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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. This shifting spatial distribution of China's population has largely been fuelled by rural-to-urban labor flows.[1] In 2010, rural migrants constituted approximately two-thirds of the total migrant population. However, recent data from the 7th National Population Census of China 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 (Cheng and Duan, 2021).

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. (2015, 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.[2] 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.

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

[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]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.

that, we compile data on the universe of individual land parcel transactions within China and we build a city-specific unit land price index. This index provides useful insights into the variations in land prices within and between cities. Using complementary individual surveys on land development and housing expenditure, we then compute, for both high- and low-skilled households separately, a city-specific housing cost index that encompasses commuting costs. It also takes into account the variation across cities in the share of land used for housing production and in the households' housing expenditure share.

We find that all three components of urban housing costs –unit land prices, land share in construction and housing share in expenditure– 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. 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 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 a low 0.027-0.029 for a city with 500,000 inhabitants up to a high 0.255-0.275 for a city of the size of Shanghai, and it is always higher for low-skilled households. Importantly, less stringent land use regulations –especially the possibility for cities to expand horizontally by allowing adjustments at the 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 of nominal income, we then show that the income-net-of-housing-costs implications of moving to larger cities also vary across cities of different size as well as between low-skilled and high-skilled households. Thanks to nominal income gains that exceed the increase in housing costs, moving to larger yet still relatively small or medium-sized cities results in an overall increase in real income of up to 35%, especially when accounting for additional gains from land area expansion and the presence of rural migrants. In contrast, moving from medium-sized cities to larger ones does not yield additional real income gains and may even result in a decline in real income, as housing costs become dominant for cities at the top of the population distribution. Compared to high-skilled households, low-skilled households are found to experience larger real income gains when they move from small to medium-sized cities, but lower real income gains, and possibly larger losses, when they move to the largest cities. By illustrating a bell-shaped curve relationship between real income and population in China, these results highlight the importance of accounting for housing urban costs in assessing who reaps the benefits of China's large urbanisation.

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; Chang et al., 2023; Rogoff and Yang, 2023). We contribute to enhancing 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 specificity of our work is that we 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.[3] Rosen-Roback's framework, or its extension to migration choices, has become a cornerstone in quantitative spatial economics

[3] Albouy (2008), Albouy et al. (2013) and Albouy (2016) have revisited these approaches for both the US and Canada.

models.[4] 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 shown 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. 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 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 the 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

[4] See Redding and Rossi-Hansberg (2017) for a review.

[5] See, for instance, evaluations of the impact of transport infrastructure on regional disparities and city growth as in Faber (2014), Baum-Snow et al. (2017), or Baum-Snow et al. (2020).

of literature on spatial misallocation (Hsieh and Moretti, 2019; Ngai et al., 2019; Hornbeck and Moretti, 2022). 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 adopted stringent land use regulations and internal migration restrictions, which may impede the efficient spatial allocation of workers. Our paper provides evidence that a specific aspect of land use regulation, namely the possibility for the urban fringe to expand, mitigates the impact of population growth on housing prices, thereby inducing larger real gains for non-landowner workers. These findings may carry significant policy implications about 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 parameters entering the housing cost index, and we derive the population elasticity of housing costs. Section 6 presents the predictions of real income 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 theoretical framework described below, 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 commute to their workplace, a location named the central business district (CBD). In order to properly assess between-city disparities (our focus here), we must control for within-city location choice, which we do using an Alonso-Muth framework (see Fujita and Thisse (2013)). In equilibrium, housing markets ensure that all agents of a particular type k (e.g. high- or low-skilled workers) derive the same level of utility across all districts within a city. We denote P_c^k the unit housing price in city c for type-k agents in the CBD where commuting costs are minimal. The intuition of the Alonso-Muth model is that locations with higher commuting costs exhibit lower housing prices while maintaining the same level of indirect utility. Consequently, the utility can be assessed at the CBD. Further assuming that all goods, except housing, are perfectly tradable (resulting in identical prices across locations), and that preferences are Cobb-Douglas, the indirect utility for an individual i of type $k(i)$ in any neighbourhood d of city c is given by:

$$V_{i,c} = \frac{w_c^{k(i)} \, A_c^{k(i)} \, \epsilon_{i,c}}{\left(P_c^{k(i)}\right)^{\gamma_c^{k(i)}}} \tag{1}$$

where γ_c^k measures the share of housing in consumption for type-k agents in city c, w_c^k denotes type-k agents' income in city c, A_c^k represents the value of city c consumption amenities for type-k agents (including minimal commuting costs as well as other amenities like climate, health, leisure, or cultural facilities), and $\epsilon_{i,c}$ is the idiosyncratic preference of agent i for city c. This follows the between-city location choice model à la Roback (1982), where not all individuals choose city c even when $\frac{w_c^k \, A_c^k}{\left(P_c^k\right)^{\gamma_c^k}}$ is higher, due to the presence of idiosyncratic preferences for locations.

Our purpose is to assess how the monetary part of the utility of type-k agents, $MV_c^k = \frac{w_c^k}{\left(P_c^k\right)^{\gamma_c^k}}$, which we refer to as type-k agents' real income, varies along with some characteristics of the cities, their size among others. In a world where individuals are mobile across cities, lower values can reflect the presence of better city amenities, A_c^k, as assessed by the 'quality of life' literature (Albouy, 2008), which we do not evaluate here.

In the absence of housing price data, we relate unit housing prices at the CBD, P_c^k, to unit land prices at this location, R_c, according to:

$$P_c^k = (R_c)^{\beta_c} \tag{2}$$

where β_c is the share of land in the housing production function if one assumes a Cobb-Douglas technology.[6] 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

[6]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.

β_c depends on k. Therefore, we are bounded to 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

$$MV_c^k = \frac{w_c^k}{\mathbb{P}_c^k} = \frac{w_c^k}{(R_c)^{\beta_c \gamma_c^k}}, \tag{3}$$

where $\mathbb{P}_c^k$ is the housing price index for type-k households in city c. To assess how real income varies across cities, we start by separately evaluating how each of the three price index components, unit land prices (R_c), land share in housing production (β_c), and housing share in expenditure (γ_c^k), depends on city characteristics. This is the first contribution of the paper.

The second contribution is to combine these three sets to estimate how the costs associated with living in a city, namely the level of expenditure E_c^k necessary to obtain utility V_c^k in the city (which we refer to as urban costs), depend on the city characteristics. Using the definition of the expenditure function:

$$E_c^k = \mathbb{P}_c^k \frac{V_c^k}{A_c^k}, \tag{4}$$

we quantify ϵ^{UX}, the elasticity of urban costs with respect to city characteristics X_c, which measures by how much expenditure must increase when X_c changes in order to keep utility constant at a given level of city amenities. ϵ^{UX} is equal to the elasticity of the housing price index. Basic consumer theory shows that it is equal to the product of the share of land in housing production (β_c), the share of housing in household expenditure (γ_c^k), and the elasticity, ϵ^{RX}, of unit land prices with respect to characteristics X_c (see Albouy, 2008; Combes et al., 2019):

$$\epsilon^{UX} = \frac{\partial\, \mathbb{P}_c^k}{\partial \log X_c} = \gamma_c^k\, \beta_c\, \epsilon^{RX} \quad \text{with} \quad \epsilon^{RX} = \frac{\partial \log R_c}{\partial \log X_c}. \tag{5}$$

The third contribution of the paper is to quantify the overall effect of city characteristics on real income by combining the evaluation of urban costs with that of nominal income, w_c^k. For income, we directly rely on the literature that estimates agglomeration gains. Specifically for China, it shows that there are gains associated with population density, city area, and the presence of rural migrants. These gains vary across groups of workers, and are the largest for high-skilled workers. As various quantitative assessments are already available, we do not present any new estimates here. Instead, we use those of Combes et al. (2020), whose two-step methodology is fully consistent with our approach for the three components of housing costs. This allows us to reconstruct real income, MV_c^k, for 254 Chinese cities, as predicted by our estimations, assuming that the cities differ only in terms of population, land area and share of rural migrants.

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.

2.2 Empirical specifications

In line with the empirical strategy proposed by Combes et al. (2019), we 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 minimal commuting costs within the city, i.e. the parameters that enter $\mathbb{P}_c^k$. 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 to a lesser extent income and the presence of rural migrants.

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

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

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 $X_{d(p)}^D$ 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 monocentrically 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 B.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, $X^D_{d(p)}$, 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:

$$\begin{aligned}\widehat{\log R_c} &= \alpha^R_1 \log pop_c + \alpha^R_2 (\log pop_c)^2 + \eta^R_1 \log area_c + \eta^R_2 (\log area_c)^2 + \rho^R \log mig_c \\ &\quad + \mu^R \log w_c + X^C_c \psi^R + \kappa^R + \nu_c \end{aligned} \tag{7}$$

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) and land area ($area_c$), as well as on average income (w_c), migrant share (mig_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.[7] 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.[8] Finally, 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.[9]

Since our land price dataset covers the period from 2007 to 2019, we pool all years

[7]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^k_c 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.

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

[9]For further discussion on the role of the population growth and other controls, see Combes et al. (2019), which our specification closely follows.

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.[10]

The elasticities of unit land prices with respect to population and land area, ϵ^{RP} and ϵ^{RA} respectively, are therefore given by:

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

ϵ^{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 tend to live in cheaper housing units of lower quality (Wang and Chen, 2019), a negative ρ^R could be obtained in that case.

Turning to the estimation of the determinants of the share of land in the housing pro-

[10]Notably, land area is a time-varying variable here because we use the official time-varying definition of cities. See Section 2.3 below for more details about the source and definition of variables.

duction function, we follow a similar two-step procedure and estimate:

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

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 $\mathbb{P}_c^k$, 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.[11] γ_c^k being city c fixed effect for type-k households, which represents the city component of the budget share in $\mathbb{P}_c^k$, we assume that the budget share g_h^k of household h located in district $d(h)$ in city $c(h)$ is given by:

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

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.[12] 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

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

[12] This specification corresponds to more general preferences compared to the Cobb-Douglas case outlined earlier. In particular, it controls for the fact that housing is often found to be a necessity good, with a housing expenditure share that decreases with income. 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.

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 (although we cannot estimate specific housing budget share parameters for rural migrants as they are not included in the household survey we use (see Section 3)).

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 the land share in housing production, and 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.[13] 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 since high housing and land prices 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, as land is an input used by firms, and attract workers because of the income shock generated, thus increasing population (and area in turn). Such

[13] 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.

a process would tend to generate an upward bias of the population impact. Reverse causality from households choosing to locate where housing prices are low would induce a downward bias. To address these concerns, we rely on the standard tools proposed by the literature, instrumental variables, in order to assess whether large biases can be expected.[14] Whereas Section 5 presents OLS estimation results only, Section 7 reports various estimations where population, area and migrant share are instrumented. IV estimations confirm the literature's findings that endogeneity biases are not of primary concern, and that they do not much affect our conclusions, potentially 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 (Carlino and Saiz, 2019), 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).[15] These three instruments isolate the variation in city population driven 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 (Wang and Murie, 1996). 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.[16]

[14] The primary objective of the article is not to propose new contribution in this particular dimension.

[15] 5A is awarded to the most important and best-maintained tourist attractions in China by the Chinese Ministry of Culture and Tourism, which published the list of 5A scenic spots in May 2007. 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 is obtained from the Urban Meteorological Data maintained by the China Meteorological Administration.

[16] As documented in Cheng and Duan (2021), migration flows to cities were minimal during the 1980s

Third, to cope more specifically with the endogeneity of the city migrant share, we build predicted past migration flows using a gravity model based on the distance between the origin and the destination of migration. This approach is similar to that used by Combes et al. (2020) and is applied to historical data from the 1995 National One Percent Sample Population Survey and from the 2000 National Population Census. We use this predicted historical migration share as an extra instrument when we instrument population, area and migrants simultaneously. 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 set of regressions described in Section 2.2 requires measures for land prices, land share in housing production and housing expenditure share. The data sources used for these variables are detailed below. Appendix A provides a description of additional city-level data sources used in the estimations. Our analysis focuses on the 4 provincial-level cities (Beijing, Shanghai, Chongqing and Tianjin) and 250 prefecture-level cities, within which we gather data for the core city (*shixiaqu*), or city-proper only.

Land price To measure land prices, 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 (from a low 92,468 in 2008 to a high 213,657 in 2013). Each transacted parcel's price and size is recorded, as well as other information including the transaction method,[17] the transaction date, the land use type (residential, commercial, industrial, or public use), both

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.

[17]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*).

developer's and seller's information, the floor area ratio, and the parcel location. We keep only parcels located in the core city and we simultaneously ignore parcels transferred through a non-market method (bilateral agreement or state allocation). That leaves us with 66,973 residential-use, 98,141 industrial-use and 47,748 commercial-use land transaction records that took place in one of the 254 provincial or prefecture cities from our main sample.[18]

Land share in housing production To measure the share of land in housing production, we exploit data on residential development projects (RDPs or *xiaoqu*) that had new properties for sale between 2010 and 2022, 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 contiguous land parcel corresponds to one RDP built by a single developer (Tan et al., 2020).

We match each RDP to the land parcel on which it was built in two steps. We first use geo-coded information to select land parcels that satisfy three criteria: they must be in close geo-proximity to the RDP, with a floor area ratio tied to the corresponding RDP's, and 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.

[18] 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 B reports our main estimations for this larger dataset, and shows that the results are very similar.

Household housing expenditure The share of housing in household expenditure is estimated using the urban sample of the Chinese Household Income Project (CHIP) survey for the years 2007, 2013, and 2018. 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, which does not enable us to estimate housing budget shares for them. Using information on the level of education of the household head, we classify registered urban households as high-skilled households if the head has at least 12 years of education and as low-skilled households otherwise.

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.[19] 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 cities in 2007, 3,721 households across 98 cities in 2013, and 5,329 households across 88 cities in 2018.

An obvious limitation of the data on land and housing share concerns the set of cities in the samples, which is smaller than the set of cities covered by land price data. Yet, this is the best that can be currently done for China, given available data sources. Moreover, there is no reason to believe that the sample of cities is biased in any direction, in terms of size for instance. As for CHIP data, the sample is even chosen to be representative. Finally, despite this limitation, we do improve on what is usually done as the literature often relies on even stronger assumptions, typically that these shares are constant across cities (Albouy, 2008; Moretti, 2013).[20]

[19]The imputed rents of current housing consist of (1) monthly expenditure on housing maintenance and management, and (2) depreciation of property assets at a rate of 2%.

[20]Although Combes et al. (2019) do not make this assumption for the housing expenditure share, they are constrained to a one-step estimation because of the limited number of cities in their dataset.

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.[21] 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). 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 (0.18), France (0.31), the UK (0.31), and Germany (0.25-0.33) (Gibbons et al., 2011; Ahlfeldt et al., 2015; Albouy et al., 2016; Combes et al., 2019; Ahlfeldt and Pietrostefani, 2019; Ahlfeldt et al., 2021).

Beyond the average, Table 1 also highlights large between-city disparities. For instance, land prices vary by a factor of 25, from a low of US$64 per square meter in an inexpensive city at the first decile to a high of US$1,543 per square meter in an expensive city at the ninth decile. Moreover, a higher land share in housing production (0.38) is observed for a residential development project (RDP) in the third quartile, approximately 65% larger than that at 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 for to properly assess between-city differences. Although they are not our primary focus here, documenting the variations in land prices within cities provides additional 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. This is done for 4 representative cities separately: Shanghai, the most populated city in China; Lanzhou, a province capital city in the North-West 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

[21] As documented by Tan et al. (2020), condominium units prevail in urban China, and residential development projects (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.

Table 1: Descriptive statistics

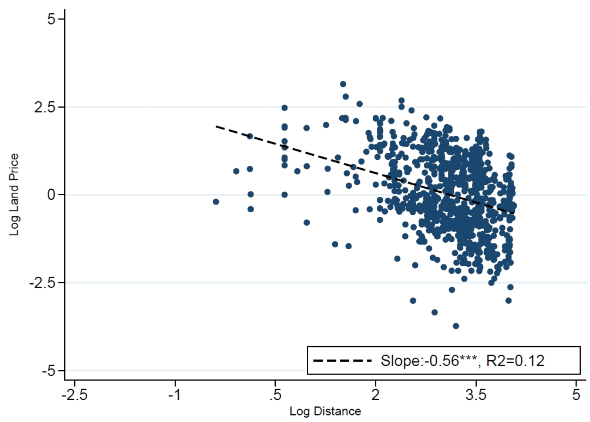
Variable	Mean	St.Error	1^{st} decile	1^{st} quartile	Median	3^{rd} quartile	9^{th} decile
Panel A. City characteristics (254 cities, 3,209 obs.)							
Population (city proper, '000)	1,969	2,950	506	694	1,130	1,929	3,604
Land area (city proper, km^2)	2,587	3,806	490	1,020	1,850	2,951	4,767
Number of 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.

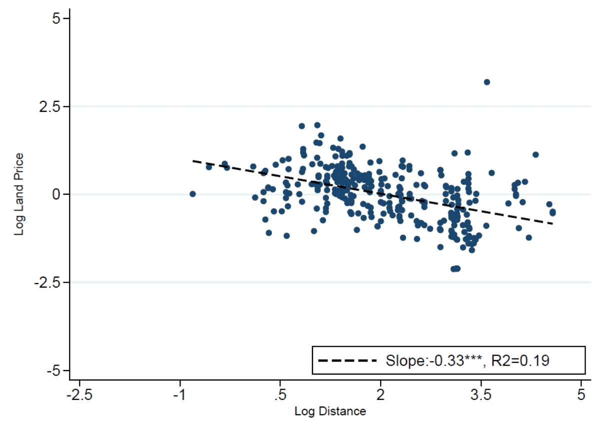
inhabitants; and Huaihua, a city in Southwestern China at the first decile, with a population of 0.56 million people. Two patterns emerge from Figure 1. First, all four plots display a monocentric pattern with a gradient that is city-specific. This is fully consistent with the monocentric city model and the Alonso-Muth condition wherein the gradients of land prices should 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, which can be the result of transport congestion. These two findings are very consistent with what is observed for developed countries as documented in Combes et al. (2019) for France, Ahlfeldt et al. (2015) for Germany, and Albouy et al. (2018) for the US.

In order to visualize the distribution of the price-distance gradients across all cities, Figure 2 plots the estimated price-distance gradient in each city in ascending order, with a highlight of the rank of the four representative cities. While Panel (a) includes no control variables, Panel (b) depicts the distribution of the estimated price-distance gradients conditional on all parcel and local controls introduced in equation (6). The figure highlights a robust pattern, with only a slightly steeper profile when controls are introduced. The city of Shenzhen, in Guangdong province, ranks first with a price-distance gradient of around -0.9 (bottom-left of the graph), which is very close in magnitude to estimates for Paris (around -1) in Combes et al. (2019) or for Chicago (-0.84) in Ahlfeldt and McMillen (2018). On

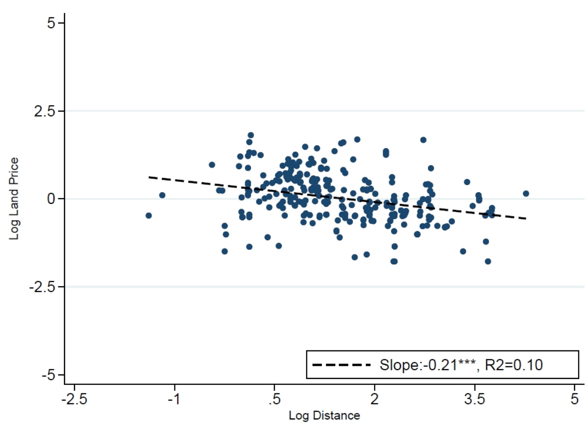
Figure 1: Residential land prices per square metre and distance to the centre for four cities



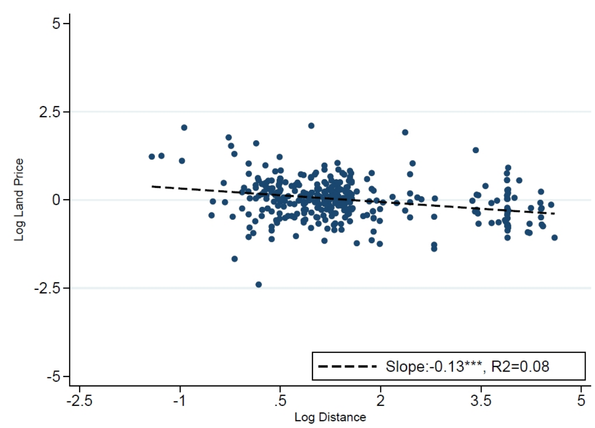
Panel (a): Shanghai



Panel (b): Lanzhou



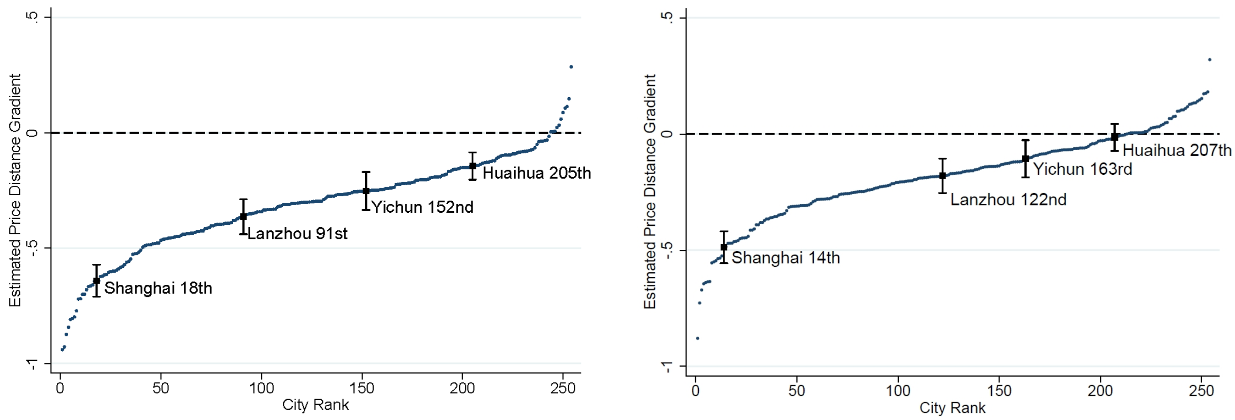
Panel (c): Yichun



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.

the other end of the distribution, there are 11 relatively small cities that display a positive price-distance gradient, with only two of them 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 controlling for the distance to the city center, with fixed effects that represent land prices at the centre, and additional controls including 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, including 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 what is observed 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, highlighting a notable consistency.[22] Column 2 no longer includes parcel characteristics but city-year fixed effects only. They explain 46.9% of the variance of residential unit land price, emphasising the importance of location at the macro-geographical level. Column 3 extends the specification with a distance effect specific to each city. The larger R^2 (at 56.4%) confirms that land prices also vary a lot within cities, in a regular way, declining from the centre to the periphery. The pretty large variations of 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 introduced.

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

[22]When the full sample is used, which additionally includes non-market-based transactions, parcel characteristics become more important, accounting for more than 30% of the variations in land prices.

the specification with the household, land supply and geography controls. Column 8 includes all parcel and local variables. The controls have a limited impact. This is partially because distance to the center is controlled for and many variables correlate with it, as expected from theory (Duranton and Puga, 2015). The estimates for city effects and distance effects are 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).[23]

Table 2 also sheds light on the between-city disparities in city fixed effects (i.e. land prices at the city center). Notably, when comparing cities at different points within the fixed effects distribution, distinct patterns emerge. Indeed, we can compute from Table 2 that cities at the first quartile and at 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 the bottom 5%). Conversely, cities at the third quartile exhibit higher unit land prices at the city center, of 53% compared to 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 to estimate Equations (7), (9) and (10). Table 3 summarizes the main findings from OLS estimations of the second step.[24] 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.

[23]The reliably 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 B.1.

[24]Estimations of the first step and robustness checks including IV are presented in section 7 and Appendices B and C respectively.

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. For cities with a population below 3.2 million inhabitants, the linear and quadratic predictions lead to similar predictions. The largest cities, notably Beijing, Shenzhen and Guangzhou, display unit land prices well above the linear prediction, reflecting stronger responses of land prices to population. This convex pattern is fully 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, line 'Not allowing for land area expansion', further illustrates how the estimated population elasticity of unit land prices, defined in Equation (8), varies with city size. The elasticity spans from 0.335 for a small city of 500,000 inhabitants, corresponding to the first 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, and this effect is more pronounced as the city size grows larger. For instance, further increasing the population of the four hypothetical cities by 10% would increase 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 average), 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 adjust when population increases mitigates the unit land prices increases, as shown in column 2 of Table 3 where land area is not controlled for.[25] Again, this perfectly matches the monocentric city model's prediction since now land supply can

[25] In the context of China, the land area of a city may undergo changes over time, and we observe such changes 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).

adjust in response to larger population. The corresponding population elasticities of unit land prices are displayed on line 'Allowing for land area expansion' in Panel A of Table 4. In the case of a small city with 500,000 inhabitants, 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 city with 1 million inhabitants, 0.632 for a city with 2 million inhabitants, and 1.094, for a city of 24 million inhabitants, representing a 30% reduction thanks to land area adjustment.

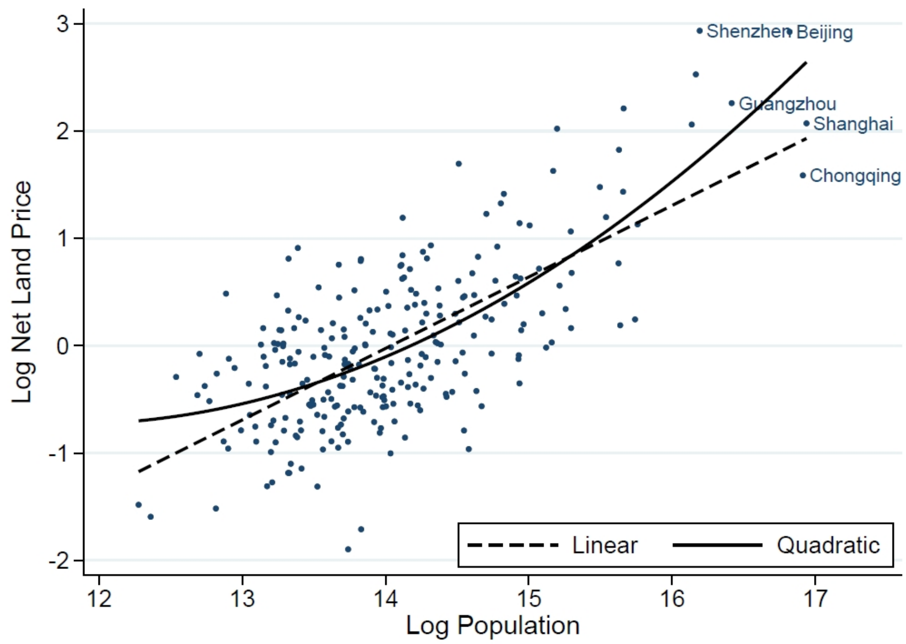
Interestingly, the estimated population elasticity of unit land prices in China is close to that of France, while the land area elasticity is much lower (Combes et al., 2019). Land use regulation seems to be less stringent in urban China, leading to a less sensitive response of land prices to horizontal expansion (Glaeser, 2011; Tan et al., 2020), even if it remains relatively large for the largest cities. A plausible explanation can also be related to the role of local politicians in China. Indeed, as argued by Wang et al. (2020), Chinese city leaders have strong promotion incentives to expand cities outward, even possibly beyond what would be socially optimal.

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 urban 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.

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).[26] The estimated semi-elasticity of the land share in housing production at the city center with respect to population amounts to 0.02, which is consistent with Muth (1969)'s argument that the share of land in housing production rises with urban development. Moreover, more populated cities with an expensive housing market tend to be more regulated and have less elastic housing supply, which leads to a higher land share in housing production (Glaeser and

[26] Quadratic terms for population and land area are not significant when added to the specification. We thus prefer to use a linear specification rather than one with non-significant quadratic terms when we compute housing costs in Section 5.2.

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.

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.

We then compute by how much the share of land in housing production increases when the city population increases. We first estimate the land share in housing production at the city center for the average city in the RDP dataset, 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 case where land expansion is allowed. 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, and we get $\beta_m = 0.48$. The land share of housing production in a city of population pop_c can then be predicted, all other things equal, as

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).

follows:

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

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, ranges from 0.44 to 0.45, 0.47 and 0.52 for cities with 500,000, 1 million, 2 million and 24 million inhabitants respectively. Again, this is lower when the city fringe can expand, at 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 of similar magnitude to estimates for France, for which it varies from 0.35 in the smallest cities to 0.46 in Paris (Combes et al., 2021), especially given that land area adjusts less there.

Housing expenditure share The share of housing in household expenditure is the third key input into the calculation of the housing cost elasticity. Columns 5 to 8 of Table 3 report the results of semi-elasticity estimations 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 of 0.036 for low-skilled households.[27] City land area and the share of migrants play no significant role in explaining the housing expenditure share across cities. Conversely, household income, which is controlled for in the first step, exhibits a significantly negative impact. This is consistent 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. We compute it from the first step at 0.24 for high-skilled households and 0.26 for low-skilled households for the mean city. As land area does not significantly impact the housing budget share, it takes the same value whether or not land area expansion is allowed. These estimates are very close to the national average of 0.24 in 2021, reported by the National Bureau of Statistics of China, which does not control for any effect, however.[28] We can then 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 reported 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

[27] As for land share in housing production, quadratic effects for population and area are ignored here because they are not significant when introduced.

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

households for housing, and it should not reflect any income effect as income is controlled at the household level.

5.2 Population elasticity of housing costs

As its three components vary with the city population, the population elasticity of housing costs defined in Equation (5) also varies with the city population. Panel D of Table 4 reports the population elasticity of housing costs computed by multiplying the values provided in Panels A, B, and C.

Table 4: Population elasticity of housing cost

Population	City 1 500,000	City 2 1 million	City 3 2 million	City 4 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.

Comparing the four hypothetical cities, the elasticity of housing costs increases with city population as expected since its three components increase. Increasing population by 1% increases housing costs about 10 times more for a mega-city of 24 million inhabitants compared to a small city of 500,000 inhabitants (the elasticity changes from 0.027 to 0.255). Doubling population from 500,000 to 1 million nearly doubles the population elasticity of housing costs (from 0.027 to 0.052), and it further increase it by 60% (0.052 to 0.083) when population doubles from 1 to 2 millions.

If we allow for the adjustment of the city fringe, 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 of 2 million, 1 million and 500,000 inhabitants, respectively. Letting the fringe adjust or not when city population expands is therefore an important decision to take for policymakers as regards the impact on housing costs, especially for the largest cities.

The population elasticity of housing costs also differs for low- and high-skilled households, but to a rather low extent. Still, housing costs appear to increase slightly less (by around 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 households 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?

Specifically, using the actual population, land area, and migrant share for each of the 254 Chinese cities, we predict the four local variables entering the real income of type-k

households defined in Equation (3) as:

$$
\begin{aligned}
\widehat{\log w_c^k} &= \kappa^W + \alpha^{W,k} \log pop_c + \eta^{W,k} \log area_c + \rho^{W,k} \log mig_c, \\
\widehat{\log R_c^k} &= \kappa^R + \alpha_1^R \log pop_c + \alpha_2^R (\log pop_c)^2 + \eta_1^R \log area_c + \eta_2^R (\log area_c)^2 + \rho^R \log mig_c + \mu^R \widehat{\log w_c^k}, \\
\widehat{\beta}_c^k &= \kappa^B + \alpha^B \log pop_c + \eta^B \log area_c + \rho^B \log mig_c + \mu^B \widehat{\log w_c^k}, \\
\widehat{\gamma}_c^k &= \kappa^{G,k} + \alpha^{G,k} \log pop_c + \eta^{G,k} \log area_c + \rho^{G,k} \log mig_c + \mu^{G,k} \widehat{\log w_c^k},
\end{aligned} \tag{13}
$$

We compute the housing costs of households as predicted from our estimations provided in Table 3, assuming that the reaction to a city's characteristics is the one estimated above and that cities are identical in all other respects. Statistically insignificant coefficients are set to zero (namely, the effect of land area on housing expenditure and the impact of migrants). For the nominal income equation, we use the values estimated by Combes et al. (2020), which are $\alpha^{W,L} = 0.0643$ and $\alpha^{W,H} = 0.0658$, $\eta^{W,L} = 0$ and $\eta^{W,H} = 0.0442$, $\rho^{W,L} = 0.123$ and $\rho^{W,H} = 0.193$ for low- and high-skilled households respectively.[29] Finally, it is worth mentioning that since the income prediction, $\widehat{\log w_c^k}$, is type-k dependent, the predicted unit land prices and land share in housing production become partially type-k dependent as well.

Then, we can predict the housing price index, $\widehat{\mathbb{P}_c^k}$, and the real income in the city, $\widehat{MV_c^k}$, as, respectively:

$$
\widehat{\mathbb{P}_c^k} = \left(\widehat{R_c^k}\right)^{\widehat{\gamma_c^k}\,\widehat{\beta_c^k}} \qquad \text{and} \qquad \widehat{MV_c^k} = \frac{\widehat{w_c^k}}{\widehat{\mathbb{P}_c^k}}. \tag{14}
$$

6.1 Predicted housing price index and nominal income across cities

Figure 4 plots the prediction of unit land price, land share, and housing expenditure share in each of the 254 Chinese cities as a function of population when city land area and the migrant share, and therefore nominal income, also vary simultaneously. From Panel (a), the

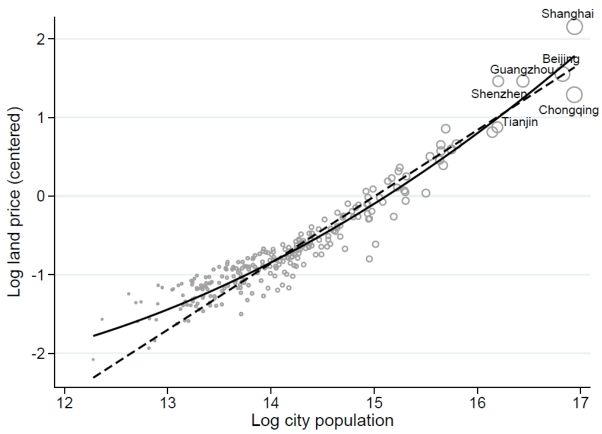
[29] Since the specification is in logarithm, the coefficient for land area in the income definition is obtained as the difference between the coefficient for land area and the coefficient for density in the original estimations. It is not significantly different from 0 for low-skilled households. Furthermore, the migrant variable is the ratio between the number of migrants and the number of low-skilled workers, not the total population, which is also what we use to predict income, with a slight abuse of notation. Last, the income estimations use employment and not population density. To be consistent, we also use total employment and not population to compute nominal income, even if, given the 0.9 correlation between population and employment across cities, this does not much affect the results, here and as documented in the literature (Combes and Gobillon, 2015).

effect of land area, in particular, does not appear strong enough to counterbalance the direct convex effect of population on unit land prices, as observed in Figure 3. Compared to the average unit land prices in Chinese cities, prices can be half as low or over ten times higher when locating in the smallest or the largest city, respectively. Moving to more populated cities leads to an almost linearly increase in the land share in production (Panel (b)) and in the housing budget share in expenditure (Panels (c) and (d)), with magnitudes similar to those presented in the previous section. The land share in housing production varies from 23.7% in the smallest city to 35.7% in Shanghai. The housing expenditure share varies from 15.4% in the smallest city to 29.8% in Shanghai for high-skilled households, and the range is even larger for low-skilled households, from 13.4% to 32.7%. It is worth noting that the strong overall role of population also reflects the correlation of both land area and the migrant share with population (which is 0.421 and 0.182 for the logarithm of land area and the migrant share, respectively). This also explains the relatively low dispersion of cities around the fitted line, which is even more pronounced for high-skilled households.

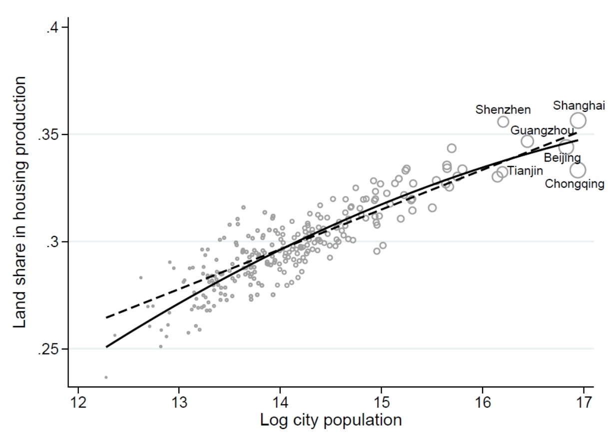
The predictions of the housing price index with respect to city population are displayed in Figure 5, Panels (a) and (b) for high- and low-skilled households, respectively. Due to the convexity of unit land prices, which is raised to the power of the product of almost linear impacts of population for the land and housing expenditure shares, housing costs present a strongly convex pattern. A large quadratic term is needed to match the largest cities' housing cost, but it is too strong to fit well with the housing costs of the smallest cities. Housing costs appear to be slightly more convex for low-skilled households. In comparison to the average city, the housing price index can be up to 3.2% lower in smaller cities for both low- and high-skilled households. Conversely, it can be 24.2% (24.9%) higher for high-skilled (low-skilled) households in the largest city, Shanghai. Overall, the housing price index increases by 36.4% (39.3%) for high-skilled (low-skilled) households when moving from the lowest housing cost city to the city where it is the highest.

As illustrated in Figure 5, Panels (c) and (d), nominal income almost linearly increases with the (log) city population, except for high-skilled households in the smallest cities, which exhibit a slightly higher income than the linear prediction. As documented by Combes et al. (2020), nominal income gains from locating in larger cities in China appear higher than in Western countries (Combes et al., 2008; Eeckhout et al., 2014; Roca and Puga, 2017). Typically, nominal income can be up to 21.4% and 19.0% lower in smaller cities for high-

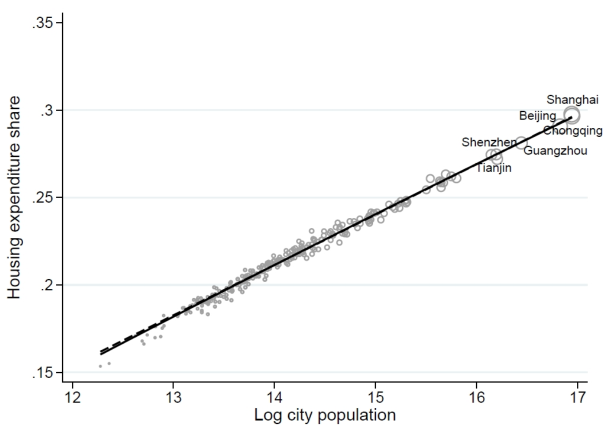
Figure 4: Predicted land price, land share, and housing share across cities



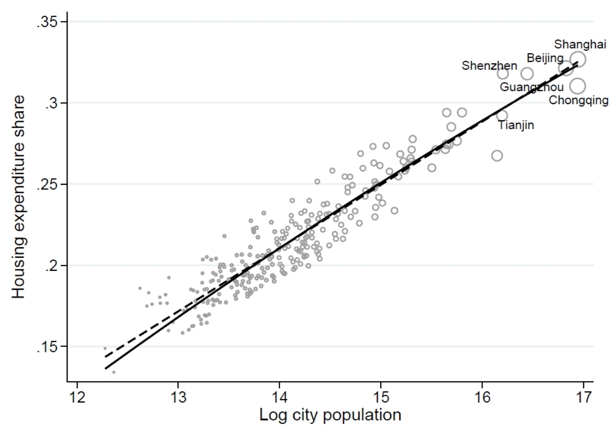
(a) Log unit land prices



(b) Land share in housing production



(c) Housing share in expenditure (High-skilled)

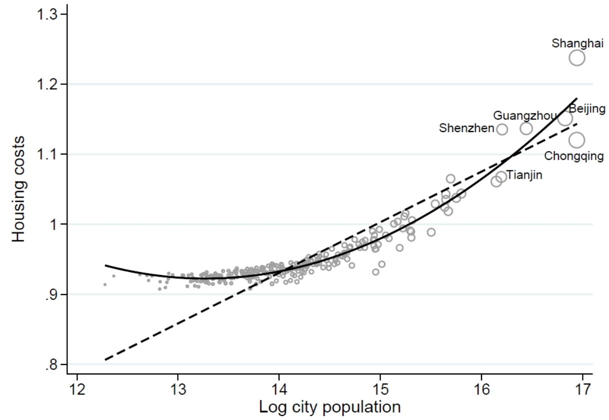


(d) Housing share in expenditure (Low-skilled)

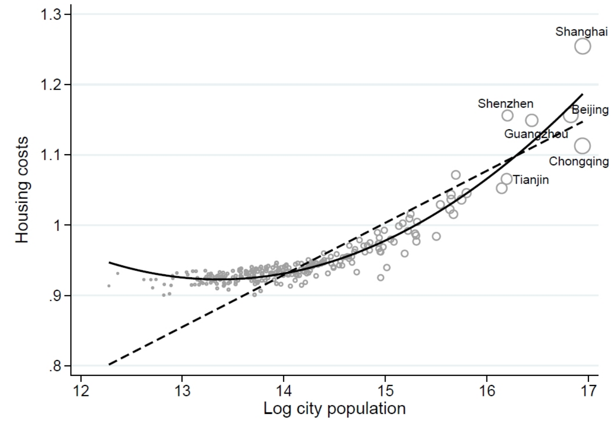
Notes: This figure predicts the unit land price (Panel a), the land share in housing production (Panel b), and the housing expenditure share (Panel c for high-skilled households; Panel d for low-skilled households) at the city centre of the 254 cities in the main sample as given by equation (13). Panels (a) and (b) correspond to high-skilled households. However, the distinction with the corresponding curves for low-skilled households comes only from their different average income (see equation 13), which leads to virtually imperceptible variations on the graph. The logarithm of unit land prices is centered with respect to the Chinese mean, allowing for a reading in relative deviation with respect to this mean. Each circle represents a city, with the circle's size proportional to the mean city population between 2007 and 2019. The largest 9 cities are labeled. The dashed and solid lines indicate linear and quadratic fits, respectively.

skilled households and low-skilled households, respectively, when compared to the average city. On the other hand, it can be 40.9-43.6% higher for high-skilled households and 26.7-28.5% higher for low-skilled households in the largest cities, like Shanghai and Beijing (where income is the highest for high-skilled households even though it is not the largest Chinese city). Overall, nominal income increases by 79.3% for high-skilled households and by 56.4%

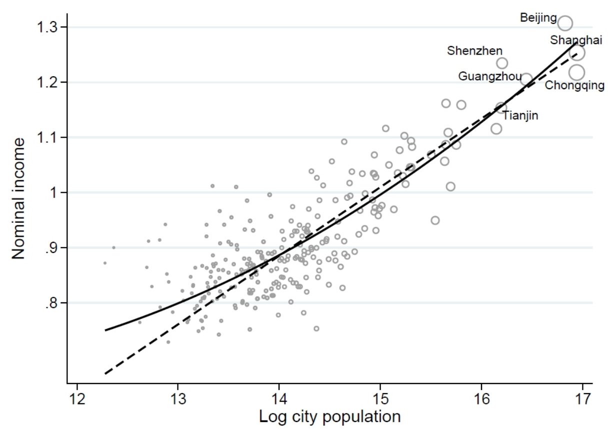
Figure 5: Predicted housing price index and nominal income across cities



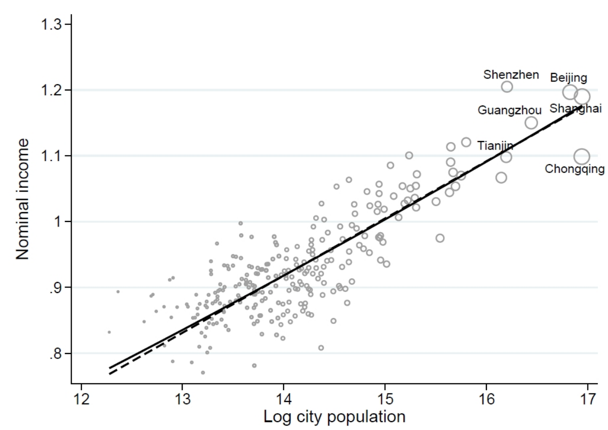
(a) Housing price index (High-skilled)



(b) Housing price index (Low-skilled)



(c) Nominal income (High-skilled)



(d) Nominal income (Low-skilled)

Notes: This figure displays the predicted housing price index (Panels a and b) and nominal income (Panels c and d), separately for high-skilled and low-skilled households, in each of the 254 cities, as defined in equation (14). Both the housing price index and income 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 9 cities are labeled. The dashed and solid lines indicate linear and quadratic fits, respectively.

for low-skilled households, when moving from the city with the lowest income to the one with the highest.

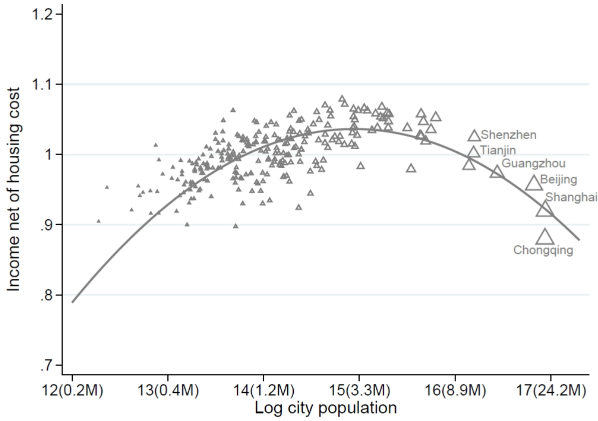
6.2 Predicted real income

We finally combine the variations in nominal income and the housing price index to assess the variations in real income when moving to larger cities. In order to better apprehend the specific role of each variable, we start by presenting, in Panels (a) and (b) of Figure 6, the predictions considering only the role of population, i.e. assuming that cities otherwise have the average land area and migrant share, or equivalently, setting the η and ρ parameters in the four equations (13) to zero (as real income is then centered with respect to the country's average). Next, the simultaneous role of population and area is presented in Panels (c) and (d), assuming that cities have the same migrant share. Finally, the role of all variables is considered in Panels (e) and (f).

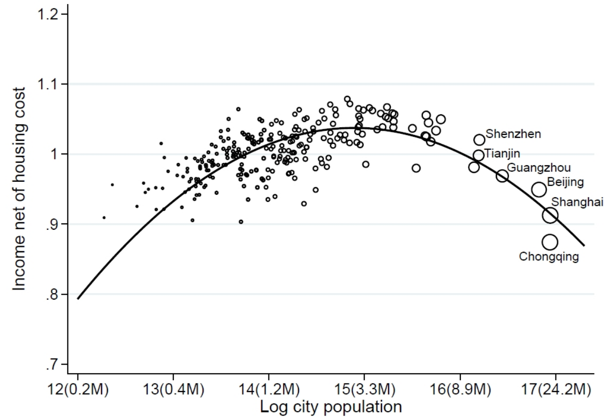
When only population impacts nominal income and the housing price index, as in Panels (a) and (b), an almost symmetrical bell-shaped curve is obtained for both low- and high-skilled households. The maximum is reached for a city with 3.4 million inhabitants, where the predicted real income is close to that of the average city with 2 million inhabitants, the curve being pretty flat between 1.9 and 5.5 million inhabitants. For cities with up to 3.4 million inhabitants, where slightly more than half of the Chinese population lives, nominal income increases faster than the housing price index, resulting in an approximately 14.8% increase in real income. However, for cities exceeding 3 million inhabitants, nominal income increases more slowly than the housing price index, leading to a gradual decline in real income. The lowest value is reached for Chongqing, where real income is 14.1% below the average city with 2 million inhabitants (and 14.5% below the city with the highest real income).

Panels (a) and (b) illustrate the worst-case scenario for larger cities because neither the positive impact of land area and migrants on nominal income nor the negative impact of land area on the housing price index is taken into account. When considering the positive impact of a larger land area, as in Panels (c) and (d), the declining part of the real income curve almost disappears for high-skilled households and substantially reduces for low-skilled ones. This strongly confirms that land supply plays a critical role in spatial inequality in real income. Real income in large Chinese cities would have been much lower if these cities had not expanded horizontally over the last decades, increasing their fringe and overall land area all while keeping land use regulations from constraining this process too much. Only in some of China's five largest cities are rising housing price indexes beginning to more than outweigh income gains. For instance, real income is nearly on par with the average city for high-skilled households in Guangzhou, Shanghai and Shenzhen, while it is higher by 12.4% and 11.4% in Beijing and Chongqing, both of which greatly benefit from their expanded land area. For low-skilled households, real income is lower than in the average city in Guangzhou,

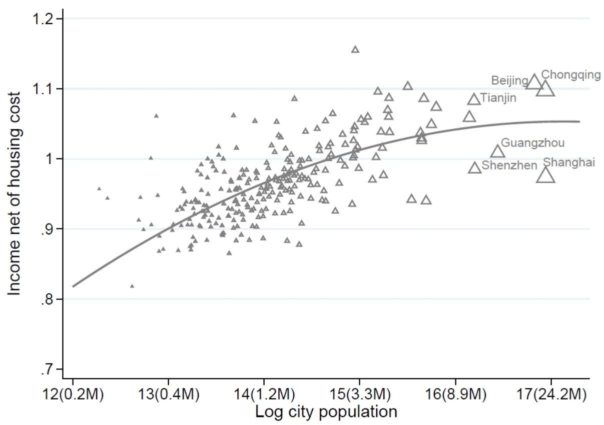
Figure 6: Predicted real income across Chinese cities



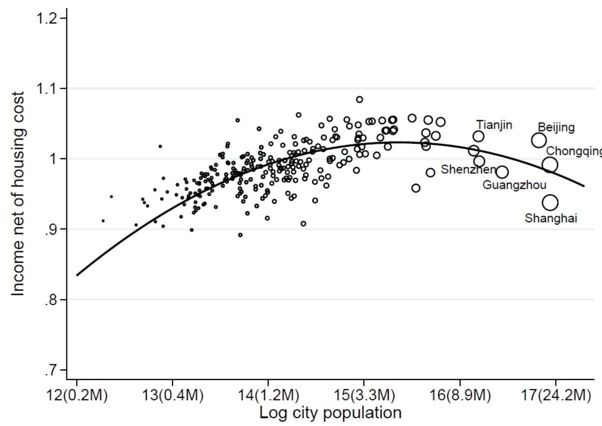
(a) High-skilled - Population only



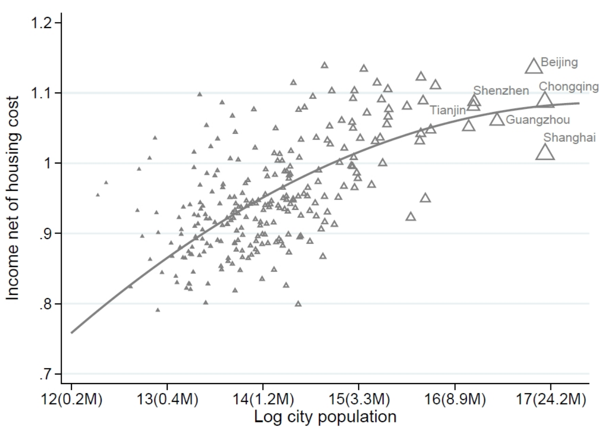
(b) Low-skilled - Population only



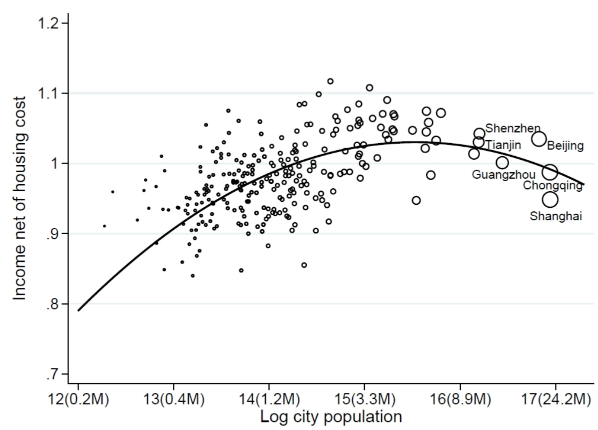
(c) High-skilled - Population and area



(d) Low-skilled - Population and area



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



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

Notes: see Figure 5. This figure displays the predicted real income corresponding to equation (14) for high-skilled households (Panels a, c, and e) and low-skilled households (Panels b, d, and f), respectively. In Panels (a) and (b), the η and ρ parameters are set to zero in the four equation (13), in Panels (c) and (d) the ρ parameter only is set to zero, and the role of all variables is considered in Panels (e) and (f). 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.

Shanghai and Shenzhen, by 4.3%, 8.5% and 2.8%, but also in Chongqing (by 3.3%), while it is similar in Beijing. In the city that offers the lowest real income, which is also the third smallest one, real income is 17.0% and 12.9% lower (relative to the average city) for high- and low-skilled households, respectively. Overall, moving to larger cities is less beneficial for low-skilled households, both because they benefit less from agglomeration economies and experience smaller increases in nominal income, and because their housing costs increase more, as documented in the previous section.

Further taking into account the role of rural migrants, as in Panels (e) and (f), makes the real-income profile even steeper for high-skilled households, and slightly more concave for low-skilled households. The presence of migrants enhances the benefits of larger cities for high-skilled households, both in absolute terms and relative to low-skilled households. As the literature shows (Eeckhout et al., 2014; Combes et al., 2020), while high-skilled households benefit from a strong positive externality from the presence of migrants, the effect is less pronounced for low-skilled households as they are more substitute to migrants in the production sector. Hence, in Beijing, Chongqing, Shenzhen, Guangzhou and Shanghai, high-skilled households typically enjoy real incomes that are 16.7%, 11.7%, 11.7%, 8.9% and 4.1% higher than those in the average city, respectively. By contrast, low-skilled households in the largest cities tend to fare much worse than if they were located in smaller cities, and they face real incomes lower by 5.1% and 1.2% in Shanghai and Chongqing, almost identical in Guangzhou, and higher only in Shenzhen and Beijing, by 4.3%, and 3.5%.

The figures provided in this section are not the actual average real income in each city, but predictions for a representative household living in a representative dwelling. These predictions ignore all factors other than population, land area and the presence of migrants, and assume that each city responds to changes in these variables as the average city. Despite these limitations, they illustrate the important role played by the three city characteristics in shaping real income across space, and they show that this impact varies for households of different types. These findings may provide insights into both the massive internal migration that takes place in China, increasingly between cities and not only from rural places, and the differences in location choices made by households with varying education levels. These differences could potentially initiate a spatial sorting along skills, similar to Western countries where high-skilled households are disproportionately concentrated in largest cities.

7 Robustness checks and extensions

This section provides various robustness checks for each of the three key parameters that enter the housing price index. 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 5 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 and use our preferred estimates of city-year fixed effects 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.[30]

Overall, Table 5 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

[30] 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.

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. 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 5: 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 output of column 3 of Table 2. Columns 4-6 use the output of column 4 of Table 2. Columns 7-9 use the output 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 relates to 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 reports a series of regressions in which we include both a quadratic and a cubic term for the log population. The estimated coefficients are generally not significant, which suggests that the convexity we observe in our baseline results is not driven solely by one or two very large cities.

Land share in housing production Table 6 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. This echoes 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; Cai 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 was observed for unit land prices in Table 2. These controls vary themselves largely in relation with the distance to the centre, thus weakening its impact but not substantially increasing the overall explanatory of the model. In any case, the land share in housing production varies less within city than unit land prices.

Table 6: 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 5. 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 lower panel presents estimations of the second step, 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 as regards the land share in housing production than for land prices, the elasticity being reduced by a third when all controls are introduced compared to its highest value with fewer controls, even if the difference is not significant given the standard errors.

Housing expenditure share Table 7 reports the results of semi-elasticity estimations 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. Similarly to land prices and land share in housing production, the various columns highlight the robustness of our estimation.

Columns 4-6 show that when household income and 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. 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 refine the precision of the estimation by using the full set of controls in the first step. The point estimates on population and land area remain unchanged.

7.2 Instrumental variable estimates

As explained in Section 2.3, local 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 C 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 of Table 5), 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 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.[31] The IV estimates of the population elasticity for

[31] The critical value for 10% maximal limited information maximum likelihood (LIML) size of Stock and Yogo (2005) weak identification test is below 3.28 for all columns.

Table 7: 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 5. 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 5. 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.

a medium-sized city with 2 million inhabitants are between 0.806 and 0.879, which is very close to 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. For the city determinants of the land share in housing production, Table A5 provides a set of IV estimates for our preferred specification (column 3 of Table 3) 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 show only slight variations from their OLS estimates. 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 vary only slightly compared to the OLS estimates. We conclude that our IV results are supportive of our baseline OLS results for all three equations.

We compute the population elasticity of housing costs using the IV estimates presented in column 7 of Tables A4, A5, and A6. 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 a more substantial increase in housing costs with city size compared to OLS estimations.

We finally check the robustness of our findings in Section 6, using IV estimates of housing costs and nominal wages, where city population, city land area, and share of migrants are all instrumented. Specifically, to predict the three local variables (i.e. land prices, land share in housing production, and housing expenditure share) composing the housing price index for type-k households defined in equation (3), we use the IV parameter values from column 7 of Tables A4, A5, and A6. When predicting the nominal income, we use IV parameter values for city population, city land area and share of migrants from Combes et al. (2020): $\alpha^{W,L} = 0.132$ and $\alpha^{W,H} = 0.141$, $\eta^{W,L} = -0.0725$ and $\eta^{W,H} = -0.0571$, $\rho^{W,L} = 0.139$ and $\rho^{W,H} = 0.241$ for low- and high-skilled households, respectively.

The results are displayed in Figure A1, Appendix C. While housing costs appear to increase even more with city size in IV estimates, the same holds for nominal income gains.

Overall, the two almost compensate, and both OLS and IV estimates lead to very similar predictions for real income variations across cities. High-skilled households still benefit from relocating to the largest cities. In Shenzhen, Beijing, Guangzhou, Shanghai, and Chongqing, they enjoy a real income that is 36.2%, 23.2%, 15.7%, 10.9%, and 5.2% higher than in the average city, respectively. In contrast, as with OLS estimates, low-skilled households in the largest cities may find themselves at times worse off than if they were to live in smaller ones. For instance, in Shanghai, their real income is 7.9% lower relative to the average city and it is almost identical to the average in Guangzhou and Shenzhen. It is slightly higher than the average in Beijing and Chongqing, by 6.7% and 5.9%, respectively.

8 Conclusion

This paper makes two main contributions. First, using various sets of individual data for Chinese cities, it estimates housing costs and assesses how they vary between cities. Our framework derives the elasticity of housing costs with respect to a city characteristics, its population typically, as 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 estimate the population elasticity of unit land prices to vary from a low 0.335 for a small city with 500,000 inhabitants up to a high 1.582 for a city of the size of Shanghai with 24 million of inhabitants. The estimated land share in housing production ranges from around 44% in a small city to 52% in Shanghai, and the housing households' expenditure share varies from 18%/20% in a small city to 31%/34% in Shanghai for high/low-skilled households, respectively. These findings imply that the population elasticity of housing costs varies from 0.027/0.029 (high/low-skilled) for a city with 500,000 inhabitants up to 0.255/0.275 for a city of the size of Shanghai. The housing price index increase by 36.4% (39.3%) for high-skilled (low-skilled) households when they move from the lowest housing cost city to the city where it is the largest. Importantly, less stringent land use regulations in China (especially the possibility for cities to expand horizontally by letting their fringe adjust) reduce the elasticity of housing costs by 22% for a small city and up to 53% for a city like Shanghai.

We combine these findings with analogous estimates for nominal income to show that income-net-of-housing-costs exhibits a bell-shaped pattern with city size. This pattern has three main implications. First, individual urban monetary gains outweigh housing costs when moving from a small city to cities with populations ranging from 1 to 3 million. Second, when relocating to the largest cities, housing costs become predominant, particularly for low-skilled households. Third, the net gains from moving to larger cities are greater for low-skilled households than for high-skilled households in small cities, but the reverse holds in the largest cities.

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 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. Spatial variations in non-housing prices are found to be of much lower magnitude than those of housing prices. 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, 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

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 city proper. 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 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 city proper is computed at city level, based on the CUCSYs. The CUCSYs also report the proportion of residential-, industrial-, and commercial-use stock land within urban built-up area.

Income and education Average urban employee annual wage can be 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.

Nighttime light data 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 Estimation variants

B.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 did in our baseline estimation. However, this is an approximation and there is no theoretical justification for assuming that the relationship is linear. Instead, the monocentric city model predicts a negative but convex relationship between land price and distance to the city center (Bertaud and Brueckner, 2005; Duranton and Puga, 2015), which may be due to an increase in housing consumption as the distance from the city center increases. 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 this issue, 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 linear model remains reasonable.

There may also be concerns about the geography we impose on urban areas with a single center. To address this, we re-estimate Equation (6) allowing for two different centres, and present results in columns 3 and 4 of Table A1. It is also worth noting that we define the geographic centroid of brightest grid cells as the city center. However, this definition of centers may introduce ambiguity, and measurement error may be more pronounced 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. Reassuringly, the results remain 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, providing additional evidence of the reliability of our conclusions.

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 (CBD and subcenters, whereby subcenters are defined as the grid cells whose pixel value exceeds 80% of 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).

B.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 separate 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	-5.707^{b}	-4.560	-1.341	-6.067^{b}	-4.929^{c}	-1.390	-5.612^{b}	-4.531^{c}	-1.543
	(2.892)	(2.930)	(2.386)	(2.949)	(2.936)	(2.424)	(2.653)	(2.651)	(2.180)
Log population squared	1.105^{c}	0.909	0.265	1.160^{b}	0.967^{c}	0.260	1.066^{b}	0.881^{c}	0.281
	(0.565)	(0.570)	(0.456)	(0.579)	(0.573)	(0.467)	(0.520)	(0.517)	(0.420)
Log population cubic	-0.056	-0.047	-0.007	-0.058	-0.049	-0.006	-0.053	-0.045	-0.007
	(0.036)	(0.036)	(0.028)	(0.037)	(0.037)	(0.029)	(0.033)	(0.033)	(0.026)
Log land area	1.044^{a}	0.896^{a}	0.655^{b}	1.046^{a}	0.897^{a}	0.694^{a}	1.068^{a}	0.928^{a}	0.693^{a}
	(0.271)	(0.275)	(0.261)	(0.266)	(0.263)	(0.241)	(0.248)	(0.245)	(0.226)
Log land area squared	-0.088^{a}	-0.078^{a}	-0.062^{a}	-0.088^{a}	-0.078^{a}	-0.063^{a}	-0.088^{a}	-0.079^{a}	-0.063^{a}
	(0.019)	(0.019)	(0.018)	(0.019)	(0.019)	(0.017)	(0.018)	(0.017)	(0.016)
Log income		1.089^{a}	0.642^{a}		1.102^{a}	0.622^{a}		1.019^{a}	0.593^{a}
		(0.219)	(0.166)		(0.215)	(0.163)		(0.204)	(0.158)
Log migrant share			0.292			0.279			0.286
			(0.255)			(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 5 and includes the cubic terms of population and land area as explanatory variables.

C 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 liml-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 liml-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. Columns 2-5 instrument city population, land area, and their squared terms. Columns 6-7 additionally instrument the migrant share. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. Standard errors clustered at the city level are between brackets. The controls for the first step (second step, respectively) are those used in column 8 of Table 2 (column 9 of Table 5, respectively). The first-stage statistics is the Kleibergen-Paap rk Wald F. Y2 indicates that both the linear and quadratic terms of the variable are used as instruments.

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 liml-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

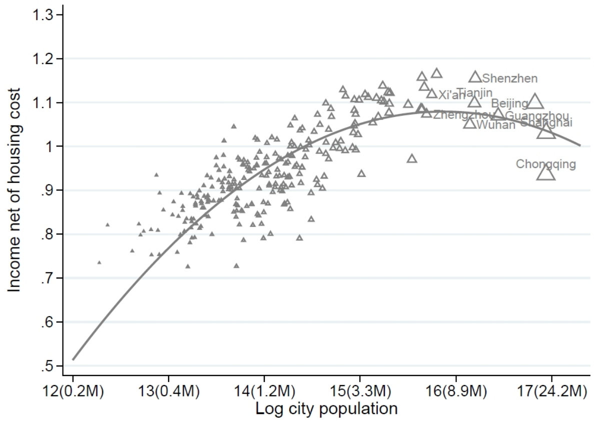
Notes: Column 1 reports OLS estimates (column 3, Table 3) for reference. Columns 2-5 instrument city population and land area. Columns 6-7 additionally instrument the migrant share. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. Standard errors clustered at the city level are between brackets. The controls are the same as in column 9 of Table 6. The first-stage statistics is the Kleibergen-Paap rk Wald F.

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

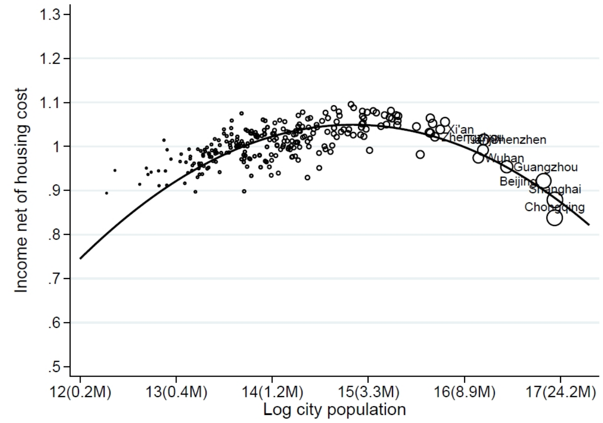
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ols	iv	iv	iv	iv	iv	iv
Panel A. High-skilled workers.							
Log population	0.034^a	0.030^b	0.035^a	0.035^b	0.033^b	0.023	0.045^b
	(0.009)	(0.014)	(0.013)	(0.014)	(0.014)	(0.016)	(0.018)
Log land area	0.010	0.004	−0.006	0.007	0.004	0.020	−0.026
	(0.010)	(0.019)	(0.018)	(0.017)	(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 liml-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 liml-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. Columns 2-5 instrument city population and land area. Columns 6-7 additionally instrument the migrant share. The superscripts a, b, and c indicate significance at 1%, 5%, and 10% respectively. Standard errors clustered at the city level are between brackets. The first-stage statistics is the Kleibergen-Paap rk Wald F.

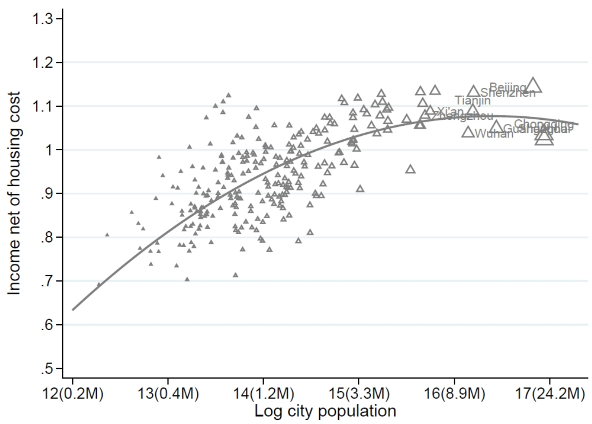
Figure A1: Predicted net income across Chinese cities with IV



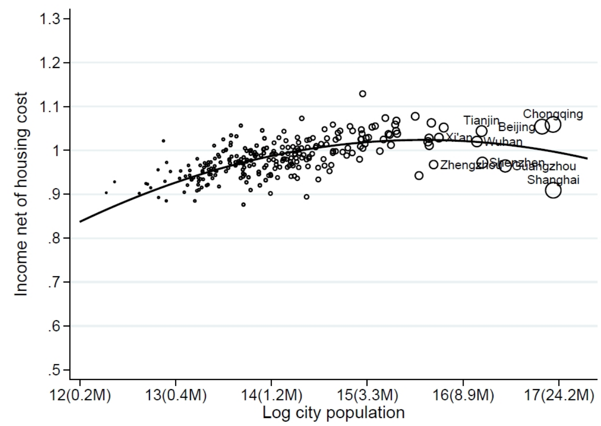
(a) High-skilled - Population only



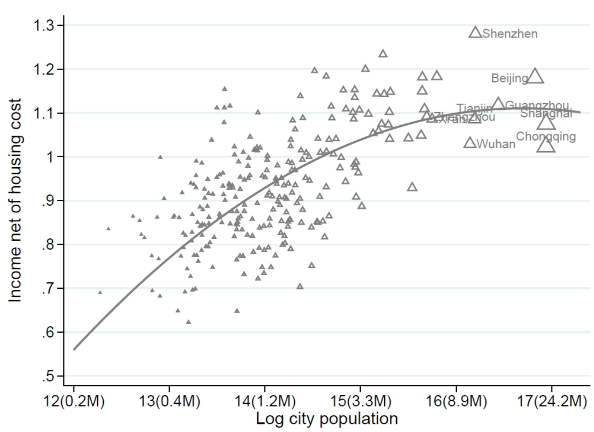
(b) Low-skilled - Population only



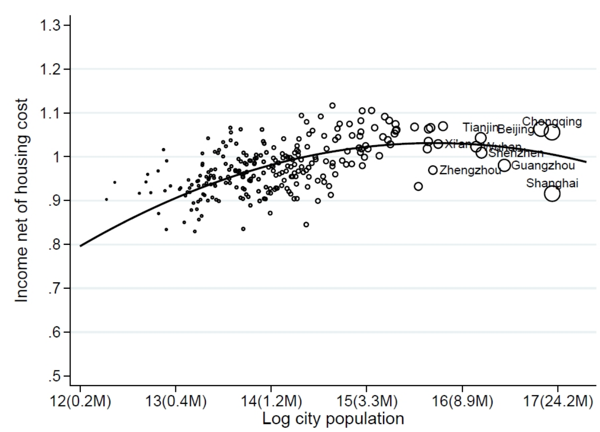
(c) High-skilled - Population and area



(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. 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.