sets of controls and/or functional forms. Second, we discuss IV results in comparison with the OLS results presented in Section 5.

7.1 Using alternative sets of controls

City determinants of land price Table 6 reports various estimations of the city determinants of residential land price (Equation (7)), using three different sets of controls for both the first step and the second step. Column 9 is identical to column 1 of Table 3.

Columns 1-3 use the first-step estimates where only city fixed effects and the log distance effect are introduced (column 3 of Table 2). Columns 4-6 add parcel characteristics to city fixed effects and the log distance effect in the first-step estimates (column 4 of Table 2). Finally, columns 7-9 duplicate the same specifications use our preferred first-step estimates from column 8 of Table 2 with the full set of controls. As for the second step of the estimation of the city determinants of unit land prices, columns 1, 4 and 7 use the most rudimentary specification, with only the log of city population, the log of city land area, and their respective quadratic terms as explanatory variables. Columns 2, 5 and 8 introduce the city mean income and the past population growth. Finally, columns 3, 6 and 9 add the city migrant share as well as controls for education, geography and geology, and land use.[23]

[23]As explained in Section 2.2, these variables exclude amenities but are otherwise similar to those used in the first step, re-computed at the city level. They include the share of high school/college degrees, the share of university degrees, the standard deviation of elevation, the share of water body, and the mean slope.

Overall, Table 6 shows very stable estimations for our main variables of interest. As the income level is positively associated with both city population and land prices at city center, adding income in the specification (columns 2, 5 and 8) lowers the estimated population elasticity, while introducing a full set of controls (columns 3, 6 and 9) increases the explanatory power and leaves the estimate of the population elasticity mostly unchanged. Column 9 is our preferred OLS estimates for two reasons. First, the dependent variable is estimated from the most complete specification for the first step, mitigating the concern that within-city heterogeneity may be captured in part by city population in the second step. Interestingly, the R^2 are slightly lower in columns 7-9, suggesting that city characteristics in the second step may capture some within-city features when not properly controlled for in the first step. Second, the full set of city-level controls conditions out the complicated socioeconomic characteristics of cities that may affect land prices beyond the role of city size.

Table 6: City determinants of unit land prices at city centre

First step	Only fixed effects			Basic controls			Full set of controls		
Controls for the second step	N	Y	Ext.	N	Y	Ext.	N	Y	Ext.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log population	-4.843^a	-3.560^b	-3.588^a	-5.334^a	-4.017^b	-4.013^a	-4.998^a	-3.802^a	-3.890^a
	(1.578)	(1.583)	(1.129)	(1.616)	(1.605)	(1.154)	(1.462)	(1.455)	(1.061)
Log population squared	0.207^a	0.158^a	0.153^a	0.224^a	0.174^a	0.168^a	0.209^a	0.163^a	0.161^a
	(0.056)	(0.056)	(0.040)	(0.057)	(0.057)	(0.041)	(0.052)	(0.051)	(0.037)
Log land area	1.124^a	0.955^a	0.664^b	1.129^a	0.959^a	0.702^a	1.144^a	0.985^a	0.703^a
	(0.296)	(0.281)	(0.259)	(0.300)	(0.275)	(0.241)	(0.279)	(0.256)	(0.227)
Log land area squared	-0.093^a	-0.082^a	-0.063^a	-0.093^a	-0.082^a	-0.064^a	-0.093^a	-0.083^a	-0.063^a
	(0.021)	(0.020)	(0.018)	(0.021)	(0.020)	(0.017)	(0.020)	(0.018)	(0.016)
Log income		1.118^a	0.640^a		1.133^a	0.621^a		1.047^a	0.592^a
		(0.216)	(0.166)		(0.213)	(0.163)		(0.203)	(0.158)
Log migrant share			0.299			0.284			0.293
			(0.254)			(0.253)			(0.249)
R^2	0.57	0.60	0.67	0.58	0.61	0.68	0.54	0.57	0.64
Observations	3,209	3,209	3,209	3,209	3,209	3,209	3,209	3,209	3,209

Notes: The dependent variable is a city-year fixed effect estimated in the first step for 3,209 city-years. Columns 1-3 use the city-year fixed effects of column 3 of Table 2 as dependent variable, Columns 4-6 use those of column 4 of Table 2, and Columns 7-9 those of column 8 of Table 2. All regressions include year fixed effects. All reported R^2 are within-time. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. Standard errors clustered at the city level are between brackets. Regarding the controls for the second step, N stands for no further explanatory variables beyond population, land area, and year effects, Y includes a sub-set of explanatory variables, and Ext. includes a full set of explanatory variables. The sub-set of controls include the city-level income and population growth (log mean wage, and past annualised population growth during 1990-2005). The extended controls additionally include the population composition of the city (as the log of 1+migrant share), education variables (share of high school/college degrees and share of university degrees), geography and geology variables (standard deviation of elevation, share of waterbody, and mean slope), and land use variables (share of residence-, production-, and commerce-use land in stock within urban built-up area, and dummy for coastal province).

As a further robustness check, Table A2 proposes additional estimates for our preferred specification (column 1 of Table 3), using variants for the first step reported in Table A1. Column 1 adds a quadratic term of the logarithm of the distance to the centre (column 2 of Table A1) in the first step. Column 2 allows for the distance to a second center to be included in the first step (column 4 of Table A1). These two variants relax the assumptions about the internal structure of the city. Column 3 uses a smaller sample, which excludes the 10% closest land parcels to the center in the first step (column 6 of Table A1) in order to deal with potential measurement errors from the definition of centers and the smaller number of observations there. Column 4 assesses the robustness of our initial sample restrictions by using a first step estimated on a sample that also contains non-market-based land transactions (column 8 of Table A1). Finally, measurement errors in the first step could possibly affect our dependent variable of the second step. To eliminate this concern, column 5 of Table A2 weights the estimates from our preferred specification using the number of observations for estimating city fixed effects. An alternative approach to our two-step procedure is to estimate all parameters in one step, which is done in column 6 of Table A2. Although the point estimates slightly vary, the results are fully consistent with our main findings with similar magnitudes. For instance, these estimates suggest that the population elasticity for a medium-sized city with 2 million inhabitants is between 0.589 and 0.829, ranging from about 25% lower to marginally (5%) higher than the corresponding OLS estimate of 0.782.

Regarding the second step, another concern is whether the estimated convexity could be driven by a very small number of large cities. As shown in Figure 3, six out of the seven largest cities are unusually expensive for their population relative to a log-linear trend. To explore this issue further, Table A3 presents a series of regressions in which we include both quadratic and cubic terms for the log population. The estimated coefficients are generally not significant, suggesting that the convexity observed in our baseline results is not driven solely by a few very large cities.

Land share in housing production Table 7 presents estimates of the semi-elasticity of the land share in housing production at the city center with respect to population using variants of Equation (9). The upper panel summarizes results from the first step, using the same three alternative sets of controls as for land prices presented above. The estimated distance gradients are significantly negative and robust across the three different specifications.

Beyond the role of unit land prices, this may echo the findings of the previously mentioned literature on land use regulation: land parcels in the city center are subject to most stringent regulatory FAR limits (Brueckner et al., 2017). It is noteworthy that the estimated distance gradient weakens after accounting for amenity access and other local controls in the third specification, similar to the observation for unit land prices in Table 2. These controls themselves vary largely in relation to the distance to the centre, thereby weakening its impact without substantially increasing the overall explanatory power of the model. In any case, the land share in housing production varies much less within city compared to unit land prices.

Table 7: City determinants of the share of land in housing production at city centre

First step	Only fixed effects			Basic controls			Full set of controls		
Controls for the second step	N	Y	Ext.	N	Y	Ext.	N	Y	Ext.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
First-step estimates									
Log distance	-0.007^a	-0.007^a	-0.007^a	-0.008^a	-0.008^a	-0.008^a	-0.004^a	-0.004^a	-0.004^a
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
R^2	0.19	0.19	0.19	0.19	0.19	0.19	0.21	0.21	0.21
Observations	47,421	47,421	47,421	47,421	47,421	47,421	47,421	47,421	47,421
Second-step estimates									
Log population	0.029^a	0.016^a	0.020^a	0.030^a	0.016^a	0.020^a	0.030^a	0.017^a	0.020^a
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Log land area	-0.002	-0.005	-0.014^a	-0.002	-0.005	-0.013^a	-0.002	-0.004	-0.013^a
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)
Log income		0.101^a	0.057^a		0.102^a	0.057^a		0.098^a	0.055^b
		(0.023)	(0.021)		(0.023)	(0.021)		(0.024)	(0.021)
Log migrant share			0.034			0.034			0.029
			(0.024)			(0.024)			(0.023)
R^2	0.15	0.22	0.30	0.16	0.22	0.30	0.16	0.22	0.30
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,223	1,223	1,223

Notes: see Table 6. The total of 47,421 observations in the first step corresponds to 1,223 representative city-years in the second step. The estimated constant in the first step corresponds to the land share in housing production in a city of average size (3.94 million inhabitants) and takes the value of 0.330 in all specifications.

The bottom panel in Table 7 presents estimations of the second step for the land share in housing production, using again the same three alternative sets of controls as for land prices. Column 9 is identical to column 3 of Table 3. Using the most simple specification with only city population and land area, column 1 highlights a significant coefficient of 0.029 for city population, but an imprecisely estimated land area effect of -0.002. Columns 2 and 3 further enrich the specification by sequentially incorporating income and the migrant share. The point estimate on population remains stable and the negative supply effect captured by the coefficient on land area becomes statistically significant. Control variables appear to be more important for the land share in housing production than for land prices. The elasticity is reduced by a third when all controls are introduced, compared to its highest value with fewer controls, although the difference is not significant given the standard errors.

Housing expenditure share Finally, Table 8 reports semi-elasticity estimates for the share of housing in expenditure separately for high-skilled (Panel A) and low-skilled (Panel B) households, using variants of Equation 10. Again, column 9 is identical to column 5 (column 7) of Table 3 for high-skilled (low-skilled) households. Similar to land prices and the land share in housing production, the various columns highlight the robustness of our estimation.

As for the land share in housing production, only a slight decline with respect to the distance to the city centre of the households' housing expenditure share within city is observed, and it is significant only when all controls are introduced. As regards second-step estimates, Columns 4-6 show that when household income and the household head's educational attainment are included in the first step, the population elasticity estimates for both groups of households are slightly higher and statistically significant even in the most complete first-step specification. Specifically, column 6 shows a population elasticity estimate of 0.034 for high-skilled households and 0.037 for low-skilled households, implying that the sorting effect caused by income heterogeneity is partially accounted for by city size in columns 1-3. Columns 7-9 use the full set of controls in the first step, which leaves the point estimates on population and land area unchanged.

7.2 Instrumental variable estimates

As explained in Section 2.3, city characteristics may be endogenous, hence biasing the OLS estimation of Equations (7), (9) and (10). To address this concern, this section presents instrumental variable (IV) estimations for the three equations, which instrument the city population and area variables as well as the share of rural migrants variable. Tables A4, A5 and A6 in Appendix D present the IV estimates, using the same instruments in corresponding columns, for Equations (7), (9) and (10), respectively.

Table A4 reports IV estimates for the city determinants of unit land prices. Panel A replicates the specification without controls in the first and the second steps (column 1

Table 8: City determinants of the share of housing in households' expenditure

First step	Only fixed effects			Basic controls			Full set of controls		
Controls for the second step	N	Y	Ext.	N	Y	Ext.	N	Y	Ext.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. High-skilled households (9,414 obs.)									
First-step estimates									
Log distance	−0.010	−0.010	−0.010	−0.013	−0.013	−0.013	-0.022^b	-0.022^b	-0.022^b
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Log income				-0.040^a	-0.040^a	-0.040^a	-0.043^a	-0.043^a	-0.043^a
				(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Second-step estimates									
Log population	0.026^b	0.029^b	0.026	0.038^a	0.042^a	0.034^a	0.038^a	0.042^a	0.034^a
	(0.013)	(0.013)	(0.016)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.009)
Log land area	0.003	0.003	−0.001	0.007	0.008	0.009	0.007	0.008	0.010
	(0.015)	(0.015)	(0.018)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.010)
Log migrant share			0.037			0.061			0.069
			(0.092)			(0.051)			(0.051)
R^2	0.16	0.16	0.18	0.25	0.27	0.30	0.25	0.27	0.31
Panel B. Low-skilled households (6,231 obs.)									
First-step estimates									
Log distance	−0.008	−0.008	−0.008	-0.011^b	-0.011^b	-0.011^b	-0.025^a	-0.025^a	-0.025^a
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Log income				-0.047^a	-0.047^a	-0.047^a	-0.046^a	-0.046^a	-0.046^a
				(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Second-step estimates									
Log population	0.024^c	0.025^c	0.022	0.044^a	0.046^a	0.037^a	0.043^a	0.046^a	0.036^a
	(0.013)	(0.013)	(0.016)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
Log land area	0.013	0.013	0.012	0.006	0.007	0.007	0.007	0.007	0.007
	(0.013)	(0.013)	(0.015)	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)
Log migrant share			0.026			0.081			0.086
			(0.105)			(0.061)			(0.063)
R^2	0.12	0.12	0.13	0.22	0.23	0.25	0.21	0.22	0.24

Notes: see Table 6. A total of 15,645 observations in each first step corresponds to the same 246 representative city-years for high-skilled and low-skilled residents (Panel A and B, respectively) in the second step. There are two main differences with the specification used in Table 6. First, the basic controls in the first step also include household composition (ratio of working adults to children and number of non-working adults), home ownership (ref. renter), household head's educational attainment, and household income. Second, the city mean wage and the quadratic terms of population and land area are not included in the second-step regressions. The estimated constant in the first step corresponds to the housing expenditure share in a city of average size (2.88 million inhabitants), and takes the value 0.24 (0.26) for high-skilled (low-skilled) workers in all specifications.

of Table 6), while Panel B duplicates our preferred OLS regression including a full set of controls in both the first and the second steps (Column 1 of Table 3). Column 1 recalls the OLS estimates for reference. Column 2 instruments city population, land area, and their quadratic terms using long lags of the endogenous variables. Columns 3-4 add exogenous amenity variables to instruments and experiment with various combinations of historical and amenity instrumental variables. Columns 6-7 further instrument the migrant share using the predicted share of migrant inflows and rural population in 1982. Almost all sets of instrumental variables are found to be strongly predictive of the endogenous variables, with the Kleibergen-Paap F statistic above the conventional level. The IV estimates of the population elasticity for a medium-sized city with 2 million inhabitants are between 0.806 and 0.879, which is slightly above the corresponding OLS estimate of 0.782. Reassuringly, OLS estimates of land area elasticity and migrant share elasticity are also robust to the IV estimates.

Table A5 provides a set of IV estimates for our preferred specification (column 3 of Table 3) for the city determinants of the land share in housing production, following the same step-by-step inclusion of IVs as for land prices. In column 7, where we instrument for city population, land area, and migrant share, the coefficients of these endogenous variables are again slightly larger than their OLS estimates, although the differences are barely significant.

Finally, Table A6 provides a set of IV estimates for our preferred specification (columns 5 and 7 of Table 3) for the housing expenditure share. Again, column 7 shows that when we instrument for city population, land area, and migrant share, the coefficient estimates slightly increases compared to the OLS estimates. We conclude that our IV results are supportive of our baseline OLS results for all three equations.

Using the IV estimates presented in column 7 of Tables A4, A5, and A6, we can compute the population elasticity of housing costs. For high-skilled households, the population elasticity of housing costs rises from 0.020 in a city with 500,000 million inhabitants to 0.541 in a city like Shanghai, compared to 0.027 and 0.255 using OLS. Similarly, for low-skilled households, the disparity across cities becomes more pronounced, with the population elasticity of housing costs ranging from 0.022 in a 500,000 inhabitant city to 0.581 in Shanghai, instead of 0.021 and 0.275 using OLS. Hence, the IV estimates suggest an even more substantial increase in housing costs with city size compared to the OLS estimates, which is due to the slightly larger impact of population on all three components of housing costs.

In a last step, we assess the impact of using IV instead of OLS on real income disparities. Besides the population elasticity of housing costs computed above, we predict nominal income using the IV estimates from Combes et al. (2020) Table 2 Panel (b), columns (2) and (5) for high- and low-skilled workers, respectively. The results are displayed in Figure A3, Appendix D. While housing costs increase even more with city size in IV estimates, consistent with the larger elasticities we have documented, the same holds true for nominal income gains. Overall, these differences almost compensate, resulting in both OLS and IV estimates leading to very similar predictions for real income variations across cities.

When the role of land area and migrants is accounted for, high-skilled households still benefit from relocating to the largest cities. In Tianjin, Shenzhen, Guangzhou, Beijing, Chongqing and Shanghai, they enjoy a real income that is 30.4%, 30.6%, 34.3%, 39%, 40.1% and 40.2% higher than in the average city, respectively, which is very close to OLS values (27.1%, 27.3%, 31.1%, 36.8%, 38.3% and 38.4%). In contrast, low-skilled households in the largest cities may be worse off compared to living in smaller cities. For instance, their real income is about 3% lower in Beijing, Shanghai and Chongqing relative to the average city. It is almost identical to the average in Guangzhou, and slightly higher than the average in Tianjin and Shenzhen, by 2%. OLS estimates give a slightly different picture, suggesting that low-skilled households always gain by moving to the largest cities, albeit marginally. Similar to OLS estimates, when positive income externalities from migrants are not considered, the gains using IV estimates are lower and may even turn negative in the largest cities for high-skilled households, while the losses are larger for low-skilled household. The situation worsens when land area does not adjust, resulting in significant losses for both groups in the largest cities.

8 Conclusion

This paper makes two main contributions. First, using various sets of individual data for Chinese cities, we estimate housing costs and assess how they vary between cities. The elasticity of housing costs with respect to a city characteristics, its population typically, is the product of three components –the elasticity of unit land prices, land share in housing production, and housing share in household expenditure–, all of which are successively studied. Second, by comparing housing costs to nominal income gains, we assess regional disparities in real income for both high- and low-skilled households. To our knowledge, this is the first attempt of this kind for a large emerging economy, many of which are undergoing large and rapid urbanisation processes, as observed in China.

We find that urban costs are large in China but lower when cities expand their land area simultaneously with their population, aligning with both urban models and findings from Western countries. Nominal gains from larger populations also respond to land area adjustments and the presence of rural migrants. Therefore, real income disparities in China largely depend on the simultaneity of these urban adjustments. When more populated cities expand over larger areas and have a higher share of migrants, as has been the case over the past decades in China, all types of households experience some real income gains when moving to larger cities, with high-skilled households benefiting even more. However, if the positive externality from migrants is not considered, households, especially low-skilled ones, experience slight real income losses when relocating to the largest cities. If the land area does not adjust either, moving to the largest cities can result in even larger real income loss, particularly for low-skilled households.

Our empirical findings are relevant for the design of urban and redistributive policies. Our framework allows assessing the potential gains from relaxing migration restrictions and land use regulations, especially regarding urban horizontal expansion. This is important in a context where internal migration restrictions, as those imposed by China's *Hukou* policy, are expected to persist at least to some extent and impact population movements between cities, especially from small to large cities. By considering the positive supply-side effect of land area on housing costs, along with the positive agglomeration effect on nominal income, larger cities can offer increased real income. However, the largest Chinese cities start reaching the size beyond which real income decreases, especially for low-skilled households. Furthermore, given that real income gains differ across skills, our findings are consistent with a reinforcement of the spatial sorting of households along skills, where high-skilled households are disproportionately concentrated in the largest cities, a pattern largely documented for Western countries.

We acknowledge that the paper does not take into account the role of the price of goods other than housing. This task is challenging and would require detailed information currently unavailable for China. Handbury (2021) emphasises the importance of estimating the extent of the preference for diversity in order to correctly assess how much the price index of non-housing goods varies with city characteristics, which, interestingly, depends on households' income. However, the proposed methodology requires bar-code data to estimate the elasticity of substitution between varieties. As an example, spatial variations in food grocery prices are found to be of much lower magnitude than those of housing prices, and the food grocery price index can even decrease with city size for high-income households. Therefore, although this should be considered when feasible, we do not believe it would reverse our conclusions. Additionally, our study does not include an assessment of the local value of consumption amenities, relating to climate, geography, schools, or leisure facilities for instance, which would be necessary for a complete welfare analysis. Our primary purpose here is to assess how the monetary part of the utility –real income– varies across Chinese cities. Going beyond that would require properly modeling not only households' amenity valuation but also intrinsic preferences for locations and moving costs, likely in a quantitative general equilibrium spatial model. This is beyond the scope of the present article but would be a valuable addition for further research.

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Appendix

A Data description

Land price We compiled land transaction data from the Land Transaction Monitoring System website (www.landchina.com). The 2007 Land Management Law requires local governments to report each land sale in their jurisdiction on this website. As a consequence, the data available cover all land transactions in China's primary land market between 2007 and 2019, and contain 2,233,917 observations with some fluctuations across years (ranging between 92,468 in 2008 to 213,657 in 2013). Each transacted parcel's price and size is recorded, as well as other information including the transaction method, as transactions can be carried out in five different ways (two-stage auction (*guapai*), invited bidding (*zhaobiao*), English auction (*paimai*), bilateral agreement (*xieyi*), and state allocation (*huabo*)). The transaction date, the land use type (residential, commercial, industrial, or public use), both developer's and seller's information, the floor area ratio, and the parcel location. We keep only parcels for residential use located in the city proper and we simultaneously ignore parcels transferred through a non-market method (bilateral agreement or state allocation). That leaves us with 66,973 residential-use land transaction records that took place in one of the 254 cities from our main sample.

We process the raw data through the following four-step procedure. First, we remove land parcels located outside cities (i.e., in rural areas), which leaves us with 839,620 land parcels, of which 329,553 (39%) are for residential use. Second, since the price of parcels transferred through a non-market method may not be representative, we keep only the sample of market-mediated transactions, resulting in 107,288 residential land parcels. Third, we geo-code the parcel addresses to obtain precise geographic coordinates. After eliminating parcels without specific location information, our sample reduces to 84,932 residential land parcels. Lastly, we remove observations with missing values in land characteristics and other matched district/neighborhood-level control variables. We also eliminate land transactions with abnormal prices very close to zero or very large (the 1st and 99th percentiles are trimmed), and we remove land parcels in cities that have fewer than 3 observations. This procedure yields a final sample of 66,973 residential land parcels. We present a robustness check that does not make the selection on the transaction methods and keeps non market-mediated transactions, yielding a sample with 190,042 residential land parcels. Appendix C reports our main estimations for this larger dataset, and shows that the results are very similar.

Land share in housing production Data on residential development projects (RDPs or *xiaoqu*) that had new properties for sale between 2010 and 2022 are sourced from Anjuke (www.anjuke.com) and Lianjia (www.lianjia.com), the two largest online real estate agencies in China. A RDP contains several residential buildings, providing commodity housing for urban residents. For each RDP, we know its average housing prices per square meter of floor area, floor area ratio (FAR), and geo-referenced address. Typically, a connected land parcel corresponds to one RDP built by a single developer (Tan et al., 2020). Condominium units (*xiaoqu*) are the most common property type in urban China, and residential buildings are systematically developed through RDPs.

We match each RDP to the land parcel on which it is built in two steps. We first use geo-coded information to select land parcels that satisfy three criteria: the land parcel must be the closest to the RDP and within 1km, have a floor area ratio tied to the corresponding RDP's, and have been transacted at least 1 year prior to the RDP completion. Then, we perform the second-round matching by checking whether the RDP developer information is consistent with the registered land developer. The matching procedure gives us 47,421 matched RDP-land pairs in 146 cities. For each RDP in the matched sample, the share of land cost in housing sales is computed as the ratio of the unit price of the parcel over the average unit housing price of the RDP on the parcel multiplied by its floor area ratio. A few RDPs are matched to more than one land parcel, in which case we average parcels' information.

Household housing expenditure We use the urban sample of the Chinese Household Income Project (CHIP) survey for the years 2007, 2013, and 2018 to measure the share of housing in household expenditure. The CHIP survey was jointly conducted by the China Institute for Income Distribution in Beijing Normal University and the National Bureau of Statistics (NBS) in order to track the dynamics of income distribution in China. This high-quality dataset reports household income and expenditure by category, household composition, and household head personal characteristics including *hukou* status, age, gender and educational attainment. Importantly, the CHIP urban sample surveys only registered urban residents, hence local urban *Hukou* holders only. As a consequence, rural migrants are not included in this dataset.

Housing expenditure is measured differently for landlords and for renters. For the former, who account for approximately 96% of the observations, the CHIP data report imputed rents on owner-occupied housing. It consists of (1) monthly expenditure on housing maintenance and management, and (2) depreciation of property assets at a rate of 2%. For the latter, their monthly rental payment is recorded. The household housing expenditure share is computed as the ratio of these measures to monthly household expenditure. Our sample contains 6,595 households across 66 representative city proper in 2007, 3,721 households across 98 cities in 2013, and 5,329 households across 88 cities in 2018.

Population We obtain population data from the China Urban Construction Statistical Yearbooks (CUCSYs, 2008-2020) maintained by China's Ministry of Housing and Urban-Rural Development. The spatial scale of interest is the city proper as for other sources. Hence, city population is measured by the number of inhabitants with city proper *hukou* and inhabitants without local *hukou* but living in city proper for over 6 months. In general, these residents are very likely to settle down in the city and purchase local houses. The past population growth between 1990 and 2005 is calculated using two sources of data from the National Bureau of Statistics (NBS), the Fourth National Population Census (1990) and the 1% National Population Sample Survey (2005).

Land use The land area of Chinese cities has been subject to changes over time due to the implementation of China's county-to-district policy launched in the late 1990s. The policy involves redefining a city's administrative boundaries by incorporating surrounding rural counties as urban districts, thereby expanding the city's jurisdiction and administrative control. Between 2007 and 2019, 74 out of the 254 provincial or prefecture cities in our main sample implemented this policy. Data on city land area are available from the China Urban Statistical Yearbooks (CUSYs, 2008-2020). The fraction of land that have been built up within the city proper is computed at the city level, based on the CUCSYs. The CUCSYs also report the proportion of residential-use stock land within urban built-up area.

Income and education Average urban employee annual wage are extracted from the CUSYs. We use the data from the 2010 China National Population Census aggregated at city and district level to measure local residents' education attainment, by taking the ratio of residents holding high school, college, or university degrees to working-age population (15-69 years old).

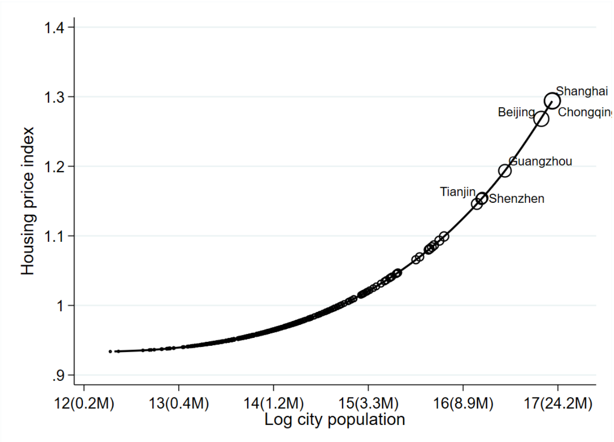
Geography and geology characteristics We compile three sources of data, calculating mean slope, share of water body, and terrain ruggedness at a fine spatial scale. We extract grid cell-level slope information from the 90-meter resolution Digital Elevation/Terrain Model (DEM) data from United States Geological Survey (USGS). To obtain water body information, we use the 30-meter resolution global land cover data maintained by China's Ministry of Natural Resources. Additionally, we construct the measure of terrain ruggedness, using the grid cell-level standard deviation of altitude from the Shuttle Radar Topography Mission (SRTM)-DEM (Nunn and Puga, 2012). The SRTM-DEM data is maintained by the National Aeronautics and Space Administration (NASA) and National Imagery and Mapping Agency (NIMA). Finally, we aggregate these high-resolution data at both district and city levels.

City centres To locate the city center, we use the 2006 Global Radiance Calibrated Nighttime Lights maintained by the National Oceanic and Atmospheric Administration (NOAA) National Geophysical Data Center (NGDC). The 2006 nighttime lights were produced without sensor saturation, which enables us to identify the brightest cell(s) in each city (i.e., city economic center and sub-centers). Note that light centers have barely changed over the past decades (Baum-Snow et al., 2017), which mitigates the concern on measurement errors.

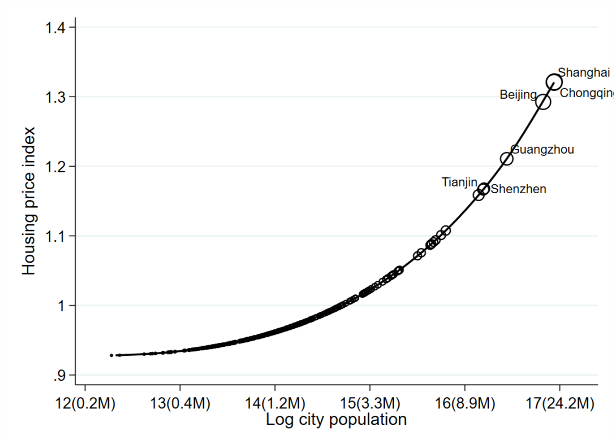
Amenity data We use the 2011 point of interests (POIs) from the China Geographical Information Monitoring Cloud Platform. This data contains detailed information, including specific category and precise geographical coordinate of various local amenities: accommodation (budget and luxury hotels); banks; schools (kindergartens, primary, middle and high school, colleges and universities, and research institutes); medical service providers (general hospitals, community clinics, and centers for disease control); retail establishments; public parks; leisure facilities (zoos, playgrounds, KTVs, cinemas, theatres, restaurants, and gyms); and public transit facilities (metro stations and train stations). We build distance matrix among parcels and amenities, which enables us to compute the minimum distance between one kind of amenities and a parcel as well as the number of each kind of amenities located within a 2-kilometer ring encircling a parcel. Additionally, the POI data aggregated at the district level can be utilized as the district-level socioeconomic control variable.

B Predicted housing costs and nominal income

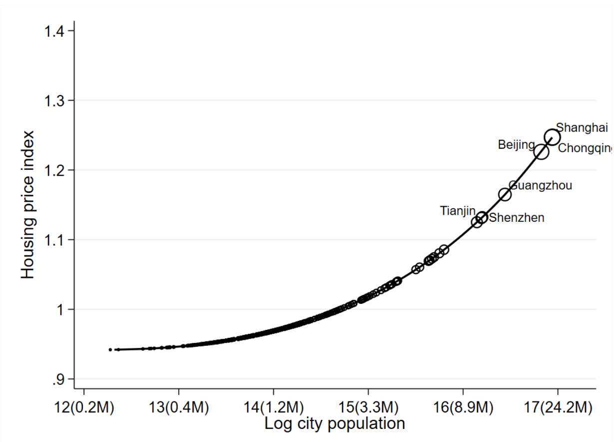
Figure A1: Predicted housing costs across Chinese cities



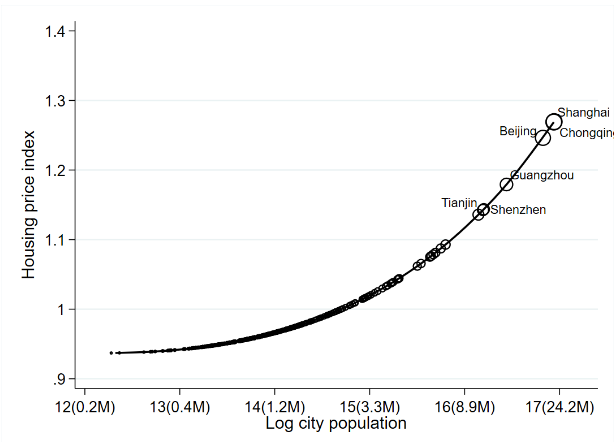
(a) High-skilled - Not allowing for urban expansion



(b) Low-skilled - Not allowing for urban expansion



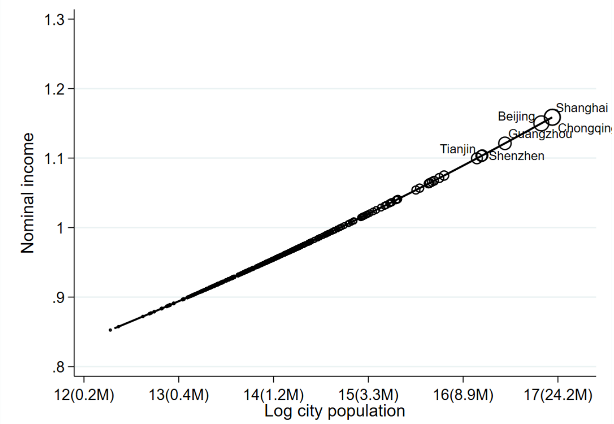
(c) High-skilled - Allowing for urban expansion



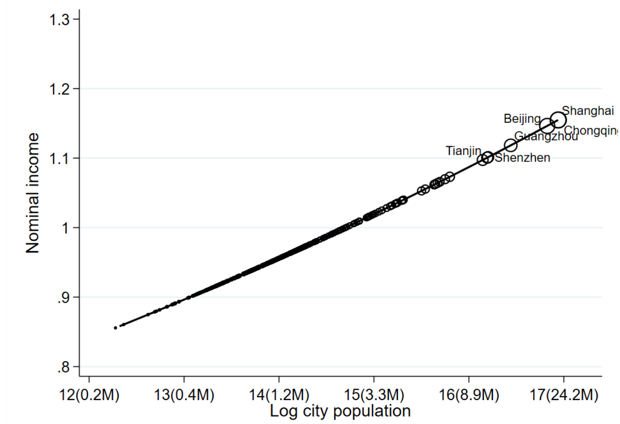
(d) Low-skilled - Allowing for urban expansion

Notes: This figure displays predicted housing costs, separately for high-skilled and low-skilled households, in each of the 254 cities, by integrating the estimated population elasticity of housing costs. Panels (a) and (b) use population elasticity from estimations that control for the city land area, whereas panels (c) and (d) use those that do not. Housing costs are normalised with respect to their average across all cities, allowing for a reading in percentage deviation relative to the mean. Each circle represents a city, with the circle's size proportional to the mean city population between 2007 and 2019. The largest 6 cities are labeled. The solid line indicate a spline fit.

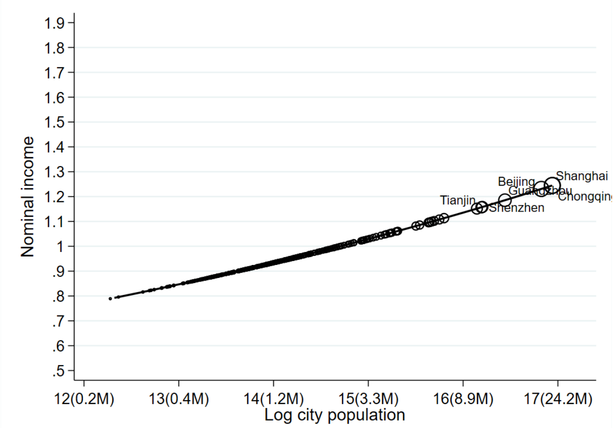
Figure A2: Predicted nominal wage across Chinese cities



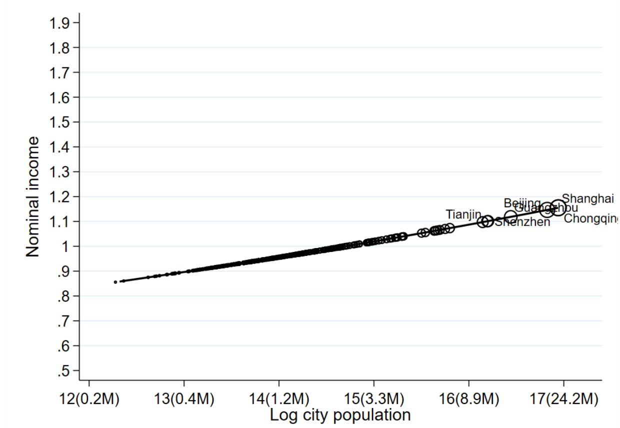
(a) High-skilled - Not allowing for urban expansion



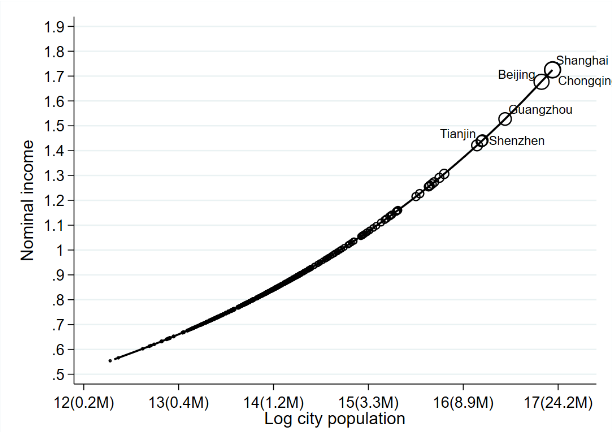
(b) Low-skilled - Not allowing for urban expansion



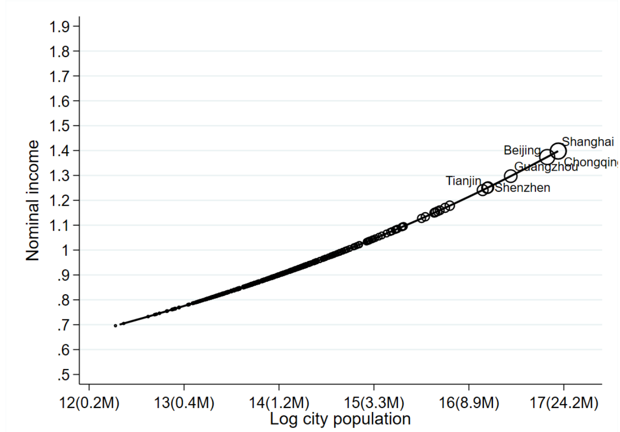
(c) High-skilled - Allowing for urban expansion



(d) Low-skilled - Allowing for urban expansion



(e) High-skilled - Allowing for urban expansion and increase in rural migrant share



(f) Low-skilled - Allowing for urban expansion and increase in rural migrant share

Notes: This figure displays the predicted nominal income, separately for high-skilled and low-skilled households, in each of the 254 cities, by integrating the estimated population elasticity of nominal income. Panels (a) and (b) use population elasticities from estimations controlling for the city land area and share of migrants, panels (c) and (d) use population elasticities encompassing indirect effects from the city land area but not the share migrants, panels (e) and (f) use population elasticities encompassing indirect effects from both the city land area and the share of migrants. The nominal income is normalised with respect to its average across all cities, allowing for a reading in percentage deviation relative to the mean. Each circle represents a city, with the circle's size proportional to the mean city population between 2007 and 2019. The largest 6 cities are labeled. The solid line indicate a spline fit.

C Estimation variants

C.1 First-step estimates for residential land prices

Several issues about the first-step estimation for the price of residential land parcels require discussion. The first pertains to our choice of functional form for the distance gradient. In most studies, a log-linear relationship between land price and the distance to city center is estimated, as we do in our baseline estimation. However, this is an approximation and there is no theoretical justification for assuming that the relationship is log-linear. Instead, the monocentric city model predicts a negative but convex relationship between land price and distance to the city center (Fujita and Thisse, 2013), which may be due to an increase in housing consumption as the distance from the city center increases or some congestion on the transport network. We caution that the structure of land transaction data may exacerbate this issue. In many large cities, there has been a discernible trend in which a greater number of land parcels located farther from the city center are being sold in the primary land market. This phenomenon may lead to a downward bias in the gradient estimates towards zero if we continue to rely on the linear model. To explore these issues, we re-estimate Equation (6) adding a quadratic term for the logarithm of distance to city center into the specifications of column 3 and 8 in Table 2. Results are reported in columns 1 and 2 of Table A1. The unchanged R^2 suggests that augmenting the specification does not substantially improve the model fitness, and that the log-linear model seems to be reasonable.

There may also be concerns about the geography we impose with urban areas having a single center. To address this, we re-estimate Equation (6) allowing for two different centres, the brightest night light and the second brightest if it has a light value that exceeds 80% of the brightest one. The shortest distance between these two centres is used as a control variable. Results are reported in columns 3 and 4 of Table A1. It is also worth noting that there more land parcel transactions far from the city centres and that the distance to the city centre can probably present larger measurement error for shorter distances. To investigate this possibility, we also report the results in columns 5 and 6 after eliminating the 10% of observations closest to the center in each urban area, both for the rudimentary and for our preferred estimation. The results are robust to variations in the definition of centers and sample restrictions.

Finally, our analytical focus is on the China's primary land market, where the local government is the sole seller. In our baseline first-step regressions, we remove 123,359 land parcels that were sold through bilateral agreement (*xieyi*) from our working sample in order to eliminate the concern about price manipulation in non-open transactions. To confirm the robustness of our findings, we replicate columns 3 and 8 of Table 2 on a sample of residential land parcels that keeps both market and non-market-based transactions. The results, reported in columns 7 and 8 of Table A1, remain stable.

Table A1: Summary statistics from the first step: Variants

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
City effect								
1^{st} quartile	-.585	-.508	-.625	-.591	-.742	-.698	-.678	-.718
Median	-.14	-.179	-.206	-.178	-.212	-.176	.026	-.148
3^{rd} quartile	.46	.434	.479	.434	.436	.386	.741	.415
Log distance effect								
1^{st} quartile			-.453	-.285	-.491	-.326	-.371	-.3
Median			-.285	-.17	-.317	-.201	-.218	-.169
3^{rd} quartile			-.161	-.045	-.172	-.055	-.087	-.045
R^2	0.575	0.593	0.563	0.582	0.569	0.588	0.652	0.721
Observations	66,683	66,683	66,683	66,683	60,164	60,164	190,042	190,042
Controls								
City fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
City-specific gradient	Y	Y	Y	Y	Y	Y	Y	Y
Parcel charac.		Y		Y		Y		Y
Geography and geology		Y		Y		Y		Y
Education		Y		Y		Y		Y
Consumption amenities		Y		Y		Y		Y

Notes: Odd columns repeat the specification from column 3 of Table 2, while even columns replicate our preferred specification from column 8 of Table 2. Columns 1 & 2 additionally include the quadratic term of log distance to the CBD identified by the brightest 1km×1km grid cell in each city's urbanized area (Baum-Snow et al., 2017; Tan et al., 2020). Columns 3 & 4 take into account the polycentric urban structure and use the distance to the nearest city centers (center and subcenters, whereby subcenters are defined as the grid cells whose pixel value exceeds 80% of the centre, the brightest grid cell's). Columns 5 & 6 exclude the 10% of observations of land parcels that are closest to the CBD in each city. Columns 7 & 8 reintroduce observations of land parcels transacted through non-market-based method (bilateral agreements).

C.2 Second-step estimates for residential land prices

Table A2: City determinants of unit land price at city centre - Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
Log population	-2.561^{c}	-3.654^{a}	-3.929^{b}	-4.935^{a}	-3.665^{a}	-3.502^{a}
	(1.307)	(1.167)	(1.556)	(1.462)	(1.204)	(0.812)
Log population squared	0.109^{b}	0.152^{a}	0.164^{a}	0.197^{a}	0.149^{a}	0.141^{a}
	(0.047)	(0.041)	(0.056)	(0.052)	(0.042)	(0.029)
Log land area	0.498^{c}	0.673^{a}	0.738^{b}	0.571^{c}	0.795^{a}	0.636^{a}
	(0.276)	(0.232)	(0.289)	(0.329)	(0.237)	(0.164)
Log land area squared	-0.049^{b}	-0.062^{a}	-0.064^{a}	-0.054^{b}	-0.066^{a}	-0.056^{a}
	(0.020)	(0.016)	(0.021)	(0.023)	(0.018)	(0.014)
Log income	0.461^{b}	0.568^{a}	0.624^{a}	0.771^{a}	0.858^{a}	0.404^{a}
	(0.183)	(0.160)	(0.169)	(0.173)	(0.192)	(0.131)
Log migrant share	0.138	0.268	0.242	0.442	0.039	0.018
	(0.275)	(0.258)	(0.291)	(0.293)	(0.297)	(0.215)
R^2	0.50	0.63	0.64	0.58	0.72	0.46
Observations	3,209	3,209	3,209	3,209	3,209	66,973

Notes: Each column is a variant of our preferred specification (Table 3 column 1). Columns 1-4 use alternative dependent variables estimated in columns 2, 4, 6, and 8 of Table A1, respectively. Column 5 incorporates weights based on the number of observations in each city pair into our preferred specification estimates. Column 6 estimates the elasticity of land prices with respect to city characteristics in a single step rather than two consecutive steps.

Table A3: City determinants of unit land price at city centre - Cubic form

First step	Only fixed effects			Basic controls			Full set of controls		
Controls	N	Y	Ext.	N	Y	Ext.	N	Y	Ext.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log population	-5.632^c	-4.542	-1.356	-5.988^b	-4.907	-1.337	-5.464^b	-4.436	-1.455
	(2.963)	(3.031)	(2.461)	(3.001)	(3.029)	(2.492)	(2.706)	(2.746)	(2.246)
Log population squared	1.089^c	0.905	0.268	1.143^c	0.962	0.249	1.034^c	0.860	0.262
	(0.582)	(0.594)	(0.473)	(0.592)	(0.596)	(0.483)	(0.533)	(0.540)	(0.436)
Log population cubic	-0.055	-0.046	-0.007	-0.057	-0.049	-0.005	-0.051	-0.043	-0.006
	(0.037)	(0.038)	(0.030)	(0.038)	(0.038)	(0.030)	(0.034)	(0.035)	(0.027)
Log land area	0.869^c	0.851^c	0.682	0.859^c	0.842^c	0.594	0.718	0.701	0.528
	(0.493)	(0.466)	(0.525)	(0.508)	(0.468)	(0.531)	(0.489)	(0.456)	(0.527)
Log land area squared	-0.061	-0.071	-0.067	-0.059	-0.070	-0.048	-0.035	-0.044	-0.037
	(0.085)	(0.082)	(0.083)	(0.088)	(0.083)	(0.085)	(0.083)	(0.079)	(0.083)
Log land area cubic	-0.001	0.000	0.000	-0.001	0.000	-0.001	-0.003	-0.002	-0.001
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Log income		1.089^a	0.642^a		1.102^a	0.621^a		1.018^a	0.591^a
		(0.219)	(0.166)		(0.215)	(0.163)		(0.204)	(0.158)
Log migrant share			0.292			0.279			0.287
			(0.256)			(0.253)			(0.250)
R^2	0.57	0.60	0.67	0.58	0.61	0.68	0.55	0.58	0.64
Observations	3,209	3,209	3,209	3,209	3,209	3,209	3,209	3,209	3,209

Notes: This table replicates Table 6 and includes cubic terms of population and land area as explanatory variables.

D IV estimations

Table A4: City determinants of unit land price at city centre - IV estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ols	iv	iv	iv	iv	iv	iv
Panel A. Residential land, without first- and second-step controls (3,209 obs.)							
Log population	-4.843^a	-7.688^a	-10.767^b	-4.760	-2.640	-9.154^a	-9.180^b
	(1.578)	(2.809)	(4.588)	(3.585)	(4.093)	(3.237)	(4.239)
Log population squared	0.207^a	0.308^a	0.420^a	0.210^c	0.140	0.361^a	0.364^b
	(0.056)	(0.099)	(0.161)	(0.125)	(0.143)	(0.114)	(0.149)
Log land area	1.124^a	2.794^c	8.615^b	3.095^c	4.559^b	4.676^a	7.318^a
	(0.296)	(1.496)	(3.391)	(1.718)	(2.233)	(1.530)	(2.657)
Log land area squared	-0.093^a	-0.216^b	-0.609^a	-0.231^b	-0.328^b	-0.343^a	-0.520^a
	(0.021)	(0.102)	(0.230)	(0.117)	(0.152)	(0.105)	(0.181)
Overidentification p-value		0.488	0.029	0.058	0.091	0.313	0.024
First-stage statistic		3.5	3.5	4.7	4.4	5.4	4.4
Panel B. Residential land, with first- and second-step controls (3,209 obs.)							
Log population	-3.890^a	-4.562^b	-5.747^a	-5.064^c	-4.402^c	-6.060^a	-6.138^a
	(1.061)	(1.923)	(2.042)	(2.621)	(2.435)	(2.117)	(2.225)
Log population squared	0.161^a	0.185^a	0.227^a	0.204^b	0.182^b	0.238^a	0.241^a
	(0.037)	(0.067)	(0.071)	(0.091)	(0.084)	(0.074)	(0.078)
Log land area	0.703^a	1.142	2.376^b	2.029^c	1.923^c	2.077^c	2.707^b
	(0.227)	(1.123)	(1.165)	(1.154)	(1.107)	(1.079)	(1.148)
Log land area squared	-0.063^a	-0.092	-0.176^b	-0.152^c	-0.145^c	-0.157^b	-0.199^a
	(0.016)	(0.075)	(0.078)	(0.078)	(0.075)	(0.073)	(0.077)
Log income	0.592^a	0.560^a	0.517^a	0.499^a	0.511^a	0.519^a	0.504^a
	(0.158)	(0.173)	(0.172)	(0.176)	(0.176)	(0.171)	(0.173)
Log migrant share	0.293	0.275	0.237	0.250	0.265	0.227	0.223
	(0.249)	(0.253)	(0.258)	(0.259)	(0.260)	(0.252)	(0.256)
Overidentification p-value		0.327	0.138	0.294	0.167	0.263	0.289
First-stage statistic		5.9	4.4	5.5	5.7	5.4	4.8
Instruments							
Urban population in 1982		Y2	N	Y2	Y2	Y2	Y2
Urban density in 1990		Y2	N	N	N	Y2	Y2
Urban area in 1990		Y2	Y2	Y2	Y2	Y1	Y
Urban population in 1990		N	Y2	N	N	N	N
Sunshine hours		N	Y	N	Y	N	N
# of starred hotels		N	Y2	Y	Y	N	Y
# of 5A scenic spots		N	N	Y2	Y	N	Y
Predicted migrant9500/Emp.90		N	N	N	N	Y	Y
Rural population in 1982		N	N	N	N	Y	Y

Notes: Column 1 reports OLS estimates (column 1, Table 3) for reference. IV estimates are reported in columns 2-7 using limited information maximum likelihood (LIML). Columns 2-5 instrument city population, land area, and their squared terms. Columns 6-7 additionally instrument the migrant share. Y and N stand for 'Yes' and 'No' and mean that the instrument is used or not. Y2 indicates that both the linear and quadratic terms of the variable are used as instruments. The controls for the first step (second step, respectively) are those used in column 8 of Table 2 (column 9 of Table 6, respectively). Standard errors clustered at the city level are between brackets. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. The first-stage statistics is the Kleibergen-Paap rk Wald F. The critical value for 10% maximal LIML size of Stock and Yogo (2005) weak identification test is below 3.28 for all columns.

Table A5: City determinants of the land share at city centre - IV estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ols	iv	iv	iv	iv	iv	iv
Log population	0.020^a	0.034^a	0.035^a	0.043^a	0.046^a	0.037^a	0.035^a
	(0.006)	(0.010)	(0.010)	(0.014)	(0.014)	(0.011)	(0.011)
Log land area	-0.013^a	-0.032^a	-0.033^a	-0.036^a	-0.037^a	-0.029^b	-0.033^a
	(0.005)	(0.011)	(0.011)	(0.013)	(0.013)	(0.013)	(0.013)
Log income	0.055^b	0.064^a	0.064^a	0.058^b	0.057^b	0.055	0.068^b
	(0.021)	(0.022)	(0.022)	(0.023)	(0.023)	(0.034)	(0.029)
Log migrant share	0.029	0.017	0.016	0.013	0.011	0.019	0.008
	(0.023)	(0.024)	(0.024)	(0.025)	(0.026)	(0.071)	(0.066)
Overidentification p-value		0.460	0.074	0.777	0.218	0.099	0.191
First-stage statistic		15.5	14.7	8.5	8.1	4.9	5.7
Instruments							
Urban population in 1982		Y	N	Y	Y	Y	Y
Urban density in 1990		Y	N	N	N	Y	Y
Urban area in 1990		Y	Y	Y	Y	Y	Y
Urban population in 1990		N	Y	N	N	N	N
Sunshine hours		N	Y	N	Y	N	N
# of starred hotels		N	Y	Y	Y	N	Y
# of 5A scenic spots		N	N	Y	Y	N	Y
Predicted migrant9500/Emp.90		N	N	N	N	Y	Y
Rural population in 1982		N	N	N	N	Y	Y
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,223

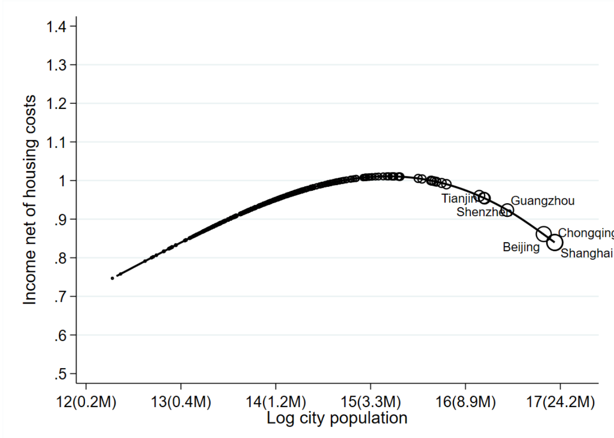
Notes: Column 1 reports OLS estimates (column 3, Table 3) for reference. IV estimates are reported in columns 2-7 using limited information maximum likelihood (LIML). Columns 2-5 instrument city population and land area. Columns 6-7 additionally instrument the migrant share. Y and N stand for 'Yes' and 'No' and mean that the instrument is used or not. The controls are the same as in column 9 of Table 7. Standard errors clustered at the city level are between brackets. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. The first-stage statistics is the Kleibergen-Paap rk Wald F. The critical value for 10% maximal LIML size of Stock and Yogo (2005) weak identification test is below 3.28 for all columns.

Table A6: City determinants of housing expenditure share - IV estimates

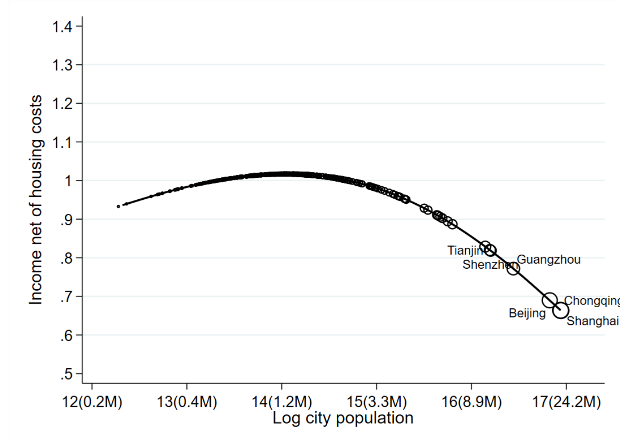
	(1) ols	(2) iv	(3) iv	(4) iv	(5) iv	(6) iv	(7) iv
Panel A. High-skilled workers.							
Log population	0.034^{a}	0.030^{b}	0.035^{a}	0.035^{b}	0.033^{b}	0.023	0.045^{b}
	(0.009)	(0.014)	(0.013)	(0.014)	(0.014)	(0.016)	(0.018)
Log land area	0.010	0.004	−0.006	0.007	0.004	0.020	−0.026
	(0.010)	(0.019)	(0.018)	(0.017)	(0.017)	(0.023)	(0.024)
Log migrant share	0.069	0.084	0.078	0.068	0.076	0.185	0.111
	(0.051)	(0.054)	(0.053)	(0.057)	(0.057)	(0.124)	(0.113)
Overidentification p-value		0.502	0.049	0.082	0.006	0.160	0.519
First-stage statistic		18.1	15.1	15.2	12.4	5.1	3.8
Panel B. Low-skilled workers.							
Log population	0.036^{a}	0.022	0.032^{b}	0.033^{b}	0.028	0.022	0.047^{b}
	(0.010)	(0.016)	(0.014)	(0.017)	(0.017)	(0.020)	(0.019)
Log land area	0.007	0.029^{c}	0.010	0.019	0.019	0.016	−0.024
	(0.007)	(0.018)	(0.016)	(0.016)	(0.016)	(0.027)	(0.021)
Log migrant share	0.086	0.100	0.094	0.081	0.095	0.228	0.163
	(0.063)	(0.073)	(0.067)	(0.074)	(0.074)	(0.198)	(0.177)
Overidentification p-value		0.400	0.022	0.065	0.007	0.110	0.141
First-stage statistic		9.6	11.3	10.7	10.9	5.2	3.4
Instruments							
Urban population in 1982		Y	N	Y	Y	Y	Y
Urban density in 1990		Y	N	N	N	Y	Y
Urban area in 1990		Y	Y	Y	Y	Y	Y
Urban population in 1990		N	Y	N	N	N	N
Sunshine hours		N	Y	N	Y	N	N
# of starred hotels		N	Y	Y	Y	N	Y
# of 5A scenic spots		N	N	Y	Y	N	Y
Predicted migrant9500/Emp.90		N	N	N	N	Y	Y
Rural population in 1982		N	N	N	N	Y	Y
Observations	246	246	246	246	246	246	246

Notes: Column 1 reports OLS estimates (columns 5 & 7, Table 3) for reference. IV estimates are reported in columns 2-7 using limited information maximum likelihood (LIML). Columns 2-5 instrument city population and land area. Columns 6-7 additionally instrument the migrant share. Y and N stand for 'Yes' and 'No' and mean that the instrument is used or not. The controls are the same as in column 9 of Table 8. Standard errors clustered at the city level are between brackets. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. The first-stage statistics is the Kleibergen-Paap rk Wald F. The critical value for 10% maximal LIML size of Stock and Yogo (2005) weak identification test is below 3.28 for all columns.

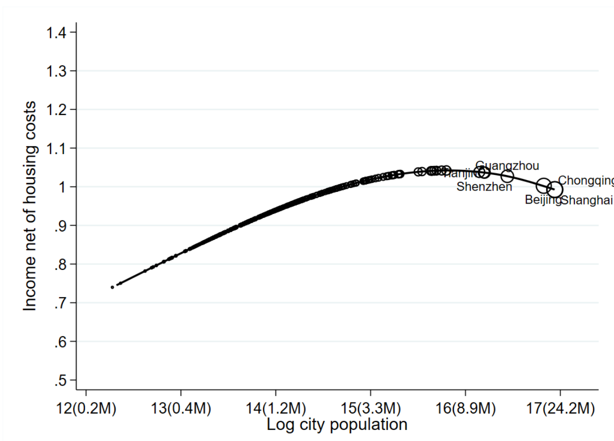
Figure A3: Predicted net income across Chinese cities with IV



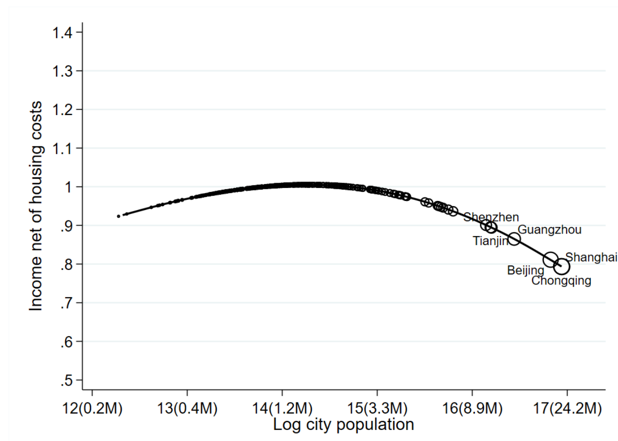
(a) High-skilled - Population only



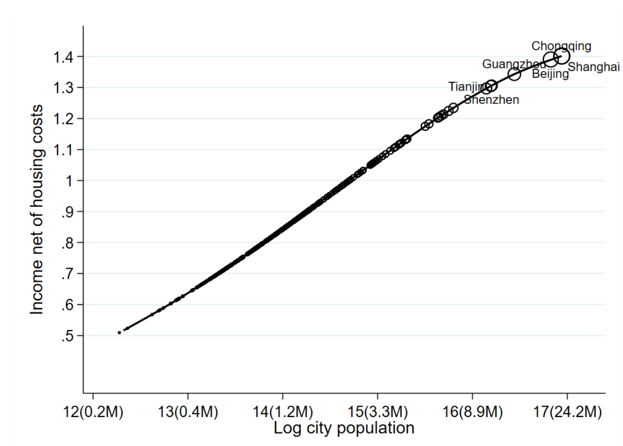
(b) Low-skilled - Population only



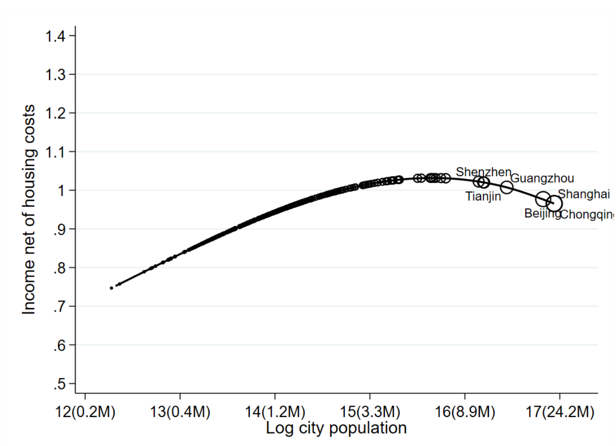
(c) High-skilled - Population and area



(d) Low-skilled - Population and area



(e) High-skilled - Population, area and migration



(f) Low-skilled - Population, area and migration

Notes: This figure displays the predicted real income for high-skilled households (Panels a, c, and e) and low-skilled households (Panels b, d, and f), separately. Panels (a) and (b) use population elasticities from estimations controlling for the city land area and share of migrants, panels (c) and (d) use population elasticities encompassing indirect effects from the city land area but not the share migrants, panels (e) and (f) use population elasticities encompassing indirect effects from both the city land area and the share of migrants. IV estimates of housing costs and nominal income are used in the predictions. Each gray triangle symbolizes a representative high-skilled household, while a black circle denotes a representative low-skilled household in one of the 254 cities. The solid line depicts a quadratic fit.