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HOUSING COSTS AND REAL INCOME DIFFERENCES ACROSS CHINESE CITIES

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Housing Costs and Real Income Differences across Chinese Cities

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Abstract

We document variations in real income for high-skilled, low-skilled, and rural migrant households across Chinese cities. Using comprehensive data on land parcel transactions along with individual data for land development and household expenditure, we construct a city-specific housing cost index and 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 city centres 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 widely between locations. While income gains outweigh housing costs when moving from smaller to larger cities, in the largest cities, housing costs begin to dominate, particularly for low-skilled and rural migrant households. This suggests a bell-shaped relationship between real income and city population in China, aligning with theoretical predictions.

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

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

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1 Introduction

In sharp contrast to the tightly regulated city expansion of earlier decades, China has undergone rapid urbanisation 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 increase from 1982. The shifting spatial distribution of China’s population has been largely fuelled by rural-to-urban labour flows, with rural migrants constituting approximately two-thirds of the total migrant population in 2010. However, the latest census data suggest a potential shift in this pattern, as urban-to-urban migration increased faster than rural-to-urban migration in the past ten years, to reach 82 million persons in 2020.¹

How does real income vary when people move to cities of different sizes? Several recent studies have investigated the nominal productivity and income gains from locating in larger cities, and found them to be large in China, as evidenced, for instance, by [Combes et al. \(2020\)](#). However, urban economics models predict that the cost of living, particularly the cost of housing, also increases with city size. This is an obvious fact in China, although it has not yet received a precise quantitative assessment.² In this article, we assess whether and to what extent rising housing costs offset the nominal income gains of urbanisation. We explore how real income, defined as nominal income net of housing and commuting costs, varies with various city characteristics such as population, land area, and the share of rural migrants. Additionally, we investigate whether these patterns differ between households of different types, defined by their skill level and *Hukou* status.

Our quantitative framework builds on recent developments in the urban economics liter-

¹Population 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 urbanisation, it has also resulted in significant disparities between rural and urban areas ([Chan, 2009](#)). Since 1997, several steps have been taken at the central and local levels to relax the *Hukou*-related constraints in order to address these disparities and promote greater labour mobility. Initially, the focus was on skilled workers from rural areas and other cities, with certain prefectures implementing targeted reforms ([Fan, 2019](#)). Starting in 2014, small and medium-sized cities (with populations of less than 1 million inhabitants) were mandated to gradually or completely eliminate *Hukou* restrictions. Figures from the 7th National Population Census of China (2020) are available at <https://www.stats.gov.cn/sj/pcsj/rkpc/d7c/202303/P020230301403217959330.pdf>, retrieved on January 13, 2025.

²The 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.

ature. We first quantify urban housing costs and assess how they vary between cities. For that, we compile data on the universe of individual land parcel transactions within China from 2007 to 2019 and document variations in land prices within and between cities. We use complementary individual surveys on land development and housing expenditure to similarly assess how the share of land used for housing production and the share of housing in households' expenditure vary across locations. Finally, we combine the three components—unit land prices, land share in construction, and housing share in expenditure—to quantify how the elasticity of housing plus commuting costs with respect to population varies with the city population, land area, and share of rural migrants. This assessment is conducted separately for high-skilled, low-skilled, and rural migrant households.

We find that unit land prices, land share in construction, and housing share in expenditure all decrease from the centre to the periphery of cities, increase with the city's population, and decrease with the city's land area, as predicted by urban economics theory. In contrast, they are not significantly affected by the share of rural migrants at a given population. Overall, housing costs in China's urban areas are high, and they vary a lot across locations, both within and between cities. Our estimates show that the population elasticity of housing costs varies across cities in a magnitude comparable to that observed in some high-income countries, the US, Germany, and France, for instance. It ranges from 0.027-0.035 for a city with 0.5 million inhabitants to 0.254-0.273 for a city of the size of Shanghai, which exceeds 20 million inhabitants, and is consistently higher for low-skilled and rural migrant households. Housing costs exhibit a strongly convex pattern, especially for low-skilled and rural migrant households. They increase by 38.5%, 42.2%, and 53.3% for high-skilled, low-skilled and rural migrant households, respectively, when moving from the lowest to the highest housing cost city. Importantly, less stringent land use regulations—especially the possibility for cities to expand their fringe—reduce the elasticity of housing costs by 38% for an average-sized city and by up to 53% for a city like Shanghai.

Comparing these variations with those in nominal income, we then show that the income-net-of-housing-and-commuting-costs implications of moving to larger cities also vary by city size and household type, and depend on whether city land area expansion and the presence of rural migrants are accounted for. First, if population alone were to affect nominal income and housing costs, an almost symmetrical bell-shaped curve would emerge for both high- and low-skilled households. In cities with up to 2.6 million inhabitants, where approximately half of

the Chinese population lives, nominal income would grow faster than housing costs, resulting in a real income increase of about 8.7%. However, in cities with over 3 million inhabitants, nominal income gains would fall behind housing costs, resulting in a gradual decline in real income of up to 10.4% and 12.5% for high- and low-skilled households, respectively, in Shanghai compared to the city with the highest real income. Rural migrant households follow a distinct pattern, with fewer small cities on the left-hand side of the curve's peak and most larger cities on the right-hand side. They would experience smaller gains and higher costs in larger cities, with real income peaking in mid-sized cities before declining by up to 21.1% in megacities like Shanghai.

When land area is considered alongside population, the decreasing portion of the real income curve is less pronounced for all three types of households. However, moving to larger cities would remain less advantageous for low-skilled households and even more so for rural migrants compared to high-skilled households. In the largest cities like Beijing, Chongqing or Shanghai, real income would be 2.1% to 2.6% lower for high-skilled households, 8% to 9% lower for low-skilled households, and 16.1% to 17.3% lower for rural migrant households compared to the city with the highest real income.

Finally, also accounting for the higher share of rural migrants that characterises larger cities in China amplifies the increase in real income with city size for high-skilled households and reduces its concavity for both low-skilled and rural migrant households. For both high- and low-skilled households, the presence of migrants makes real income increase monotonically with population, particularly for the former. In Beijing, Chongqing, and Shanghai, high-skilled households would typically enjoy real incomes about 37-39% higher than those in the average city, while low-skilled households would follow a more concave real income profile, remaining approximately 10% higher in the largest cities compared to the average city. Rural migrants would also benefit from a positive externality due to their own presence, although it is less pronounced than for high- and low-skilled households. As a result, their real income profile would rise with city size, peaking at 2.5 million inhabitants before declining by up to 9.7% in the largest cities.

Instrumented estimations addressing the potential endogeneity of city characteristics yield even stronger increases in the elasticities and levels of housing costs with city population. However, since this also holds for nominal income gains, the overall pattern of

real income across Chinese cities remains similar, whether instrumented or not, although it becomes slightly more concave when instrumented.

The importance of land and housing markets for the overall Chinese economy has only recently been acknowledged. For instance, [Rogoff and Yang \(2024\)](#) stress that the existing literature has overlooked the benefits but also the risks that these markets exert on China’s long-term development. Thanks to newly accessible data, a series of articles has started to assess the determinants of the dynamics of Chinese land and housing markets, particularly their booms and busts ([Fang et al., 2016](#); [Glaeser et al., 2017](#); [Henderson et al., 2022](#); [Rogoff and Yang, 2024](#)). We contribute to the understanding of these markets by shading a specific light on the spatial dimension, both across cities throughout the entire Chinese territory and within cities, while also looking at the specific role of city characteristics in shaping land and housing market disparities.

A distinctive feature of our work is to adopt an urban economics theory perspective to assess how much space, and more broadly, location within a global economy, contributes to overall inequality between households. In the context of the US, [Moretti \(2013\)](#) stresses the importance of accounting for the role of the local cost of living, particularly housing costs, when assessing income inequality and its evolution over time, across households that not only differ in skills and education levels, but also, importantly, live in cities with different characteristics. [Moretti \(2013\)](#) emphasises 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](#); [Couture et al., 2023](#)). However, these assessments have primarily focused on the US economy, occasionally extending to countries such as 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 \(2008\)](#) and [Albouy \(2016\)](#) have revisited these approaches for both the US and Canada.

models (see [Redding and Rossi-Hansberg, 2017](#), for a review). We also adopt a Rosen-
Roback perspective, although we make no attempt here to quantify the value of specific
local amenities.

Compared to both the literature on real income and quality of life, our study, in addition
to 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 si-
multaneously at two distinct geographical levels that play different roles in spatial inequality:
the neighbourhood within the city and the city itself. Although not feasible in studies relying
on data already averaged at the city level, as in most of the previously cited articles, [Albouy
and Lue \(2015\)](#), [Combes et al. \(2019\)](#), and [Ahlfeldt et al. \(2021\)](#) have demonstrated, from
a theoretical perspective, the importance of controlling for within-city location, specifically
commuting costs, when comparing cities. This is essential to obtain consistent estimates of
how city characteristics, such as size, impact the cost of living, which includes both housing
and commuting costs. To address this, we adopt the two-step empirical strategy proposed
by [Combes et al. \(2019\)](#), which nets out the role of 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 stance⁴, has largely
overlooked the role of differences in land and housing costs, partly because of the absence
of relevant and consistent data. We contribute to this literature by explicitly taking into
account housing and commuting costs that we compare to nominal income gains in cities with
different characteristics, estimated in an earlier work ([Combes et al., 2020](#)). This approach
allows us to quantify the real income gains associated with locating in larger cities, i.e.,
nominal income gains adjusted for housing and commuting costs.

Finally, although somewhat more tangentially, our article also contributes to a growing

⁴See, for instance, evaluations of the impact of transport infrastructure on regional disparities and city
growth as in [Faber \(2014\)](#) and [Baum-Snow et al. \(2017\)](#).

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

The rest of the paper is organised as follows. In Section 2, we describe the conceptual framework and our empirical strategy. Section 3 introduces the data and Section 4 provides a descriptive analysis of the spatial distribution of unit land prices in China, both within and between cities. In Section 5, we estimate the impact of city characteristics on the three key components of housing costs, and we study the variations of the population elasticity of housing plus commuting costs. Section 6 presents the predictions of real income disparities across Chinese cities. Section 7 discusses various robustness checks. Section 8 concludes.

2 Conceptual framework

2.1 Theoretical background

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

and of an idiosyncratic preference for the city, $\epsilon_{i,c}$. One assumes that

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

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

Beyond idiosyncratic preferences and amenities, moving to a larger city typically induces nominal income gains, due to the presence of agglomeration economies in production, but also urban costs, due to the increase in the cost of living. This paper focusses on the disparities in the monetary part of the utility between cities, denoted V_c^k , which we refer to as the real income of type- k agents in city c , i.e., the value of $v(h_i, x_i)$ once maximised under the budget constraint. Our purpose is to assess how real income varies with certain characteristics of the city, their size, among others.⁵

As the literature shows, to properly assess between-city disparities in the cost of living, within-city variations in housing prices and commuting costs must be properly accounted for. This can be easily grasped using an Alonso-Muth framework where, in equilibrium, within-city housing markets ensure that all agents of a particular type k derive the same level of utility in all locations they occupy within a city (see [Fujita and Thisse, 2013](#)). Hence, locations with higher commuting costs exhibit lower housing prices while maintaining the same level of indirect utility. As a consequence, utility can be assessed in any specific location, which explains why the real income V_c^k above does not depend on d , the district chosen by the household. In particular, we can measure the utility in CBD, where the commuting costs are the lowest and the unit housing price, denoted P_c^k , is the highest.

In line with urban economics models and empirical studies showing that the prices of non-housing goods vary much less between cities than housing prices ([Handbury, 2021](#)), we assume that all goods except housing are perfectly tradable, resulting in identical prices across locations.⁶ As we assess urban costs through housing prices in the CBD, where they are the highest within the city, these costs encompass not only housing costs but also the extra commuting costs incurred throughout the city, beyond their minimal value at the CBD. We also set this minimal value to zero, implying that any potential commuting costs at the

⁵Note that lower values can reflect the presence of better amenities in the city, as proposed by the ‘quality of life’ literature when households are mobile, i.e., $\epsilon_{i,c}$ is not large ([Roback, 1982](#); [Albouy, 2008](#)). We do not intend to evaluate this dimension here.

⁶Data for China, as for many countries, is unavailable to fully replicate [Handbury \(2021\)](#). However, in [Section 7.3](#), we show that the prices of many non-housing goods do not increase with city size.

CBD are considered part of the city’s amenities and enter the utility through A_c^k . Under these assumptions and applying basic consumer theory, [Combes et al. \(2019\)](#) show that the elasticity of real income for type- k agents in city c with respect to the city population, Pop_c , denoted $\epsilon_c^{V,k}$, is equal to the difference between the elasticity of nominal income, $\epsilon_c^{W,k}$, and the elasticity of housing plus commuting costs, which we refer to as urban costs, $\epsilon_c^{C,k}$:

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

where urban costs correspond to the expenditure compensation needed to keep utility constant when relocating to a larger city.⁷ The elasticity of urban costs is itself equal to the product of the share of housing in expenditures, γ_c^k , and the elasticity of unit housing prices

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

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

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

where β_c is the share of land in the housing production function assuming a Cobb-Douglas technology.⁸ As we lack information about the individuals who will occupy the housing units constructed on the land parcel, specifically their skill type k , neither R_c nor β_c depends on k . Therefore, we estimate unit housing prices for the average Chinese household (with local skills composition controlled for at the district level in estimations), although we are able to estimate type- k agents’ specific parameters for nominal income and for the housing budget share. Overall, we have

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

⁷Some authors, such as [Hoxie et al. \(2023\)](#), suggest directly computing the difference between nominal income and housing expenditure. However, unlike the elasticity calculations presented here, this approach does not account for how households re-optimize their consumption when relocating and facing different price systems. As a consequence, this method may lead to misleading conclusions if interpreted in terms of welfare inequality, as spatial utility differences depend not only on nominal income and housing expenses but also on how households adjust their consumption patterns across locations.

⁸Data 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.

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

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

2.2 Empirical specifications

In line with the necessity to account for within-city location choices discussed in the previous section, we follow [Combes et al. \(2019\)](#) and adopt a two-step procedure to estimate the impact of city characteristics on each of the three components entering urban housing costs. In the first step, we regress the variable of interest at the micro level (the parcel for unit land prices and land share in the production of housing, and the household for the housing expenditure 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 computed 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

land supply factors, and commuting costs equal to those at the city centre. In the second step, we regress the city fixed effect on relevant city-level characteristics. As detailed below, our main variables of interest are the population and area of the city and the share of rural migrants, although we also consider income, for instance, as an extra source of local demand difference.

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

$$\log r_p = \log R_{c(p)} + \delta_{c(p)}^R \log dis_p + X_p^P \lambda^R + X_{d(p)}^D \varphi^R + \varepsilon_p \quad (6)$$

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 suggests controlling 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, but we can 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 moncentrically 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. Moreover, 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 neighbourhoods and is reflected in local housing prices (Brueckner et al., 1999). To compute unit prices for a neighbourhood that would benefit from the average level of amenities in the city, we use a number of local consumption amenities (schools, hospitals, parks, rail stations) as control variables, $X_{d(p)}^D$, which we compute in a radius of 2 kilometres around the parcel. To capture the potentially non-random distribution of neighbourhood variables within the city only, supply factors, education and amenities within cities, all these characteristics are centred with respect to their city mean, so that the city fixed effect still fully captures their between-city differences.

The specification for the second step is given by:

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

where the city fixed effect estimated in the first step, $\widehat{\log R_c}$, is regressed on our main variables of interest, city population (pop_c), land area ($area_c$) and the share of rural migrants (mig_c), as well as on average income (w_c) and additional city controls (X_c^C). κ^R is a constant term 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. Amenity variables are not introduced since our purpose is to isolate the role of real income within the indirect utility from the average provision of amenities at the city level that separately enters utility (see term A_c^k in Eq. (1)).⁹ This enables us to obtain the unit land price elasticity with respect to city characteristics for a representative parcel located in the city centre, benefitting from

⁹In the first step, amenities only control for between-neighbourhood differences within city, but not for their average effect at the city level since they are centred with respect to the city average.

the city’s average amenities and purchased by an average household. To further control for land 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.¹⁰ 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 rural migrant share. It can also control for potential discrepancies between land prices –recorded in the data– and land rents, which should theoretically be used instead (see [Combes et al., 2019](#), for a discussion on the role of population growth).

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

The elasticity of unit land prices with respect to population, ϵ^{RP} , is therefore given by:

$$\epsilon_c^{RP} = \alpha_1^R + 2\alpha_2^R \log pop_c. \quad (8)$$

ϵ_c^{RP} measures the impact on land prices of increasing the population of the city, a housing demand effect, while simultaneously keeping the city fringe (therefore land area, or the land supply) as well as average income and the share of rural migrants constant. ϵ^{RP} is expected to be positive. Conversely, the impact of increasing the spatial extent of the city, its land area (a land supply effect) at given demand (population, income and rural migrants, but also population growth typically) 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

¹⁰[Tan et al. \(2020\)](#) convincingly argue that land use regulation largely differs between coastal cities and other cities in China, which this dummy captures. [Combes et al. \(2019\)](#) also control for the average building height to further account for land use restrictions that may vary at the neighbourhood level. Unfortunately, precise data on building heights for China are not currently available, as existing datasets typically cover only tall buildings exceeding 100 metres. As an initial indication, [Chen et al. \(2025\)](#) find no significant relationship between the number of tall buildings and land prices in Chinese cities. This suggests that height regulations may not play a crucial role, which warrants further investigation.

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 , is specific to the Chinese context and aligns with the approach used for income in [Combes et al. \(2020\)](#). A substantial body of literature has explored the impact of international migration on local wages in high-income countries, with a notable focus on the Mexican-US case. This literature emphasises that the effect of migration largely depends on the skill distribution of both migrants and natives, as well as on the degree of substitutability or complementarity between the two groups. Recent estimates increasingly document a positive impact of migrants on the employment outcomes of natives (see [Lewis and Peri, 2015](#), for a review). For China, [Combes et al. \(2020\)](#) showed a significant positive effect of rural migrants at the city level on the wages of urban high- and low-skilled natives, and, to a lesser extent, even on those of rural migrant workers themselves. These findings suggest complementarity between migrants and local residents in Chinese cities, as migrants often occupy distinct roles in the labour market, benefiting local residents, particularly skilled workers. Two mechanisms are at play. First, rural migrants provide cheap labour in sectors critical for urban development, creating local positive externalities. This is evident in construction, which supports the building and improvement of roads, network infrastructure (e.g. water and electricity), business premises, and housing units. Second, by taking jobs at the lower end of the skills distribution, rural migrants incentivise native workers to shift into better-rewarded and higher-skilled occupations.

On the housing cost side, several mechanisms could explain why migrants might influence housing prices. On the one hand, migrants may increase demand in local housing markets ([Fang and Huang, 2022](#)), thereby driving up land prices and resulting in a positive ρ^R . On the other hand, since the overall population level is controlled for in the specification, the migrant variable captures a composition effect at a given population size and nominal income. Given that migrants are generally poorer and tend to reside in lower-quality, less expensive housing units ([Wang and Chen, 2019](#)), a negative ρ^R could also emerge. Assessing the impact of rural migrants on housing costs in China represents a novel contribution to the literature.

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

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

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

where b_p is the land share in housing production on parcel p . β_c is a city fixed effect that represents the land share in housing production on a representative parcel in the city, the parameter that enters $\epsilon_c^{C,k}$ in Eq. (5). The control variables are the same as those defined in Eqs. (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. The expected signs for city characteristics are the same as for land prices. Indeed, assuming that non-land input prices in the housing production do not vary much across locations 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 in expenditure separately for type- k (high-skilled, low-skilled, and rural migrant) households, using the same two-step procedure.¹¹ Let γ_c^k be a city c fixed effect corresponding to the budget share parameter that enters $\epsilon_c^{C,k}$ for households of type 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:

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

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

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

¹²This accounts for possibly non-homothetic preferences. Our household-level data allow us to directly consider the role of each household income rather than relying solely on the city average, which is therefore removed from the estimation of the second step.

area are expected to have an effect of the same sign as for land prices, positive and negative respectively. Finally, to match what is assumed for land price, land share and income, we also control for the city migrant share.

2.3 Estimation issues

A first concern in assessing the role of location on individual outcomes is the potential non-random spatial sorting of individuals based on characteristics that directly affect the outcome. For instance, a large literature shows that failing to properly control for individual skills may lead to overestimating agglomeration gains by a factor of 2 (Combes and Gobillon, 2015). To address this issue, we use individual data and control for the characteristics of the parcels in the estimation of land prices and of the land share in housing production, and 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 Eq. (7) (and similarly, Eqs. (9) and (10)), to which the literature has paid most of its attention, is the endogeneity of local characteristics, mostly city size that reflects in the city population and area variables, and the share of rural migrants. Some of the control variables can also be affected, albeit to a lesser extent.

Endogeneity may arise from omitted local variables that affect both population and prices, or from reverse causality, as high housing and land prices can deter migration to a city. For instance, a positive productivity shock for firms within a city can simultaneously drive up local land prices –since land is an input for firms–, and attract workers because of the resulting income shock, thereby increasing the population (and, in turn, area). This process tends to generate an upward bias in estimating the population impact. Conversely, reverse causality from households choosing to locate where housing prices are low would induce a downward bias. To address these concerns, and given that this article does not primarily aim to contribute to this specific issue, we follow standard instrumental variable strategies from the literature to assess whether large biases can be expected. Section 5 presents OLS estimation results, while Section 7 reports various estimations where population, land area and migrant share are instrumented. IV estimations confirm the literature's findings that

endogeneity biases do not seem to be of primary concern. They have little impact on our conclusions, only slightly reinforcing the trends we document.

Three sets of instruments are used. The first set is inspired by [Roback \(1982\)](#)'s model where exogenous amenities determine population, and in turn area, but do not directly determine land prices. In the spirit of the literature on urban growth, we construct three proxies for collective natural amenities: a city-level count of '5A' scenic spots, a count of starred hotels and a climate indicator on sunshine duration in January (over the period 1960-2010).¹³ 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. 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.¹⁴

Third, to specifically address the endogeneity of the city migrant share, we use past migration flows predicted by [Combes et al. \(2020\)](#). They use a gravity model based on the distance between migration origin and destination and apply it to historical data from the 1995 National One Percent Sample Population Survey and from the 2000 National Population Census. We use this variable as an additional instrument when simultaneously instrumenting population, area and migrants. This instrument is motivated by the idea that migration

¹³'5A' is awarded to the most important and best-maintained tourist attractions in China by the Chinese Ministry of Culture and Tourism. As of 2020, there are 279 tourist attractions listed as '5A'. To determine the number of starred hotels in each city, we rely on 2011 POI data (see Appendix A). The sunshine duration data is obtained from the Urban Meteorological Data maintained by the China Meteorological Administration.

¹⁴As documented in [Cheng and Duan \(2021\)](#), migration flows to cities were minimal during the 1980s and 1990s, but started to accelerate towards the late 1990s, coinciding with the relaxation of the stringent constraints of the *Hukou* system initiated in 1997.

patterns are relatively stable over time and the role of distance in particular is present at any period; but, reversely, the distance predicted value of migrant inflows does not drive the current demand and supply of housing. Lagging in time further reinforces the exogeneity condition, with the same intuition as for historical instruments.

3 Data

Implementing the regressions described in Section 2.2 requires measures for land prices, land share in housing production, and housing expenditure share. Data sources for these variables are briefly described below, while Appendix A provides a full description of these sources and additional city-level data used in the estimations. Our analysis focusses on 4 provincial-level cities (Beijing, Shanghai, Chongqing, and Tianjin) and 250 prefecture-level cities, gathering data for the core city (*shixiaqu*) or city proper only, the urban part of prefecture cities. City centres are defined as the brightest cell(s) in each city identified with nighttime light data.

Land prices are extracted from the Land Transaction Monitoring System website, which records all primary land market transactions in China from 2007 to 2019, totalling 2,233,917 observations. We include only transactions of residential land parcels with market-mediated methods in core cities, resulting in 66,973 transaction records after data cleaning and geocoding.¹⁵

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

Finally, information on household income, expenditure, and composition is drawn from two complementary sources. The Chinese Household Income Project (CHIP) survey data from 2007, 2013, and 2018 provide information for urban households, while the China Migrants Dynamic Survey (CMDS) data from 2011 to 2017 cover migrant households. The CHIP sample includes 6,595 urban households across 66 representative cities in 2007, 3,721

¹⁵Appendix D.1 provides a robustness check using all kinds of residential land transactions (190,042 observations).

households across 98 cities in 2013, and 5,329 households across 88 cities in 2018. The housing expenditure share is computed using imputed rents for homeowners and actual rental payments for renters. The CMDS sample includes 381,048 rural migrant households, with annual sample sizes varying between 44,986 and 82,053 households across 211 to 239 cities over six survey years. We restrict the CMDS sample to rural migrants living in formal housing for two reasons: (1) the quality and price of informal housing are difficult to assess, making comparisons with formal residential land parcels in our land price and land share data difficult; and (2) urban migrants in formal housing have heterogeneous skill levels, which do not align with the migrant category used by [Combes et al. \(2020\)](#) for nominal income estimations. We also exclude the year 2015 due to missing data on housing type and ownership.

An obvious limitation of the data on land and housing shares is that the set of cities is smaller than the set covered by the comprehensive land price data. However, given the available data sources, this is the best that can currently be done for China. Furthermore, there is no reason to believe that the city sample is biased in any particular way, such as in terms of size. In particular, the CHIP data sample is specifically chosen to be representative. Despite this limitation, our approach improves on the usual practice, as the literature often relies on even stronger assumptions, typically that the shares of land in housing production and of housing in expenditures are constant across cities ([Albouy, 2008](#); [Moretti, 2013](#)).¹⁶

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 metres and sells for an average of US\$675 per square metre.¹⁷ 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

¹⁶Although [Combes et al. \(2019\)](#) do not make this assumption, their estimation of the housing expenditure share is constrained to a one-step specification due to the limited number of cities in their data set compared to their land parcel transaction data.

¹⁷As documented by [Tan et al. \(2020\)](#), condominium units prevail in urban China and each RDP typically provides housing for more than 500 households. This explains the large average parcel area compared to countries like France where individual houses are common.

and low-skilled households).¹⁸ The average land share in our sample aligns with the levels found for high-income countries, including Germany (0.32), the US (0.36), France (0.39), and the UK (0.54) (Knoll et al., 2017). Similarly, the average housing expenditure share is comparable to that of the US (0.23-0.32), France (0.31), the UK (0.15-0.31), and Germany (0.25-0.33) (Ahlfeldt et al., 2015; Combes et al., 2019; Ahlfeldt and Pietrostefani, 2019; Ahlfeldt et al., 2021; Overman and Xu, 2022).

Beyond the average, Table 1 also highlights large disparities between cities. Land prices vary by a factor of 25, ranging from a low of US\$64 per square metre in a city at the first decile to a high of US\$1,543 per square metre in a city at the ninth decile. Similarly, the land share in housing production for a residential development project in the third quartile is approximately 65% larger than in the first quartile. Finally, households in the first decile allocate between 9% and 13% of their monthly expenditure to housing, depending on their type, while those in the ninth decile spend about 40 percentage points more.

Table 1: Descriptive statistics

Variable	Mean	St.Error	1 st decile	1 st quartile	Median	3 rd quartile	9 th decile
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
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
Land share in housing production (146 cities, 47,421 obs.)							
Overall	.32	.11	.19	.23	.3	.38	.47
Household housing expenditure share (137 cities, 15,645 obs., CHIP data)							
High-skilled households	.24	.21	.04	.09	.19	.33	.5
Low-skilled households	.26	.21	.05	.12	.21	.35	.51
Household housing expenditure share (259 cities, 381,048 obs., CMDS data)							
Rural migrants	.25	.73	.08	.13	.21	.33	.5

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.

As detailed in Section 2, within-city variations must be controlled to properly assess between-city differences. Although these variations are not our primary focus, documenting

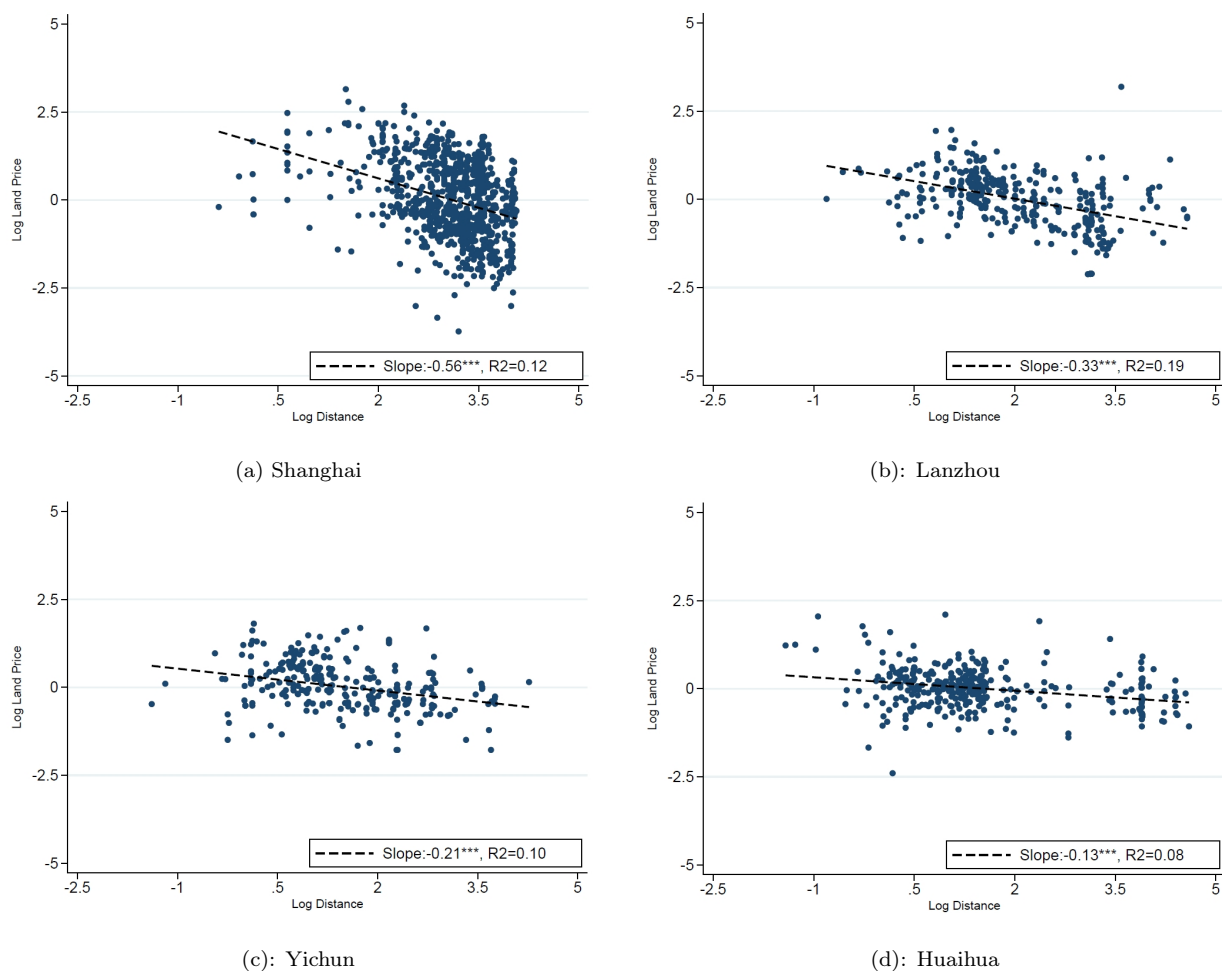
¹⁸Using information on the level of education of the household head from the CHIP surveys, we classify registered urban households as high-skilled households if the household head has at least 12 years of education and as low-skilled households otherwise.

land price variations within cities provides valuable insights into urban development in China. Fig. 1 plots the logarithm of unit land prices against the logarithm of the distance between a land parcel’s centroid and the barycentre of its city for 4 representative cities separately: Shanghai, China’s most populous city, with 24 million inhabitants; Lanzhou, a provincial capital in the Northwest, close to the sample average, with 2.15 million inhabitants; Yichun, a city in Central China just below the median population, with 1.19 million inhabitants; and Huaihua, a city in Southwestern China in the first decile of the population distribution, with 0.56 million inhabitants. Two conclusions emerge from Fig. 1. First, all four plots display a mono-centric pattern with a city-specific gradient. This is consistent with the mono-centric city model and the Alonso-Muth condition, where land price gradients match the marginal cost of commuting to jobs that are more abundant near the centre. Second, the distance gradient is steeper in more densely populated cities, possibly due to transport congestion. These two findings align with observations for high-income countries as largely documented, recently by [Combes et al. \(2019\)](#) for France, [Ahlfeldt et al. \(2015\)](#) for Germany, and [Albouy et al. \(2018\)](#) for the US.

To visualise the distribution of the price-distance gradients across all cities, Fig. 2 plots the estimated price-distance gradient for each city in ascending order, highlighting the ranks of the four representative cities. Fig. 2(a) includes no control variables, while Fig. 2(b) depicts the distribution of the estimated gradients conditional on all parcel and local controls introduced in Eq. (6). The figure reveals a robust pattern, with only slightly lower distance gradients in absolute value when controls are introduced. Shenzhen, in Guangdong province, ranks first with a price-distance gradient of around -0.9 (bottom-left of the graph), which is very close to the estimates for Paris (around -1) in [Combes et al. \(2019\)](#) or for Chicago (-0.84) in [Ahlfeldt and McMillen \(2018\)](#). At the other end of the distribution, still with all controls, 11 relatively small cities display a positive price-distance gradient, with only two showing a gradient significantly different from zero. Out of the 254 cities, 208 exhibit significantly negative gradients.

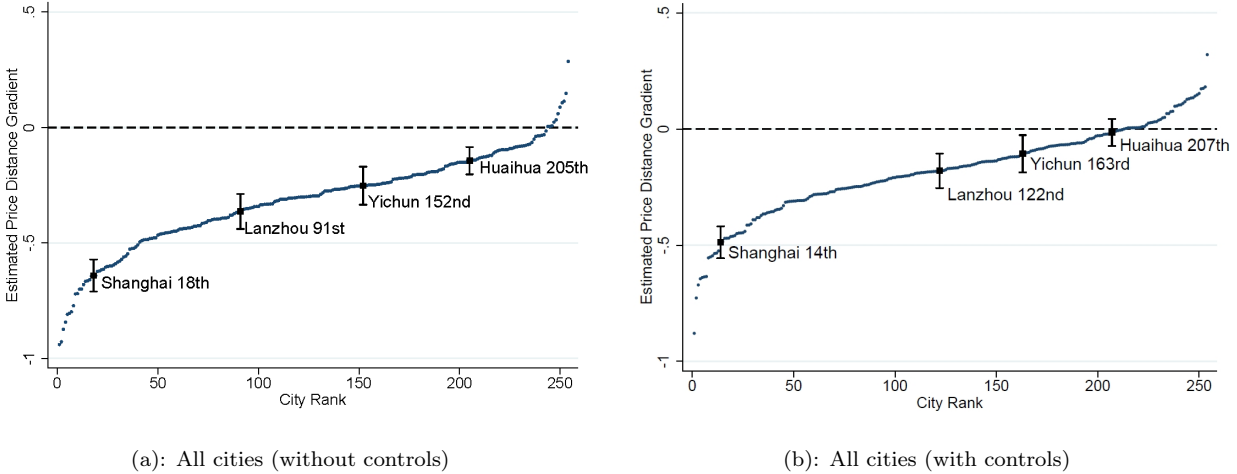
To further document the within-city land price variation, we use the first-step estimation for the price of residential land parcels as specified in Eq. (6). As described in Section 2.2, Eq. (6) estimates an individual land price equation that controls for the distance to the city centre, with fixed effects representing land prices at the centre. It also includes controls for parcel characteristics, geography and geology, education and consumption amenities.

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



Notes: Figs. 1(a) to 1(d) plot the land price-distance gradient for 4 illustrative cities, namely Shanghai, Lanzhou, Yichun, and Huaihua. The logarithm of the distance between the land parcel and the city centre is shown on the horizontal axis, while the vertical axis represents the residualised 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



Notes: Fig. 2(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. Fig. 2(b) duplicates Fig. 2(a) with a full set of control variables when calculating the residualised logarithm of the land transaction prices.

Table 2 presents various quantiles of the distribution of the city fixed effects (with the mean normalised 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, i.e., the log parcel area, its square, and a dummy for the land parcel transaction type. With only 2% of the variance explained, the explanatory power of the parcel characteristics is much lower than in high-income countries (e.g., 48% in France [Combes et al., 2019](#)). A primary factor contributing to this low explanatory power is the homogeneity of residential land parcels in our restricted sample, especially in terms of their size. The standard deviation of the parcel size is only 1.5 times the mean, indicating notable consistency.¹⁹ Column 2 excludes parcel characteristics and includes only city-year fixed effects, which explain 46.9% of the variance of residential unit land prices. This emphasises the importance of location at the macro-geographical level, between cities. Column 3 extends the specification by adding a city-specific distance effect. The larger R^2 at 56.4% confirms that land prices also vary a lot within cities, declining from the centre to the periphery for most cities (negative effect of distance). The substantial variation in

¹⁹When the full sample is used, which includes non-market-based transactions, parcel characteristics become more important, accounting for over 30% of the variations in land prices (see Appendix Table A2), even though other results are not much affected.

the gradients between cities observed in Fig. 2 is also confirmed, since the gradient in the first quartile is, for instance, 6 times greater than in the third quartile when all controls are included in Column 8.

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
Variables introduced								
City fixed effects		Y	Y	Y	Y	Y	Y	Y
City-specific gradient			Y	Y	Y	Y	Y	Y
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 Eq. (6). All reported R^2 are within-year. The city 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 neighbourhood-level controls are centred relative to their city mean.

Column 4 adds parcel characteristics to location effects, while Columns 5, 6 and 7 enrich the specification with the household, land supply, and geography controls. Column 8 includes all parcel and local variables. The controls have a limited impact, partly because distance to the centre is controlled for and many variables correlate with it, as expected from theory. The estimates for city effects and distance effects remain very stable across specifications. Specifically, the pairwise correlation between the city effects estimated in Columns 3-8 is

strong (0.9 or higher), and a similar pattern holds for the distance effects (0.98 or higher).²⁰

Finally, the first rows of Table 2 shed light on between-city disparities in city fixed effects (i.e., land prices at the city centre) and reveal distinct patterns. Specifically, cities at the first quartile and the median of the fixed effects exhibit negative gaps in land prices of 46% and 16%, respectively, compared to cities at the mean (with a 76% gap for cities at the bottom 5%). In contrast, cities at the third quartile have higher unit land prices at the city centre, 53% above the average city (rising to 810% for cities in the top 5%).

5 City determinants of housing costs

5.1 Land prices, land share and housing share

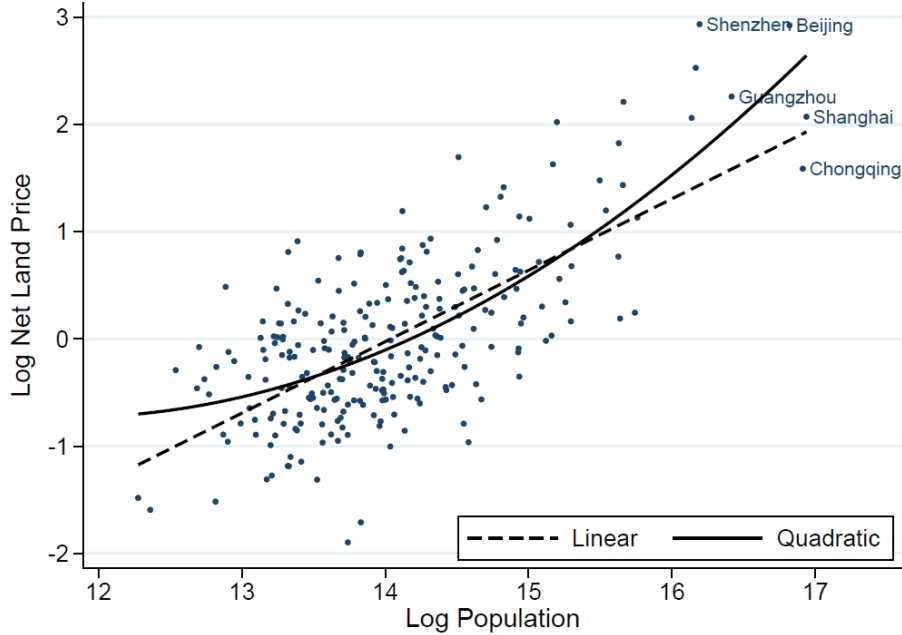
As detailed in Section 2.2, we employ a two-step procedure. Table 3 summarises the second-step OLS estimation. First-step estimations and robustness checks including IV are presented in Section 7 and Appendices D and E, respectively. To complement the estimation results, Table 4 illustrates how the population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

Residential unit land prices As a preliminary visualisation, Fig. 3 plots the logarithm of the unit land price at the city centre, net of all control variables except population, against the logarithm of city population. A very strong positive correlation emerges. Whereas both linear and quadratic models yield similar predictions for cities with a population below 3.2 million inhabitants, the largest cities like Beijing or Shenzhen display unit land prices well above the linear prediction, reflecting a stronger response of land prices to population. This convex pattern is consistent with standard urban economics predictions of increasing land congestion in larger cities.

Column 1 of Table 3 presents the land price estimation of Eq. (7). The point estimates

²⁰These 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 D.1.

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



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

for population and its square confirm the non-linear relationship observed in Fig. 3. Using these estimates, Panel A of Table 4 illustrates how the estimated population elasticity of unit land prices, defined in Eq. (8), varies with the city population when the city land area is fixed. The elasticity spans from 0.335 for a small city of 0.5 million inhabitants (1st 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 megacity of 24 million inhabitants like Shanghai. Hence, at given land area, average income and migrant share, the city population drives unit land prices up, with this effect becoming more pronounced as the city size increases. For instance, a 10% population increase in the four hypothetical cities would raise unit land prices by 3.4%, 5.6%, 7.9%, and 16.4%, respectively.

Similarly, we compute the land area elasticity of unit land prices. It varies from -0.080 for a small city with an area of 500 km² (1st decile) to -0.255 for a city covering 2,000 km² (approximately the median), -0.306 for a city covering 3,000 km² (approximately the mean), and -0.632 for the largest city with an area of roughly 40,000 km². The negative impact of land area reflects the role of increasing land supply at given demand, which also presents a

convex shape.

Letting the city fringe expand when population increases mitigates the rise in unit land prices, as shown in Column 2 of Table 3 where land area is not controlled for.²¹ This finding is consistent with the mono-centric city model’s prediction, as land supply can now adjust in response to a larger population. The corresponding population elasticities of unit land prices are displayed in Panel A of Table 4 under ‘Allowing for land area expansion’. For a small city, the population elasticity is slightly higher than without area expansion, at 0.374, primarily because of a minor change in convexity. However, for other cities, population elasticities are smaller, at 0.503 for a median-sized city, 0.632 for an average-sized city, and 1.094 for a mega-city, representing a 30% reduction thanks to land area adjustment.

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

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

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 Eq. (9). As quadratic terms for population and land area are not significant when added to the specification, we prefer to use a linear specification rather than one with non-significant quadratic terms when computing housing costs in Section 5.2. The semi-elasticity of the land share in housing pro-

²¹In the context of China, the land area of a city changed over time, as observed during our study period from 2007 to 2019. For example, Beijing incorporated two counties in 2015, Miyun (2,229.5 km²) and Yanqing (1,994.9 km²).

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		Housing Share Rural migrants	
	(1)	Y (2)	(3)	Y (4)	(5)	Y (6)	(7)	Y (8)	(9)	Y (10)
Log population	-3.890 ^a (1.061)	-2.067 ^c (1.100)	0.020 ^a (0.006)	0.010 ^b (0.005)	0.033 ^a (0.009)	0.037 ^a (0.008)	0.035 ^a (0.011)	0.039 ^a (0.010)	0.022 ^a (0.005)	0.023 ^a (0.004)
Log population squared	0.161 ^a (0.037)	0.093 ^b (0.038)								
Log land area	0.703 ^a (0.227)		-0.013 ^a (0.005)		0.008 (0.010)		0.007 (0.012)		0.001 (0.004)	
Log land area squared	-0.063 ^a (0.016)									
Log income	0.592 ^a (0.158)	0.523 ^a (0.169)	0.055 ^b (0.021)	0.048 ^b (0.022)						
Log migrant share	0.293 (0.249)	0.382 (0.264)	0.029 (0.023)	0.036 (0.024)	0.073 (0.052)	0.069 (0.049)	0.098 (0.064)	0.094 (0.063)	-0.034 (0.022)	-0.034 (0.022)
Observations	3,209	3,209	1,223	1,223	246	246	246	246	1,360	1,360
R ²	0.64	0.62	0.30	0.29	0.30	0.30	0.25	0.25	0.11	0.11
Controls										
Population growth	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Education	Y	Y	Y	Y						
Geography, geology	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Land use	Y	Y	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 Eqs. (6) for Columns 1-2, (9) for Columns 3-4, and (10) for Columns 5-10. The coefficient for income reported in Columns 5-10 is estimated in the first step, see Eq. (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 water-body, 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 city).

duction at the city centre with respect to population is estimated at 0.020. This is consistent with standard urban economics models where the share of land in housing production increases with urban development (Fujita and Thisse, 2013). Moreover, more populated cities with an expensive housing market tend to be more regulated and have less elastic housing supply, resulting in a higher land share in housing production (Glaeser and Gyourko, 2018). As reported in Column 4, allowing for urban expansion lowers the population elasticity of land share to 0.010. At a given population, the positive and significant effect of income also reflects a positive housing demand effect on the land share, while the statistically significant negative coefficient for land area captures a positive supply effect. Finally, the share of migrants plays no significant role in explaining the cross-section variations of the land share in housing production.

Next, we quantify how much larger the share of land in housing production is in larger

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

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

where $\alpha^B = 0.020$ and $\alpha^A = 0.010$ are the marginal effect of population when controlling or not for land area (Eq. (9) and Table 3).

As reported in Panel B of Table 4, the land share in housing production when city area expansion is not allowed equals 0.44, 0.45, 0.47 and 0.52 for cities with 0.5 million, 1 million, 2 million and 24 million inhabitants, respectively. When the city fringe can expand, these values decrease to 0.31, 0.32, 0.32 and 0.35, respectively. The estimated average value when allowing for city expansion is consistent with the mean land share of 0.31 for 30 major Chinese cities calculated by Tan et al. (2020). This is also comparable in magnitude, although lower, than estimates for France, where it ranges from 0.35 in the smallest cities to 0.46 in Paris (Combes et al., 2021), particularly considering that land area adjusts less there.

Housing expenditure share Table 3 presents the semi-elasticity estimates for the household housing budget share (Eq. (10)), reported separately for high-skilled (Columns 5 and 6), low-skilled (Columns 7 and 8), and rural migrant (Columns 9 and 10) households. The findings indicate a semi-elasticity of 0.033 for high-skilled households, 0.035 for low-skilled households, and 0.022 for rural migrants.²² City land area and the share of migrants play no significant role in explaining the housing expenditure share across cities. Conversely, household income, controlled for in the first step, exhibits a significantly negative impact. This aligns with non-homothetic preferences for housing, as commonly found in empirical studies (Combes et al., 2019; Dustmann et al., 2022).

Let γ_m^k denote the share of housing expenditure in the city centre for the average city of

²²As for the land share in housing production, quadratic effects for population and area are ignored here as they are not significant when included.

the sample of type- k households, computed from the first step. It is equal to 0.24 for high-skilled households, 0.26 for low-skilled households, and 0.27 for rural migrants. As land area does not significantly impact the housing budget share, it takes the same value regardless of whether land area expansion is allowed. These estimates are very close to the national average of 0.24 in 2021, as reported by the National Bureau of Statistics of China, which, however, does not control for any effect.²³ Then, we can compute the housing expenditure share for each type of household in any city with population pop_c as:

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

where $\alpha^{C,k}$ is the marginal effect of population (Eq. 10, Columns 5, 7, and 9 in Table 3).

As shown in Panel C of Table 4, the housing expenditure share in cities with 0.5 million, 1 million, 2 million and 24 million inhabitants is 0.18, 0.20, 0.23, and 0.31 for high-skilled households, 0.20, 0.22, 0.25, and 0.34 for low-skilled households, and 0.24, 0.25, 0.27, and 0.32 for rural migrant households. Since estimations are performed separately for each group, with income effects controlled only within groups, the higher housing expenditure share estimated for low-skilled households –and even more so for rural migrants– is consistent with a between-group income effect, where lower-income households spend a higher proportion of their income on housing. However, the smaller increase in housing expenditure share with city population for rural migrants results in similar housing expenditure shares across the three groups in the largest city.

5.2 Population elasticity of housing costs

Panel D of Table 4 reports the population elasticity of housing costs defined in Eq. (5) and computed by multiplying the values provided in Panels A, B, and C. As expected, the elasticity of housing costs increases with city population, reflecting the increase in all three components of housing costs. A 1% increase in population causes housing costs to rise nearly 10 times more in a mega-city than in a small city for high- and low-skilled households (from 0.027 to 0.254 and from 0.029 to 0.273, respectively) and about 7.5 times more for rural migrants (from 0.035 to 0.264). Doubling the population from 0.5 to 1 million nearly doubles the population elasticity of housing costs for all three household types, and when the

²³http://www.stats.gov.cn/english/PressRelease/202201/t20220118_1826649.html

population doubles again from 1 to 2 million, the elasticity increases further by 60%. The housing cost elasticity is higher for low-skilled households and even higher for rural migrants. For instance, in a median city with a population of 1 million, the elasticity values are 0.052, 0.057 and 0.064 for high-skilled, low-skilled, and rural migrant households, respectively. However, in the largest city, the elasticity for rural migrants falls between those of high- and low-skilled households due to its slightly lower rate of increase with city population (0.264 for rural migrants, compared to 0.254 and 0.273, respectively).

When the adjustment of the city fringe is allowed, the elasticity of housing costs with respect to city population decreases sharply, by 54% in the largest cities, and by 43%, 37% and 21% for high-skilled households in cities with 2 million, 1 million and 0.5 million inhabitants, respectively. Similar reductions are observed for both low-skilled and rural migrant households. Therefore, allowing the fringe to adjust as the city population expands is a crucial decision for policymakers, as it impacts housing costs for all types of households, especially in the largest cities.

6 Real income gains from moving to larger cities

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

6.1 Population elasticity of nominal income and real income

To answer these questions, we begin by calculating the population elasticity of nominal income for high-skilled, low-skilled and rural migrant households separately, using the values estimated by [Combes et al. \(2020\)](#).²⁴ We aim to compare the population elasticity of income

²⁴See their Table 2 Panel (b), Columns (1), (4), and (7) for high-skilled, low-skilled and rural migrant households, respectively. Since the specifications are in logarithm, the coefficient for land area in the income specification is obtained as the difference between the coefficient for land area and the coefficient for density in the original estimations. This gives 0.043, 0.0052, and -0.010 for high-skilled, low-skilled and rural

Table 4: Population elasticity of housing cost

Population	Small city 0.5 million	Median city 1 million	Average city 2 million	Mega-city Shanghai
Panel A: Population elasticity of unit land prices				
Not allowing for city area expansion	0.335	0.559	0.782	1.582
Allowing for city area expansion	0.374	0.503	0.632	1.094
Panel B: Land share in housing production				
Not allowing for city area expansion	0.440	0.454	0.467	0.517
Allowing for city area expansion	0.309	0.316	0.323	0.348
Panel C: Share of housing in households' expenditure				
High-skilled				
Not allowing for city area expansion	0.182	0.205	0.228	0.310
Allowing for city area expansion	0.182	0.205	0.228	0.310
Low-skilled				
Not allowing for city area expansion	0.199	0.223	0.247	0.334
Allowing for city area expansion	0.199	0.223	0.247	0.334
Rural migrants				
Not allowing for city area expansion	0.238	0.254	0.269	0.323
Allowing for city area expansion	0.238	0.254	0.269	0.323
Panel D: Population elasticity of overall housing costs				
High-skilled				
Not allowing for city area expansion	0.027	0.052	0.083	0.254
Allowing for city area expansion	0.021	0.033	0.047	0.118
Low-skilled				
Not allowing for city area expansion	0.029	0.057	0.090	0.273
Allowing for city area expansion	0.023	0.035	0.050	0.127
Rural migrants				
Not allowing for city area expansion	0.035	0.064	0.098	0.264
Allowing for city area expansion	0.028	0.040	0.055	0.123

Notes: In Panel A, Row 1, the unit land price population elasticity estimates are marginal effects calculated from Table 3, Column 1. Row 2 presents estimates excluding city land area as a control (Table 3, Column 2). Panel B uses estimates from Columns 3 and 4, while Panel C relies on Columns 5 to 10 of Table 3. Panel D reports the housing cost elasticity, obtained by multiplying the housing expenditure share, the land share in housing production, and the population elasticity of land prices, as defined in Eq. (5).

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

with and without controlling for land area, as done in the housing elasticity estimations. Additionally, we seek to control for the presence of migrants –or not– since they now play a significant role in income. As we do not have income estimations that exclude controls for land area or migrants, we evaluate the population elasticity allowing for land area expansion using the following procedure. First, we regress the logarithm of land area on the logarithm of population, using the same controls as in the housing estimations, including the share of migrants. This gives an elasticity of 0.737, 0.636, and 0.380 for high-skilled, low-skilled and rural migrant households, respectively. We then multiply this population elasticity of land area by the land area elasticity from the income estimation described in the previous paragraph. Finally, we add this product to the population elasticity. We use a similar procedure to obtain a population elasticity that does not control for the share of migrants.²⁵

As shown in Panel A of Table 5, the population elasticity of nominal income is slightly higher for high-skilled households (0.066) than for low-skilled households (0.064). While still significantly positive, the elasticity is more than half lower for rural migrants, which is consistent with the types of jobs they hold, as discussed in Combes et al. (2020). The elasticity does not vary across the four hypothetical cities because of the linear specification of the nominal wage equation. When city fringe adjustment is allowed, the elasticity increases by 48.5% (to 0.098) for high-skilled households but remains unchanged for low-skilled and rural migrant households, as land area does not give them any additional gains. Finally, if we also allow for an increase in the migrant share, the population elasticity of nominal wage rises to 0.244, 0.149 and 0.061 for high-skilled, low-skilled and rural migrant households, respectively. The three groups benefit progressively less from city size and the rural migrant externality, ultimately resulting in large between-group disparities in the gains from locating in more populated cities.

We then assess how the population elasticity of real income –defined as the difference between the nominal income elasticity and the housing cost elasticity in Eq. (2)– varies across cities (Panel B of Table 5). While the elasticity of real income for both high-skilled and low-skilled households is positive in small and median-sized cities, it turns negative in average-sized and mega-cities when neither changes in land area nor in the migrant share are

²⁵The elasticities obtained differ across household types because of their varying distribution across cities. Census sampling weights are used to make the data representative. This strategy is also used when we compute real income across cities in Section 6.2. For further details, see Appendix B.

Table 5: Population elasticity of nominal income and real income

Population	Small city 0.5 million	Median city 1 million	Average city 2 million	Mega-city Shanghai
Panel A: Population elasticity of nominal income				
High-skilled				
Allowing for neither city area nor migrant share changes	0.066	0.066	0.066	0.066
Allowing for city area but not migrant share changes	0.098	0.098	0.098	0.098
Allowing for both city area and migrant share changes	0.244	0.244	0.244	0.244
Low-skilled				
Allowing for neither city area nor migrant share changes	0.064	0.064	0.064	0.064
Allowing for city area but not migrant share changes	0.064	0.064	0.064	0.064
Allowing for both city area and migrant share changes	0.149	0.149	0.149	0.149
Rural migrants				
Allowing for neither city area nor migrant share changes	0.028	0.028	0.028	0.028
Allowing for city area but not migrant share changes	0.028	0.028	0.028	0.028
Allowing for both city area and migrant share changes	0.061	0.061	0.061	0.061
Panel B: Population elasticity of real income				
High-skilled				
Allowing for neither city area nor migrant share changes	0.039	0.014	-0.017	-0.188
Allowing for city area but not migrant share changes	0.077	0.065	0.051	-0.020
Allowing for both city area and migrant share changes	0.223	0.211	0.197	0.126
Low-skilled				
Allowing for neither city area nor migrant share changes	0.035	0.007	-0.026	-0.209
Allowing for city area but not migrant share changes	0.041	0.029	0.014	-0.063
Allowing for both city area and migrant share changes	0.126	0.114	0.099	0.022
Rural migrants				
Allowing for neither city area nor migrant share changes	-0.007	-0.036	-0.070	-0.236
Allowing for city area but not migrant share changes	0.000	-0.012	-0.027	-0.095
Allowing for both city area and migrant share changes	0.033	0.021	0.006	-0.062

Notes: In rows 1, 4 and 7 of Panel A, the estimates of the nominal income elasticity for high- and low-skilled households are marginal effects calculated from [Combes et al. \(2020\)](#). In rows 2, 5 and 8, we add the effect of land area changes. In rows 3, 6 and 9, we use also adds the role of changes in the migrant share. Panel B reports the population elasticity of real income, defined as the difference between the population elasticity of nominal income and housing costs, as given in Eq. (2).

accounted for (Rows 1 and 4). In essence, this means that while nominal income tends to increase faster than housing costs in small cities, the trend reverses in larger cities. For rural migrants, this holds even in relatively small cities (of no more than 0.4 million inhabitants). Allowing for city land area adjustment significantly increases the elasticity of real income for all three groups of households. For high-skilled households, the elasticity rises by 97.4% in small cities and by 364.3% in median-sized cities. In average-sized cities, it turns positive, with an absolute value three times higher, and in Shanghai it decreases by 89.4%, though it remains negative (Row 2). The pattern for low-skilled households is similar, albeit with smaller percentage increases (Row 5). For rural migrants, except in small cities, they continue

to experience losses from city size expansion, although to a lesser extent. When we further allow for an increase in the migrant share, the elasticity of real income becomes positive for both high- and low-skilled households across all four hypothetical cities (Rows 3 and 6), though it decreases as city size increases. The elasticity is particularly large for high-skilled households, from 0.223 in the smallest cities to 0.126 in the largest city. High-skilled households benefit largely from the combined effects of a larger population, expanded land area, and a higher share of rural migrants, as the cost of living increases at a slower rate. This also holds true for low-skilled households, but to a lesser extent. They gain less from population growth and rural migrants, do not benefit from land area expansion, and face a higher housing cost elasticity. Importantly, rural migrants also begin to gain from the population expansion of their city. However, their gains remain smaller compared to those of low-skilled households, and they continue to experience losses from population expansion in the largest city.

6.2 Predicted real income across cities

This section examines real income disparities across Chinese cities, separately for high-skilled, low-skilled, and rural migrant households. To do this, we integrate the estimated population elasticity of nominal income, housing costs, and, by difference, real income to compute real income across cities. The computation steps are detailed in Appendix Section B. To better understand the specific role of each city characteristic, we begin by presenting, for each figure (Fig. A1, A2 and 4), the role of population alone in (a), (b) and (c), assuming that cities otherwise have average land area, migrant share, and other controls. Next, the simultaneous roles of population and area are presented in (d), (e) and (f), assuming that cities have the same migrant share and controls. Finally, the combined effects of all three variables are taken into account in (g), (h) and (i).

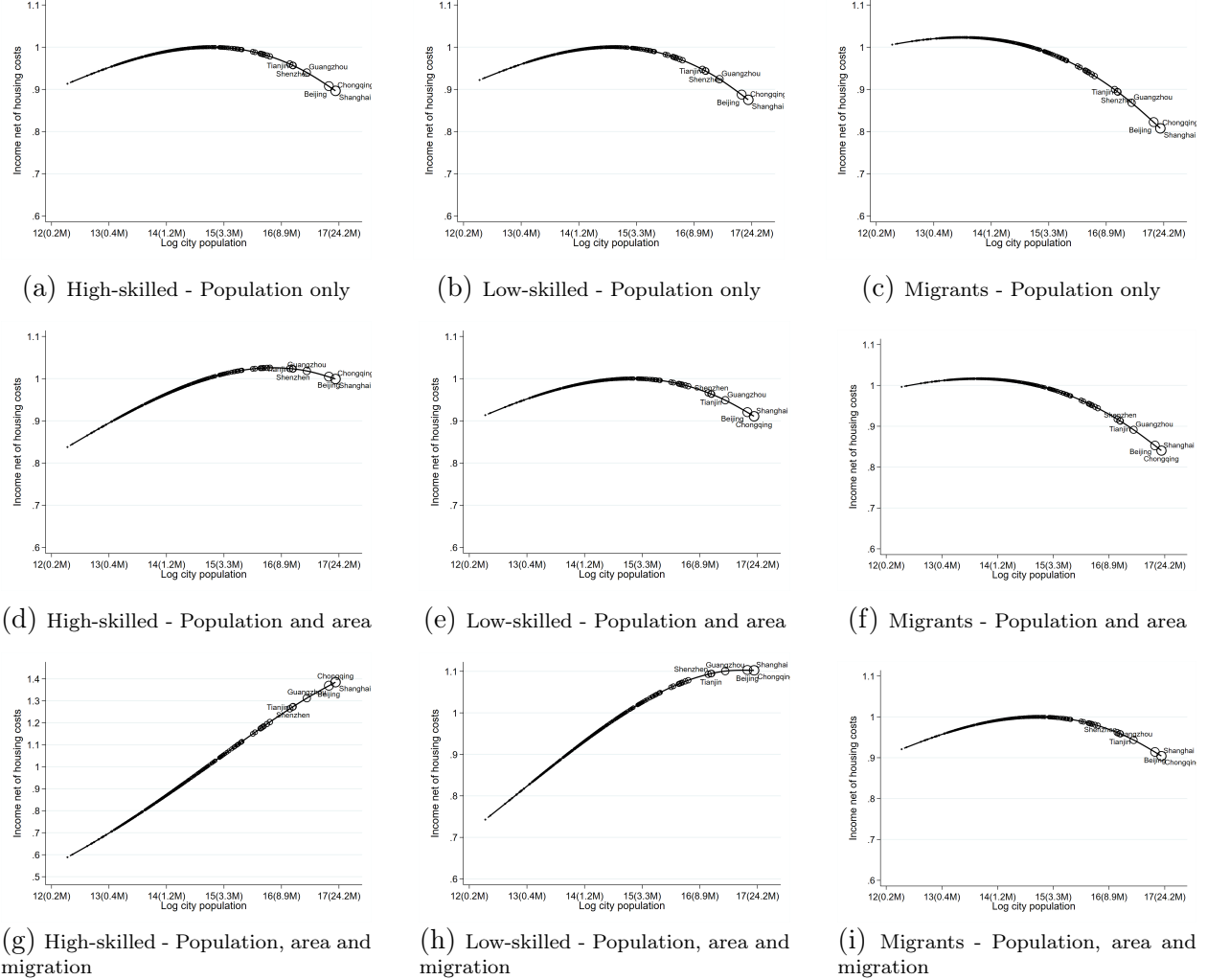
We first plot the predictions for housing costs and nominal income separately, as shown in Appendix C, Figs. A1 and A2, respectively. Housing costs exhibit a strongly convex pattern, driven by the convexity of unit land prices, further raised to the power of the product of almost linear impacts of population for the land and housing expenditure shares (Figs. A1(a) to A1(c)). While a large quadratic term is necessary to match the housing costs of the largest cities, it is too strong to accurately fit the housing costs in the smallest

cities. Housing costs also appear slightly more convex for low-skilled households and even more so for rural migrants. For instance, housing costs increase by 38.5%, 42.2%, and 53.3% for high-skilled, low-skilled, and rural migrant households, respectively, when moving from the city with the lowest housing costs to the city with the highest. This increase is slightly smaller when city land area expansion is considered: housing costs rise by 32.3%, 35.4%, and 44.5%, respectively, in this scenario (Figs. A1(d) to A1(f)).

Nominal income predictions, presented in Figs. A2(a) to A2(c), increase almost linearly with the (log) city population. As documented by Combes et al. (2020), nominal income gains from locating in larger cities in China are higher than in high-income countries. For instance, nominal income increases by 35.9%, 35%, and 14.2% for high-skilled, low-skilled, and rural migrant households, respectively, when moving from the smallest to the largest city. This increase is magnified when accounting for city land area expansion (Figs. A2(d) to A2(f)), particularly for high-skilled households, and it becomes even more pronounced when allowing for an increase in the migrant share as nominal income rises by 211.3%, 100.9%, and 32.9% for high-skilled, low-skilled, and rural migrant households in the same scenario (Figs. A2(g) to A2(i)).

The predictions for real income with respect to city population are depicted in Fig. 4. When only population impacts nominal income and the housing costs, as in Figs. 4(a), 4(b) and 4(c), an almost symmetrical bell-shaped curve emerges for both high- and low-skilled households. The maximum is reached for a city with 2.6 million inhabitants, where the predicted real income closely aligns with that of the average city with 2 million inhabitants, the curve being pretty flat between 1.2 and 4.5 million inhabitants. In cities with up to 2.6 million inhabitants, where about half of the Chinese population lives, nominal income increases faster than housing costs, resulting in an 8.7% rise in real income for both high-skilled and low-skilled households. However, for cities exceeding 3 million inhabitants, nominal income growth lags behind the housing costs, leading to a gradual decline in real income. For high-skilled households, the lowest value is reached in Shanghai, where real income falls 10.3% below that of the average city with 2 million inhabitants (and 10.4% below the city with the highest real income). For low-skilled households, regional disparities in real income are slightly more pronounced: in Shanghai, real income is 12.5% lower than both the average city and the city with the highest real income. Rural migrant households exhibit a different pattern, with fewer small cities positioned on the left-hand side of the curve's peak and

Figure 4: Predicted real income across Chinese cities



Notes: This figure displays the predicted real income corresponding to the integral of Eq. (2) for high-skilled households (Figs. 4(a), 4(d), and 4(g)), low-skilled households (Figs. 4(b), 4(e), and 4(h)), and rural migrant households (Figs. 4(c), 4(f), and 4(i)). Figs. 4(a), 4(b) and 4(c) consider only the role of city population; Figs. 4(d), 4(e) and 4(f) additionally account for the impact of land area; and Figs. 4(g), 4(h) and 4(i) incorporate the effects of all three variables. Each black circle symbolizes a representative household in one of the 254 cities, and the solid line depicts a spline fit. For ease of comparison across figures, note that the vertical axis is at 1.1 in all figures except Fig. 4(g), where this limit could not be applied.

most larger cities on the right-hand side. This reflects both smaller gains and higher costs associated with living in larger cities for rural migrant households. Real income increases by 1.7% when moving from the smallest city to the city at the peak, which has a population of 0.7 million, but then declines by up to 21.1% compared to the maximum when relocating to Shanghai.

Figs. 4(a), 4(b) and 4(c) illustrate the worst-case scenario for larger cities as the prediction does not account for the positive impact of land area and migrant share on nominal income, nor the negative impact of land area on housing costs. When the impact of a larger land area is considered, as shown in Figs. 4(d), 4(e) and 4(f), the declining portion of the real income curve diminishes for all three types of households, confirming the critical role of land supply in shaping spatial disparities in real income. For high-skilled households, real income in Tianjin, Shenzhen and Guangzhou is nearly on par with the city that has the highest real income, while in Beijing, Chongqing and Shanghai, it is lower by only 2.1%, 2.6%, and 2.6%, respectively. For low-skilled households, real income is 3.7% lower than in the city with the highest real income in Shenzhen and Tianjin, 5.1% lower in Guangzhou, 8% lower in Beijing, 8.9% lower in Chongqing, and drops to 9% in the largest city that offers the lowest real income, namely Shanghai. Rural migrants continue to face substantial losses when locating in large cities, with real income decreasing by about 0.3% in a city with a population of 5 million, and by up to 17.3% in Shanghai compared to the city with the highest real income. Overall, as previously observed, moving to larger cities is less advantageous for low-skilled households and even more so for rural migrants. This is primarily because they benefit less from agglomeration economies associated with the expansion of city land areas and experience smaller increases in nominal income. Additionally, their housing costs increase more, even when land area adjusts.

Further accounting for the role of rural migrants, as shown in Figs. 4(g), 4(h) and 4(i), accentuates the steepness of the real income profile for high-skilled households and reduces its concavity for both low-skilled and rural migrant households. For high-skilled households, the presence of migrants amplifies the benefits of larger cities, both in absolute terms and relative to low-skilled households. As the literature shows (Combes et al., 2020), high-skilled households benefit from a strong positive externality associated with the presence of migrants, without a corresponding increase in housing costs. In contrast, this effect is less pronounced for low-skilled households, who are more substitutable with migrants in the production sec-

tor. Nevertheless, for both high- and low-skilled households, moving to a larger city never reduces real income when migration is accounted for. In Tianjin, Shenzhen, Guangzhou, Beijing, Chongqing and Shanghai, high-skilled households typically enjoy real incomes that are 27.2%, 27.3%, 31.2%, 36.9%, 38.5% and 38.5% higher, respectively, than those in the average city. Low-skilled households exhibit less pronounced real income advantages of approximately 10% in these six largest cities. Rural migrants also benefit from an externality effect linked to their presence, but to a lesser extent than high- and low-skilled households. Nonetheless, this leads to an upward-sloping real income profile across most cities, reaching a peak at 2.5 million inhabitants before declining by up to 9.7% in the largest cities.

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

The fact that real income decreases with city population in the largest cities –even when the three main characteristics of cities are considered– for rural migrants, and to a lesser extent for low-skilled households, may seem puzzling given observed migratory patterns, which still involve movement toward these cities rather than to smaller ones. Several explanations may be proposed.²⁶ First, although the *Hukou* policy has been significantly relaxed, relocation costs may still prevent Chinese households from being perfectly mobile, thereby limiting their ability to capture potential gains from moving. More importantly, it is essential to recall that our analysis focuses on real income, not utility, and does not account for the role

²⁶Using data from the 2005 One-Percent Population Survey of China, [Xing and Zhang \(2017\)](#) show that rural-urban migrants exhibit a strong preference for larger cities. They propose several possible explanations, though without formal testing, including opportunities for human capital accumulation, better future prospects, broader consumption choices, more inclusive social environments, and thicker labour markets that improve job matching and skill complementarity.

of local amenities that also shape household location decisions. Low-skilled households and rural migrants may anticipate better amenities in large cities beyond the real income they earn, such as improved access to schools, universities, or healthcare services for themselves or their children. Additionally, households may expect extra dynamic nominal income gains from prolonged stays in larger cities –an effect that has yet to be quantified for Chinese cities and is therefore not included here. It is also possible that households underestimate housing costs in larger cities *ex ante*, leading them to overestimate the potential benefits of moving. Our findings would suggest that these households gain less than they might initially expect. Furthermore, it is important to note that our analysis includes only rural migrants living in formal housing, excluding those in informal housing, where housing prices are typically lower. Even among rural migrants in formal housing or low-skilled households, the quality of dwellings is reflected only through the housing expenditure share in our analysis. For unit housing prices, it is controlled indirectly at the district and city levels through the local household composition variables; however, all households are assumed to face identical unit prices at given income and district characteristics. In practice, rural migrants may live in lower-quality dwellings with lower unit prices, even when their income is comparable to that of other households. In any case, as documented in Table 4, the elasticities of housing costs in the largest cities do not differ substantially across groups, and we do not expect any further quality effects to largely alter these results. Ultimately, the lower real income observed for low-skilled and rural migrant households in the largest cities, compared to high-skilled households, is driven primarily by their smaller nominal income gains.

7 Robustness checks and extensions

In this section, we provide various robustness checks for each of the three key parameters that enter the housing cost elasticity. First, we present variants of the estimates using alternative sets of controls and/or functional forms. Second, we discuss IV results in comparison with the OLS results presented in Section 5. Third, we show that encompassing the role of prices for goods other than housing should not alter our findings.

7.1 Using alternative sets of controls

City determinants of land price Table 6 reports various estimations of the city determinants of residential land price (Eq. (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, our preferred estimation.

Columns 1 to 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 to 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 to 9 use our preferred first-step estimates from Column 8 of Table 2 with the full set of controls. As for second step controls, 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.²⁷

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

²⁷As explained in Section 2.2, these variables exclude amenities but are otherwise similar to those used in the first step, recomputed 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. Additionally, land use variables only available at the city level are also introduced, including the city share of residential, industrial, and commercial land uses in the built-up stock, as well as a dummy for coastal cities.

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

First step	Only fixed effects			Basic controls			Full set of controls		
Controls for the second step	N	Y	Ext.	N	Y	Ext.	N	Y	Ext.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log population	-4.843 ^a (1.578)	-3.560 ^b (1.583)	-3.588 ^a (1.129)	-5.334 ^a (1.616)	-4.017 ^b (1.605)	-4.013 ^a (1.154)	-4.998 ^a (1.462)	-3.802 ^a (1.455)	-3.890 ^a (1.061)
Log population squared	0.207 ^a (0.056)	0.158 ^a (0.056)	0.153 ^a (0.040)	0.224 ^a (0.057)	0.174 ^a (0.057)	0.168 ^a (0.041)	0.209 ^a (0.052)	0.163 ^a (0.051)	0.161 ^a (0.037)
Log land area	1.124 ^a (0.296)	0.955 ^a (0.281)	0.664 ^b (0.259)	1.129 ^a (0.300)	0.959 ^a (0.275)	0.702 ^a (0.241)	1.144 ^a (0.279)	0.985 ^a (0.256)	0.703 ^a (0.227)
Log land area squared	-0.093 ^a (0.021)	-0.082 ^a (0.020)	-0.063 ^a (0.018)	-0.093 ^a (0.021)	-0.082 ^a (0.020)	-0.064 ^a (0.017)	-0.093 ^a (0.020)	-0.083 ^a (0.018)	-0.063 ^a (0.016)
Log income		1.118 ^a (0.216)	0.640 ^a (0.166)		1.133 ^a (0.213)	0.621 ^a (0.163)		1.047 ^a (0.203)	0.592 ^a (0.158)
Log migrant share			0.299 (0.254)			0.284 (0.253)			0.293 (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 the city-year fixed effect estimated in the first step for 3,209 city-years. Columns 1 to 3 use the city-year fixed effects of Column 3 of Table 2 as dependent variable, Columns 4 to 6 use those of Column 4 of Table 2, and Columns 7 to 9 those of Column 8 of Table 2. All regressions include year fixed effects. All reported R^2 are within-time. The superscripts *a*, *b*, and *c* indicate significance at 1%, 5%, and 10% respectively. Standard errors clustered at the city level are between brackets. Regarding the controls for the second step, N stands for no further explanatory variables beyond population, land area, and year effects, Y includes a sub-set of explanatory variables, and Ext. includes a full set of explanatory variables. The sub-set of controls include the city-level income and population growth (log mean wage, and past annualised population growth during 1990-2005). The extended controls additionally include the role of rural migrants (log of 1 plus the migrant share in the population), education variables (share of high school/college degrees and share of university degrees), geography and geology variables (standard deviation of elevation, share of water-body, 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 city).

As a further robustness check, Table A3 proposes additional estimates for our preferred specification (Column 1 of Table 3), using variants for the first step reported in Table A2. Column 1 adds a quadratic term of the logarithm of the distance to the centre (Column 2 of Table A2) in the first step. Column 2 allows for the distance to additional centres to be included in the first step (Column 4 of Table A2). 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 centre in the first step (Column 6 of Table A2) in order to deal with potential measurement errors from the definition of centres 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 A2). 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 A3 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 A3. 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 benchmark estimate of 0.782.

Regarding the second step, another concern is whether the estimated convexity could be driven by a very small number of large cities. As shown in Fig. 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 A4 presents a series of regressions in which we include both quadratic and cubic terms for the log population. The estimated coefficients are generally not significant, suggesting that the convexity observed in our baseline results is not driven solely by a few very large cities.

Land share in housing production Table 7 presents estimates of the semi-elasticity of the land share in housing production at the city centre with respect to population using variants of Eq. (9). The upper panel summarises 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 in all three specifications. Beyond the role of unit land prices, this finding may reflect the stricter regulatory FAR limits imposed on land parcels in city centres, as highlighted in the literature on land use regulation (Brueckner et al., 2017). Notably, the estimated distance gradient weakens after accounting for amenity access and other local controls in the third specification, similar to the pattern observed for unit land prices in Table 2. These controls themselves vary largely with distance to the centre, thereby weakening its impact without substantially increasing the overall explanatory power of the model. In any case, the land share in housing production varies much less within cities compared to unit land prices.

The bottom panel in Table 7 presents estimations of the second step for the land share in housing production, using the same three alternative sets of controls as for land prices. Column 9 replicates Column 3 of Table 3. In the simplest specification, which uses only

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

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

Notes: see Table 6. The total of 47,421 observations in the first step corresponds to 1,223 representative city-years in the second step. The estimated constant in the first step corresponds to the land share in housing production in a city of average size (3.94 million inhabitants) and takes the value of 0.330 in all specifications. The quadratic effects of population and land area are not considered because they are not significant in the most complete specification.

city population and land area (Column 1), the coefficient for city population is 0.029 and statistically significant, while the land area effect is negative (-0.002) but imprecisely estimated. Columns 2 and 3 sequentially expand the specification by adding income and past population growth, followed by the migrant share and all other city controls. Compared to land prices, control variables appear to have a greater influence on the land share in housing production. The estimated population elasticity is reduced by one-third when all controls are introduced, compared to its highest value with fewer controls, although the difference is not significant given the standard errors. Meanwhile, the negative supply effect captured by the land area coefficient becomes statistically significant.

Housing expenditure share Finally, Table 8 reports semi-elasticity estimates for the share of housing in expenditure, presented separately for high-skilled (Panel A), low-skilled (Panel B), and rural migrant (Panel C) households, using variants of Eq. 10. As before, Column 9 is identical to Column 5 (Columns 7 and 9, respectively) of Table 3 for high-skilled (low-skilled and rural migrant) households. In line with the results for land prices and the land share in housing production, the various columns highlight the robustness of

our estimations.

Similarly to the land share in housing production, the housing expenditure share also shows a slight decline with increasing distance from the city within cities. In the second-step estimates, Columns 4 to 6 show that when household income and the household head's educational attainment are included in the first step, the population elasticity estimates for the three households groups are slightly higher and statistically significant, even in the most complete first-step specification. Specifically, Column 9 shows population elasticity estimates of 0.033, 0.035, and 0.022 for high-skilled, low-skilled, and rural migrant households, implying that the sorting effect caused by income heterogeneity is partially captured by city size in Columns 1 to 3. Columns 7 to 9 use the full set of controls in the first step, leaving the point estimates on population and land area almost unchanged.

7.2 Instrumental variable estimates

As explained in Section 2.3, city characteristics may be endogenous, hence biasing the OLS estimation of Eqs. (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 A6, A7 and A8 in Appendix E present the IV estimates, using the same instruments in corresponding columns, for Eqs. (7), (9) and (10), respectively.

Table A6 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 6), while Panel B duplicates our preferred OLS regression including a full set of controls in both the first and the second steps (Column 1 of Table 3). Column 1 recalls the OLS estimates for reference. Column 2 instruments city population, land area, and their quadratic terms using long lags of the endogenous variables. Columns 3-4 add exogenous amenity variables to instruments and experiment with various combinations of historical and amenity instrumental variables. Columns 6-7 further instrument the migrant share using the predicted share of migrant inflows and rural population in 1982. Almost all sets of instrumental variables are found to be strongly predictive of the endogenous variables, with the Kleibergen-Paap F statistic above the conventional level. Over-identification tests are also passed, except in two cases for the estimation without control variables, a more

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

First step	Only fixed effects			Basic controls			Full set of controls		
Controls for the second step	N	Y	Ext.	N	Y	Ext.	N	Y	Ext.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A. High-skilled households (9,414 obs.)									
First-step estimates									
Log distance	-0.010 (0.011)	-0.010 (0.011)	-0.010 (0.011)	-0.013 (0.011)	-0.013 (0.011)	-0.013 (0.011)	-0.022 ^b (0.011)	-0.022 ^b (0.011)	-0.022 ^b (0.011)
Log income				-0.040 ^a (0.007)	-0.040 ^a (0.007)	-0.040 ^a (0.007)	-0.043 ^a (0.006)	-0.043 ^a (0.006)	-0.043 ^a (0.006)
Second-step estimates									
Log population	0.028 ^b (0.013)	0.031 ^b (0.013)	0.027 (0.017)	0.039 ^a (0.008)	0.042 ^a (0.008)	0.034 ^a (0.009)	0.038 ^a (0.008)	0.042 ^a (0.008)	0.033 ^a (0.009)
Log land area	-0.001 (0.015)	0.000 (0.015)	-0.004 (0.018)	0.006 (0.010)	0.006 (0.010)	0.008 (0.010)	0.006 (0.010)	0.007 (0.010)	0.008 (0.010)
Log migrant share			0.031 (0.093)			0.064 (0.052)			0.073 (0.052)
R ²	0.15	0.15	0.17	0.25	0.26	0.30	0.25	0.26	0.30
Panel B. Low-skilled households (6,231 obs.)									
First-step estimates									
Log distance	-0.008 (0.006)	-0.008 (0.006)	-0.008 (0.006)	-0.011 ^b (0.006)	-0.011 ^b (0.006)	-0.011 ^b (0.006)	-0.025 ^a (0.007)	-0.025 ^a (0.007)	-0.025 ^a (0.007)
Log income				-0.047 ^a (0.007)	-0.047 ^a (0.007)	-0.047 ^a (0.007)	-0.046 ^a (0.007)	-0.046 ^a (0.007)	-0.046 ^a (0.007)
Second-step estimates									
Log population	0.029 ^b (0.014)	0.030 ^b (0.014)	0.029 (0.019)	0.043 ^a (0.010)	0.046 ^a (0.010)	0.035 ^a (0.011)	0.044 ^a (0.010)	0.046 ^a (0.010)	0.035 ^a (0.011)
Log land area	0.005 (0.016)	0.005 (0.016)	-0.001 (0.020)	0.007 (0.011)	0.007 (0.010)	0.009 (0.011)	0.006 (0.011)	0.007 (0.011)	0.007 (0.012)
Log migrant share			0.028 (0.109)			0.095 (0.062)			0.098 (0.064)
R ²	0.12	0.12	0.13	0.22	0.23	0.26	0.22	0.22	0.25
Panel C. Rural migrants (386,303 obs.)									
First-step estimates									
Log distance	-0.018 ^a (0.002)	-0.018 ^a (0.002)	-0.018 ^a (0.002)	-0.018 ^a (0.002)	-0.018 ^a (0.002)	-0.018 ^a (0.002)	-0.016 ^a (0.002)	-0.016 ^a (0.002)	-0.016 ^a (0.002)
Log income				-0.014 ^a (0.002)	-0.014 ^a (0.002)	-0.014 ^a (0.002)	-0.015 ^a (0.002)	-0.015 ^a (0.002)	-0.015 ^a (0.002)
Second-step estimates									
Log population	0.018 ^a (0.004)	0.020 ^a (0.004)	0.022 ^a (0.005)	0.017 ^a (0.004)	0.019 ^a (0.004)	0.022 ^a (0.005)	0.017 ^a (0.004)	0.019 ^a (0.004)	0.022 ^a (0.005)
Log land area	-0.002 (0.004)	-0.002 (0.004)	-0.001 (0.004)	0.000 (0.004)	0.000 (0.004)	0.001 (0.004)	0.000 (0.004)	0.000 (0.004)	0.001 (0.004)
Log migrant share			-0.033 (0.023)			-0.030 (0.021)			-0.034 (0.022)
R ²	0.03	0.03	0.05	0.08	0.09	0.12	0.08	0.08	0.11

Notes: see Table 6. A total of 15,645 observations in each first step corresponds to the same 241 representative city-years for high-skilled and low-skilled residents (Panel A and B, respectively) in the second step. Additionally, 386,303 observations for the same step are linked to 1,360 city-years for rural migrants (Panel C). There are two main differences with the specification used in Table 6. First, the basic controls in the first step include household composition (the ratio of working adults to children and the number of non-working adults), home ownership (reference: renter), the household head's educational attainment, and household income. Second, the city mean wage and the quadratic terms for population and land area are excluded from the second-step regressions. The former because income is introduced at the household level, the latter because not significant in the most complete specification. The estimated constant in the first step corresponds to the housing expenditure share in a city of average size (2.88 million inhabitants) and is 0.24 for high-skilled workers and 0.26 for low-skilled workers in all specifications. For rural migrants, the estimated constant is 0.27 in an average city with 2.11 million inhabitants in all specifications.

demanding but not our preferred specification. The IV estimates of the population elasticity for a medium-sized city with 2 million inhabitants that incorporate control variables in both steps range from 0.806 and 0.879, slightly above the corresponding OLS estimate of 0.782. Reassuringly, OLS estimates of land area elasticity and migrant share elasticity are also robust to the IV estimates.

Table [A7](#) provides a set of IV estimates for our preferred specification (Column 3 of Table [3](#)) for the city determinants of the land share in housing production, following the same step-by-step inclusion of IVs as for land prices. In Column 7, where we instrument for city population, land area, and migrant share, the coefficients of these endogenous variables are again slightly larger than their OLS estimates, although the differences are barely significant.

Finally, Table [A8](#) presents a set of IV estimates for our preferred specification (Columns 5, 7, and 9 of Table [3](#)) for the housing expenditure share. As shown in Column 7, when city population, land area, and migrant share are instrumented, the coefficient estimates slightly increase compared to the OLS estimates for high-skilled and low-skilled households, while remaining unchanged for rural migrant households. We conclude that these IV results support our baseline OLS findings across all three equations.

Using the IV estimates presented in Column 7 of Tables [A6](#), [A7](#), and [A8](#), we can compute the population elasticity of housing costs. For high-skilled households, the population elasticity of housing costs rises from 0.020 in a city with 0.5 million inhabitants to 0.541 in a city like Shanghai, compared to 0.027 and 0.254 using OLS. Similarly, for low-skilled households, the disparity across cities becomes more pronounced, with the population elasticity of housing costs ranging from 0.021 in a 0.5 million inhabitant city to 0.591 in Shanghai, instead of 0.029 and 0.273 using OLS. For rural migrant households, the population elasticity of housing costs increases from 0.029 in a city with 0.5 million inhabitants to 0.518 in a city like Shanghai, compared to 0.035 and 0.264 using OLS. Hence, the IV estimates suggest an even greater increase in housing costs with city size compared to the OLS estimates, up to twice higher in the largest cities, which is due to the slightly larger impact of population on all three components of housing costs.

In a last step, we assess the impact of using IV instead of OLS on real income disparities. Besides the population elasticity of housing costs computed above, we predict nominal income using the IV estimates from [Combes et al. \(2020\)](#) Table 2 Panel (b), Columns (2), (5) and

(8) for high-skilled, low-skilled, and rural migrant workers, respectively. The results are displayed in Fig. A3, Appendix E. While housing costs increase more sharply with city size in IV estimates, consistent with the larger elasticities we have documented, the same holds true for nominal income gains. Overall, these differences nearly offset each other, resulting in both OLS and IV estimates producing very similar predictions for real income variations across cities.

When accounting for the role of land area and migrants, high-skilled households continue to benefit from relocating to the largest cities. In Tianjin, Shenzhen, Guangzhou, Beijing, Chongqing and Shanghai, their real income is 30.5%, 30.6%, 34.3%, 39%, 40.1% and 40.2% higher than in the average city, respectively. These values are very close to the OLS estimates of 27.2%, 27.3%, 31.2%, 36.9%, 38.5% and 38.5%. In contrast, low-skilled households in the largest cities may be worse off than in smaller cities. For example, their real income is about 5% lower in Beijing, Shanghai and Chongqing compared to the average city. In Guangzhou, it is almost identical to the average, while in Tianjin and Shenzhen, it is slightly higher by 0.5%. In comparison, OLS estimates give a slightly different picture, suggesting that low-skilled households always gain from moving to the largest cities, albeit marginally. For rural migrant households, substantial losses persist when moving from the average city to larger cities. Their real income decreases by 15.7%, 15.8%, 19.4%, 25.7%, 27.6% and 27.7% in Tianjin, Shenzhen, Guangzhou, Beijing, Chongqing and Shanghai, respectively. Similar to OLS estimates, when positive income externalities from migrants are not accounted for, the gains using IV estimates are lower and may even turn negative for high-skilled households in the largest cities, while the losses for low-skilled households are larger, and rural migrants experience even greater declines. The situation deteriorates further when land area does not adjust, resulting in significant losses for all three groups in the largest cities.

7.3 The price of goods other than housing

We acknowledge that our study does not account for the role of prices for goods other than housing. Addressing this issue is challenging and would require detailed data, which is currently only partially available for China. However, we do not believe this omission significantly alters our conclusions for two main reasons. First, there is a consensus in urban economics that spatial variations in the prices of non-housing goods are much smaller than

those observed for land and housing, and non-housing price indexes may even decline with city size. Second, using a specification similar to our second-step estimation, we analyse available Chinese non-housing price data and find no evidence of a correlation with city size.

[Handbury and Weinstein \(2015\)](#) emphasise, in the context of the US, the importance of (i) precisely controlling for the quality of goods, and (ii) accounting for preferences for diversity to accurately assess how the price index of non-housing goods varies with city characteristics. Although raw unit prices increase with city size in the US, they show that the food price index slightly declines because both quality and variety are greater in larger cities. The proposed methodology is demanding and typically requires barcode-level data. [Feenstra et al. \(2020\)](#) use such data for four goods –laundry detergent, personal washing items, shampoo, and toothpaste– across 22 Chinese cities. They find that the price index for these goods decreases with city size, with a relatively modest magnitude of the estimated elasticity (-0.26 for laundry detergent, -0.12 for personal washing items, -0.11 for shampoo, and -0.16 for toothpaste).

Data necessary to replicate this methodology across a broad range of goods, various household types, and a large number of cities are currently unavailable for China. However, we provide an initial assessment using data on non-housing goods and services sourced from the National Development and Reform Commission Price Monitoring Center for 84 cities.²⁸ The results are presented in [Table 9](#).

Among the 15 food items analysed, only beef shows an increase in price in the most populated cities. However, this effect is largely compensated for by the negative impact of land area. When considering only linear effects ([Appendix D.3, Table A5](#)), city size has no significant impact on the prices of food items, including beef, except for chicken and bananas whose prices are positively influenced by city population and negatively by land area. For transportation, taxi fares are slightly higher in larger cities. The prices of education and health services do not appear to increase with city size. Overall, given the small consumption share of the items and the small magnitude of the price effects when significant, the available data suggest that city size does not affect the prices of non-housing goods to any degree comparable to its impact on land and housing prices.

²⁸Further data description is provided in [Appendix A](#).

Table 9: City determinants of non-housing good prices by sub-category

Dep. Variable	Non-housing item prices (Logged)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Food (Vegetables & fruits)	Cabbage	Tomato	Cucumber	Banana	Apple	Pear
Log population	-1.113 (1.115)	-0.952 (0.857)	0.592 (0.722)	-1.253 (1.289)	-1.266 (0.814)	0.133 (0.961)
squared Log population	0.0402 (0.0375)	0.0352 (0.0288)	-0.0192 (0.0242)	0.0483 (0.0433)	0.0443 (0.0273)	-0.00429 (0.0323)
Log land area	0.655 (0.429)	0.564 ^c (0.330)	0.215 (0.278)	0.419 (0.496)	0.668 ^b (0.314)	0.158 (0.370)
squared Log land area	-0.0478 ^c (0.0282)	-0.0430 ^c (0.0217)	-0.0178 (0.0183)	-0.0386 (0.0326)	-0.0428 ^b (0.0206)	-0.00558 (0.0243)
R^2	0.42	0.54	0.36	0.44	0.36	0.24
Panel B: Food (Meat & animal products)	Pork	Beef	Fish	Chicken	Egg	Milk
Log population	-0.615 ^c (0.346)	-1.034 ^b (0.419)	-0.673 (0.588)	-0.200 (0.631)	-0.467 (0.366)	-0.311 (0.625)
squared Log population	0.0193 (0.0116)	0.0352 ^b (0.0140)	0.0207 (0.0197)	0.0110 (0.0212)	0.0166 (0.0123)	0.00843 (0.0210)
Log land area	0.0249 (0.133)	0.602 ^a (0.157)	0.134 (0.226)	0.178 (0.243)	0.0519 (0.142)	-0.139 (0.241)
squared Log land area	-0.000680 (0.00875)	-0.0400 ^a (0.0103)	-0.00617 (0.0149)	-0.0159 (0.0160)	-0.00531 (0.00929)	0.0101 (0.0158)
R^2	0.26	0.42	0.24	0.41	0.34	0.16
Panel C: Food (Cooking condiments)	Soybean oil	Salt	Soy sauce			
Log population	-0.231 (0.387)	0.742 (0.913)	-0.721 (0.859)			
squared Log population	0.00755 (0.0130)	-0.0273 (0.0307)	0.0251 (0.0289)			
Log land area	0.144 (0.148)	-0.235 (0.352)	0.0436 (0.331)			
squared Log land area	-0.00884 (0.00979)	0.0201 (0.0231)	-0.00724 (0.0217)			
R^2	0.20	0.23	0.13			
Panel D: Telecom. & Transportation	Mobile phone	Landline phone	Bus	Taxi		
Log population	0.470 (1.122)	-0.208 (0.186)	-0.467 (0.748)	-1.119 ^c (0.575)		
squared Log population	-0.0146 (0.0378)	0.00759 (0.00626)	0.0172 (0.0252)	0.0404 ^b (0.0194)		
Log land area	-0.607 (0.415)	0.0811 (0.0688)	0.246 (0.277)	0.382 ^c (0.213)		
squared Log land area	0.0435 (0.0276)	-0.00560 (0.00457)	-0.0201 (0.0184)	-0.0269 ^c (0.0141)		
R^2	0.29	0.19	0.47	0.61		
Panel E: Education & medical care	High school	Hospital regis.	Outpatient	Appendectomy	Urinalysis	
Log population	-1.733 (1.738)	-0.162 (1.719)	-3.400 ^c (1.873)	0.124 (1.314)	0.186 (2.755)	
squared Log population	0.0609 (0.0583)	0.00178 (0.0580)	0.115 ^c (0.0633)	-0.00249 (0.0442)	-0.0107 (0.0927)	
Log land area	0.170 (0.633)	0.0106 (0.593)	0.630 (0.703)	0.371 (0.486)	2.098 ^b (1.020)	
squared Log land area	-0.00837 (0.0420)	-0.000208 (0.0395)	-0.0508 (0.0474)	-0.0276 (0.0323)	-0.126 ^c (0.0677)	
R^2	0.42	0.20	0.49	0.35	0.17	
Observations	84	84	84	84	84	84

Notes: This table reports estimates of city determinants of non-housing item prices. All regressions repeat the regression specifications used in Column 9, Table 6 but do not include year fixed effects since a single year of data is used. The dependent variables are the logarithm of the price of non-housing items, including food, transportation, telecommunication, education, and medical care. Standard errors are reported in parentheses.

8 Conclusion

This paper makes two main contributions. First, using various sets of individual data for Chinese cities, we estimate housing costs and assess how they vary across cities. The elasticity of housing costs with respect to city characteristics, such as population, is the product of three components –the elasticity of unit land prices, the land share in housing production, and the 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 separately for high-skilled, low-skilled, and rural migrant households. To our knowledge, this is the first attempt of its kind for a large emerging economy, many of which are undergoing rapid urbanisation, as observed in China.

We find that urban costs in China are high but decrease when cities expand their land area alongside population, aligning with urban models and findings for high-income countries. Since nominal gains also respond to population, land area, and the presence of rural migrants, real income disparities in China largely depend on the simultaneity of these urban adjustments. When cities are larger in both population and land area while accommodating a higher share of migrants, as has been the case in recent decades in China, both high- and low-skilled households experience real income gains when moving to larger cities, with high-skilled households benefiting the most. Rural migrants also benefit, although their real income peaks in cities with 2.5 million inhabitants before slightly declining, especially in the six largest cities. In contrast, if the positive externality from migrants were not considered, moving to larger cities would be less advantageous for low-skilled households and even more so for rural migrants. Finally, if city land area did not adjust either, real income for high- and low-skilled households would peak at 2.6 million inhabitants, and beyond 3 million inhabitants, moving to larger cities would lead to real income loss as nominal income gains fall behind housing costs. Rural migrants would face smaller gains and greater losses, with their real income peaking in cities with a population of 0.7 million. We conduct a series of robustness checks using alternative specifications, instrumental variable estimates, and an analysis of non-housing goods prices, all of which confirm these conclusions.

Our findings are relevant to the design of urban and redistributive policies. Our framework allows assessing potential real income gains from relaxing migration restrictions and

land use regulations, particularly those affecting urban horizontal expansion. This is especially important in a context where internal migration restrictions, such as those imposed by China's *Hukou* policy, are expected to persist at least to some extent, influencing population movements between cities, particularly from smaller to larger ones. 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 are approaching a size threshold beyond which real income begins to decline, particularly for low-skilled and rural migrant households. Furthermore, since real income gains differ by skill level, our findings are consistent with a reinforcement of the spatial sorting of households along skills, where high-skilled households are disproportionately concentrated in the largest cities—a pattern largely documented for high-income countries.

We acknowledge that our study does not assess the local value of household amenities, such as climate, geography, schools, or leisure facilities, which would be necessary for a comprehensive welfare analysis. Our primary objective is to examine how the monetary component of the utility—real income—varies across Chinese cities. Extending this analysis would require properly modelling not only households' amenity valuation, but also intrinsic preferences for locations and moving costs. Although this is beyond the scope of the present study, it represents a valuable direction for future research. Furthermore, provided the necessary data are available, exploring potential differences in the quality of accommodation for different household types could further enhance our understanding of urban housing markets and serve as another important extension.

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Appendix

A Data description

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

We process the raw data through the following four-step procedure. First, we remove land parcels located outside cities (i.e., in rural areas), which leaves us with 839,620 land parcels, of which 329,553 (39%) are for residential use. Second, since the price of parcels transferred through a non-market method may not be representative, we keep only the sample of market-mediated transactions, resulting in 107,288 residential land parcels. Third, we geo-code the parcel addresses to obtain precise geographic coordinates. After eliminating parcels without specific location information, our sample is reduced to 84,932 residential land parcels. Lastly, we remove observations with missing values in land characteristics and other matched district/neighbourhood-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 D reports our main estimations for this larger dataset and shows that the results are very

similar.

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

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

Household housing expenditure We use the urban sample of the Chinese Household Income Project (CHIP) survey for the years 2007, 2013, and 2018 to measure the share of housing in household expenditure for officially registered urban households. The CHIP survey, jointly conducted by the China Institute for Income Distribution at Beijing Normal University and the National Bureau of Statistics (NBS), tracks income distribution dynamics in China. This high-quality data set provides detailed information on household income and expenditure by category, household composition, and household head characteristics, including *Hukou* status, age, gender, and educational attainment.

Housing expenditure is measured differently for landlords and renters. For landlords, who account for approximately 96% of the observations, CHIP reports imputed rents on owner-occupied housing, consisting of (1) monthly expenditure on housing maintenance and

management, and (2) property assets depreciation at a 2% annual rate. For renters, their monthly rental payments are recorded. The share of household housing expenditure is then calculated as the ratio of these measures to the total monthly household expenditure. Our sample includes 6,595 households across 66 representative city proper in 2007, 3,721 households across 98 cities in 2013, and 5,329 households across 88 cities in 2018.

The CHIP urban sample surveys only registered urban residents (local urban *Hukou* holders). To include migrants in our analysis, we complement this dataset with data from the China Migrants Dynamic Survey (CMDS) for 2011–2017. Conducted annually by the National Health Commission of China since 2009, the CMDS is a comprehensive national survey of the floating population across 31 provinces. Using a stratified, multistage sampling design with a probability proportional to size (PPS) method, the survey ensures high representativeness and reliability. It samples nearly 200,000 households annually, targeting individuals aged 15 and above who do not hold a local *Hukou* and have lived in their current residence for at least one month. The survey covers a broad range of topics, including demographic characteristics, employment, income, and residence.

Housing expenditure in the CMDS is measured as the monthly rent payments for renters. For landlords (about 10% of the observations), the CMDS does not include data on property values, making it impossible to impute their monthly housing expenditure. Our sample is restricted to rural migrants living in formal housing for two reasons: (1) the quality and price of informal housing are difficult to assess, and (2) urban migrants in formal housing have heterogeneous skill levels that do not align with the income estimation framework of [Combes et al. \(2020\)](#). Additionally, we exclude 2015 due to missing data on housing type and ownership. Our final sample includes 44,986 migrant households across 218 cities in 2011, 55,111 households across 228 cities in 2012, 72,329 households across 211 cities in 2013, 82,053 households across 237 cities in 2014, 60,935 households across 234 cities in 2015, and 65,634 households across 239 cities in 2017.

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

National Bureau of Statistics (NBS), the Fourth National Population Census (1990) and the 1% National Population Sample Survey (2005).

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

Income and education Average urban employee annual wages are extracted from the CUSYs. To measure the educational attainment of local residents, we use data from the 2010 China National Population Census, aggregated at the city and district levels. Educational attainment is calculated as the ratio of residents holding high school, college, or university degrees to the working age population (15-69 years).

Prices for goods other than housing We collect data on non-housing item prices from the National Development and Reform Commission Price Monitoring Centre (chinaprice.com.cn). This data set contains price information for over 60 non-housing items included in the basket used to calculate China's Consumer Price Index (CPI). It covers urban areas in 84 cities as of Spring 2014, including four municipalities, 40 large cities with populations exceeding 2 million, 21 cities with populations between 1 and 2 million, 14 cities with populations between 0.5 million and 1 million, and five smaller cities. Our analysis focusses on the unit prices of four main categories of non-housing items, which collectively account for 63.5% of household expenditure. These categories include (1) food (29.8%), including items such as cabbage, tomatoes, cucumbers, bananas, apples, pears, pork, beef, fish, chicken, eggs, milk, soybean oil, salt, and soy sauce; (2) telecommunication and transportation (13.1%), covering mobile and landline phone rates, bus fares, and taxi fares per kilometre; (3) education (10.8%), represented by high school tuition fees; and (4) healthcare and medical services (8.8%), including hospital registration fees, outpatient fees, appendectomy fees, and urinalysis fees.

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 a terrain ruggedness measure based on the standard deviation of altitude at the grid cell level, using data 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 the National Imagery and Mapping Agency (NIMA). Finally, we aggregate these high-resolution data at both district and city levels.

City centres To locate city centres, we use the 2006 Global Radiance Calibrated Night-time 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 centre and sub-centres). Note that light centres 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 dataset provides detailed information, including specific categories and precise geographical coordinates of various local amenities. These amenities include accommodation (budget and luxury hotels), banks, schools (kindergartens, primary, middle and high schools, colleges and universities, research institutes), medical service providers (general hospitals, community clinics and centres 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 a distance matrix among parcels and amenities, enabling us to compute both the minimum distance from a parcel to each type of amenity and the number of each type of amenity within a 2-kilometre radius of a parcel. Additionally, the POI data aggregated at the district level can serve as the district-level socioeconomic control variable.

B Steps in real income calculation

We present how the real income for each of the three household categories in each Chinese city can be reconstructed by integration, based on the estimated elasticities, under three scenarios. In the first scenario, only the city population varies, while all other characteristics remain constant. In the second scenario, the city's land area varies simultaneously with its population. In the third scenario, population, land area, and the share of rural migrants vary simultaneously.

According to Eq. (2), the elasticity of real income ($\epsilon_c^{V,k}$) is the difference between the elasticity of nominal income ($\epsilon_c^{W,k}$) and the elasticity of housing costs ($\epsilon_c^{C,k}$). As given in Eq. (5), the elasticity of housing costs is the product of three components: the population elasticity of land prices (ϵ_c^R), the land share in housing production (β_c), and the housing share in expenditure (γ_c^k), that can be computed from Eqs. (7), (9), and (10), respectively. The elasticity of nominal income is borrowed from Combes et al. (2020).

Let us first consider the first scenario where only population changes between cities. In this case, using the formulations of β_c and γ_c^k provided in Eqs. (11) and (12), the three components entering the housing cost elasticity reduce to:

$$\begin{aligned}\epsilon_c^R &= \alpha_1^R + 2\alpha_2^R \log pop_c, \\ \beta_c &= \alpha^B (\log pop_c / pop_m) + \beta_m, \\ \gamma_c^k &= \alpha^{G,k} (\log pop_c / pop_m) + \gamma_m^k,\end{aligned}$$

where pop_m is the mean city population.

By multiplying these three expressions, $\epsilon_c^{C,k}$ emerges as a polynomial function of degree 3 in $\log pop_c$:

$$\epsilon_c^{C,k} = P_3(\log pop_c)^3 + P_2(\log pop_c)^2 + P_1(\log pop_c) + P_0.$$

where parameters P_j are functions of the estimated parameters.

By integration, we can obtain housing costs in a city of population pop_c relative to the city with average population pop_m as:

$$\begin{aligned}\log C_c^k / C_m^k &= \int_{\log pop_m}^{\log pop_c} \epsilon_c^{C,k} d(\log pop_c) \\ &= \frac{P_3}{4} (\log pop_c / pop_m)^4 + \frac{P_2}{3} (\log pop_c / pop_m)^3 + \frac{P_1}{2} (\log pop_c / pop_m)^2 + P_0 (\log pop_c / pop_m).\end{aligned}$$

From [Combes et al. \(2020\)](#), the elasticity of nominal income with respect to population is constant ($\alpha^{W,k}$), which directly gives:

$$\log W_c^k / W_m^k = \alpha^{W,k} \log pop_c / pop_m.$$

Finally, we can predict how real income (V_c^k) varies across cities relatively to the city with average population when population only varies using:

$$\frac{V_c^k}{V_m^k} = \exp(\log W_c^k / W_m^k - \log C_c^k / C_m^k).$$

Let us now consider the second scenario where the land area of a city simultaneously varies with its population. Let us first consider unit land prices. Since their elasticity with respect to land area at given population is:

$$\epsilon_c^{RA} = \eta_1^R + 2\eta_2^R \log area_c,$$

the elasticity of unit land prices with respect to population when land area adjusts to population is:

$$\epsilon_c^R = \alpha_1^R + 2\alpha_2^R \log pop_c + (\eta_1^R + 2\eta_2^R \log area_c) \cdot \frac{\partial \log area_c}{\partial \log pop_c}.$$

Therefore, we need to specify the adjustment process of land area with respect to population, $\frac{\partial \log area_c}{\partial \log pop_c}$. We assume that a city's land area adjusts as it does on average over all cities, keeping all other characteristics constant. For that purpose, we estimate, controlling for the same variables as for land prices (see Eq. (7)):

$$\log area_c = \theta^R \log pop_c + \rho^R \log mig_c + \mu^R \log w_c + X_c^C \psi^R + \kappa^R + \varepsilon_c.$$

Therefore, we obtain:

$$\epsilon_c^R = \alpha_1^R + 2\alpha_2^R \log pop_c + \eta_1^R \theta^R + 2\eta_2^R (\theta^R)^2 \log pop_c. \quad (13)$$

We proceed similarly to compute how the share of land in housing production and the share of housing expenditure vary when the land area adjusts to the population. Note that the area adjustment is specific to each variable, although of the same order of magnitude empirically, as it is not estimated using the exact same sample of cities. This leads to values θ^B and $\theta^{G,k}$ for the land share and the housing share, respectively. Moreover, $\theta^{G,k}$ depends on the household type k , as different households do not locate in the same cities. For instance, $\theta^{G,k}$ for low-skilled households is lower than that for high-skilled households. This means that on average, when low-skilled households locate in more populated cities, they tend to do so in cities with larger land areas, but to a lesser extent than high-skilled households. Our

simulations account for this differing spatial patterns in the location choices of the various groups of households.

Finally, we assess the variations in real income when the share of rural migrants also adjusts, the third scenario. We first regress the rural migrant share on city population and other control variables for each sample to obtain the respective elasticities of the migrant share to population, ϕ^R , ϕ^B , $\phi^{G,k}$. These elasticities are then incorporated into the definitions of the elasticity of unit land prices, as well as of land and housing shares.

Overall, when population, land area and migrant share all adjust, we obtain

$$\begin{aligned}\epsilon_c^R &= \alpha_1^R + 2\alpha_2^R \log pop_c + \eta_1^R \theta^R + 2\eta_2^R (\theta^R)^2 \log pop_c + \rho^R \phi^R, \\ \beta_c &= (\alpha^B + \eta^B \theta^B + \rho^B \phi^B) (\log pop_c / pop_m) + \beta_m, \\ \gamma_c^k &= (\alpha^{G,k} + \eta^{G,k} \theta^{G,k} + \rho^{G,k} \phi^{G,k}) (\log pop_c / pop_m) + \gamma_m^k.\end{aligned}\tag{14}$$

When the rural migrant share does not adjust, in the second scenario, the corresponding equations are obtained by only setting $\phi^R = \phi^B = \phi^{G,k} = 0$ in these ones, and similarly below for nominal income.²⁹

By multiplying these three expressions together, we obtain the elasticity of housing costs with respect to population when the three variables adjust. It is now a polynomial of degree 3 in $\log pop_c$, which we then integrate to compute the housing cost in a city relative to the average city.³⁰

We proceed similarly for nominal income, considering now the full specification of [Combes et al. \(2020\)](#), which leads to the following nominal income elasticity when population, land area and the rural migrant share adjust:

$$\epsilon^{W,k} = \alpha^{W,k} + \eta^{W,k} \theta^{W,k} + \rho^{W,k} \phi^{W,k}.$$

which can be integrated with respect to $\log pop_c$.

By calculating the difference between nominal income and housing costs, we can finally compute the real income in each city, relative to that of a city with average population, when

²⁹Note that ϕ^R , ϕ^B and $\phi^{G,k}$ do not affect housing cost even when considering adjustments in the rural migrant share, because the rural migrant share does not significantly impact any of its any components, $\rho^R = \rho^B = \rho^{G,k} = 0$.

³⁰Note that these computations do not account for an extra potential feedback effect of higher income in more populated cities on housing costs, at a given population, land area, and share of rural migrants. The challenge is that income in our estimations controls for both individual sorting and a potential externality effect. Only the latter should have been considered in the computations, but we cannot separately identify if from sorting given the available data.

all three variables adjust simultaneously.

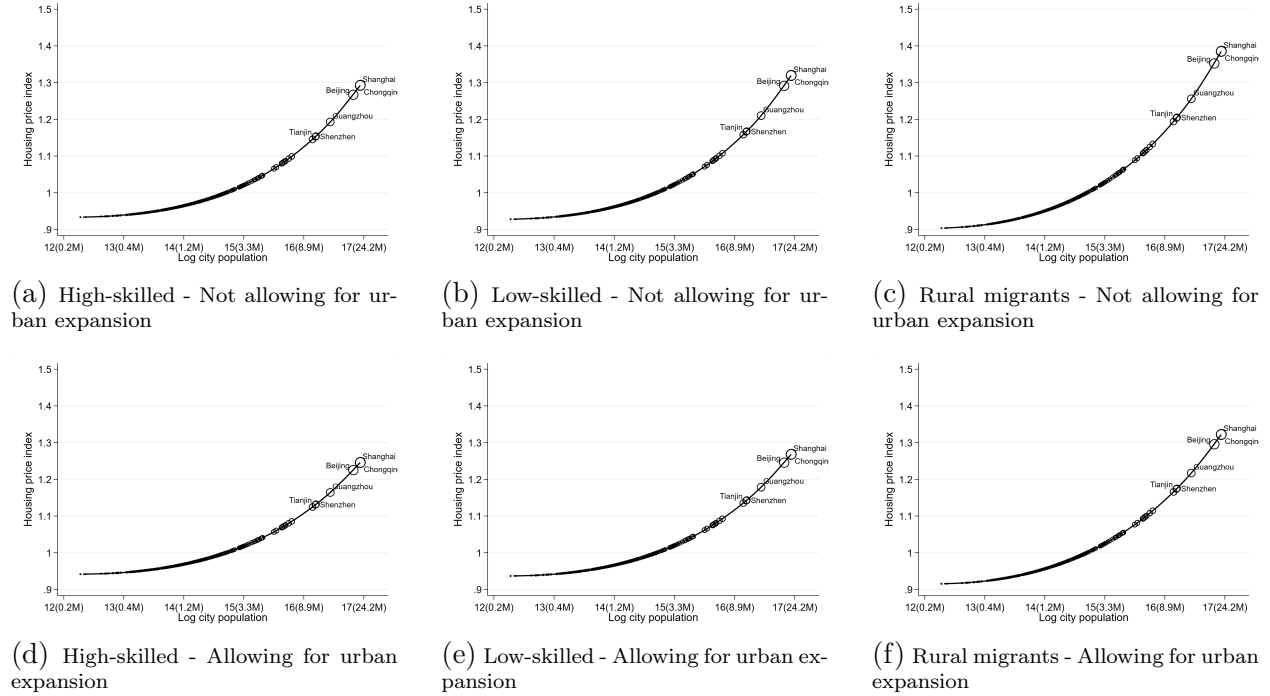
The values of the parameters we use, from the estimations in the present paper and [Combes et al. \(2020\)](#), are reported in Table A1.

Table A1: Parameters used in predicting housing costs, nominal income, and real income

	(1)	(2)		(3)	(4)
Parameter	ols	iv	Parameter	ols	iv
Land prices			Land share		
α_1^R	-3.89	-6.14	α^B	.02	.035
α_2^R	.16	.24			
η_1^R	-.063	-.2	η^B	-.013	-.033
η_2^R	.7	2.71			
ρ^R	0	0	ρ^B	0	0
θ^R	.5	.	θ^B	.75	.
ϕ^R	0	.	ϕ^B	.031	.
Housing share			Nominal income		
$\alpha^{G,high}$.033	.045	$\alpha^{W,high}$.066	.16
$\alpha^{G,low}$.035	.050	$\alpha^{W,low}$.064	.07
$\alpha^{G,migrant}$.022	.021	$\alpha^{W,migrant}$.028	0
$\eta^{G,high}$	0	0	$\eta^{W,high}$.043	0
$\eta^{G,low}$	0	0	$\eta^{W,low}$	0	0
$\eta^{G,migrant}$	0	0	$\eta^{W,migrant}$	0	0
$\rho^{G,high}$	0	0	$\rho^{W,high}$.19	.2
$\rho^{G,low}$	0	0	$\rho^{W,low}$.12	.12
$\rho^{G,migrant}$	0	0	$\rho^{W,migrant}$.053	.053
$\theta^{G,high}$.49	.	$\theta^{W,high}$.74	.
$\theta^{G,low}$.49	.	$\theta^{W,low}$.64	.
$\theta^{G,migrant}$.55	.	$\theta^{W,migrant}$.38	.
$\phi^{G,high}$.083	.	$\phi^{W,high}$.76	.
$\phi^{G,low}$.083	.	$\phi^{W,low}$.69	.
$\phi^{G,migrant}$.059	.	$\phi^{W,migrant}$.62	.

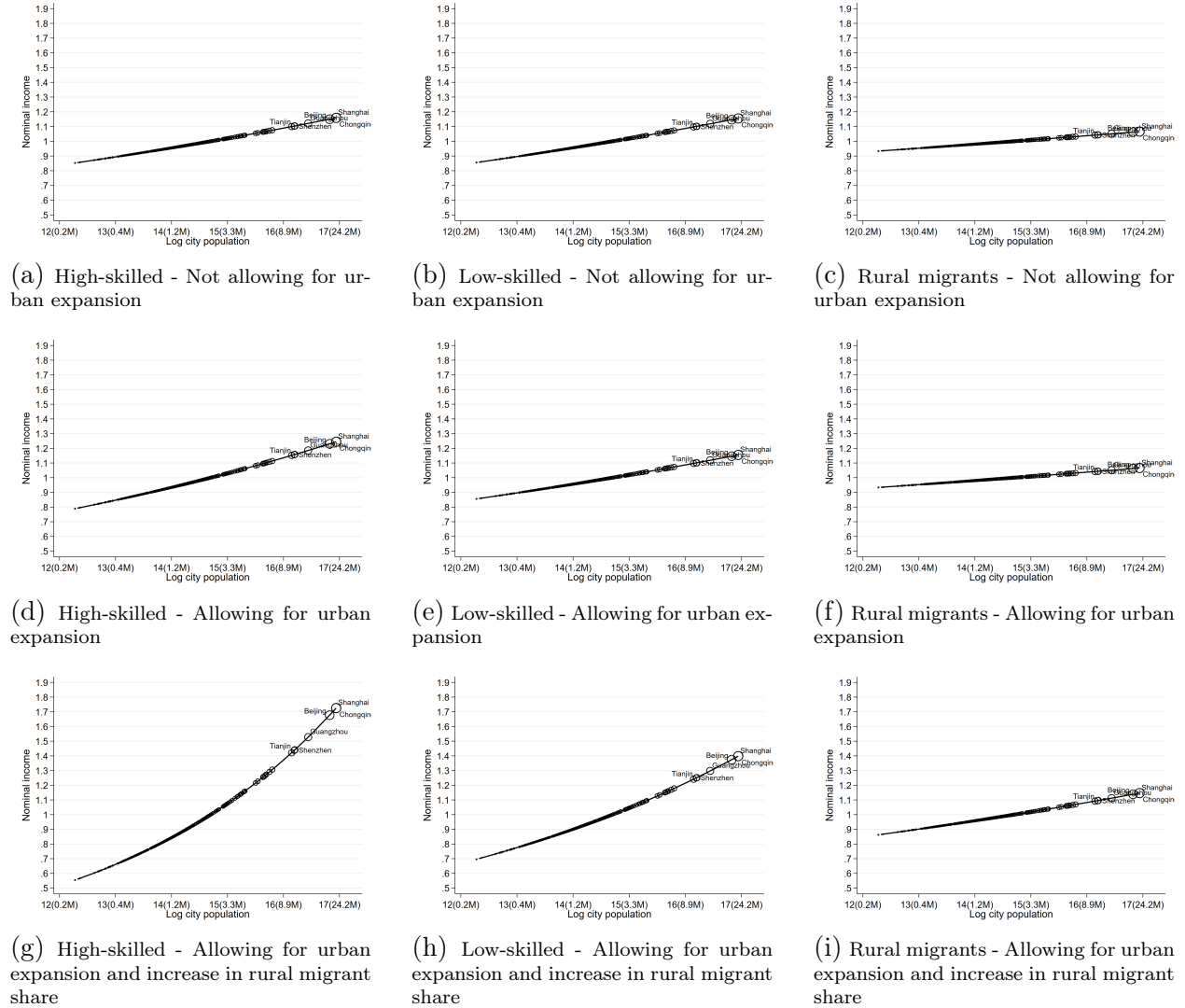
C Predicted housing costs and nominal income

Figure A1: Predicted housing costs across Chinese cities



Notes: This figure displays predicted housing costs, separately for high-skilled, low-skilled, and rural migrant households, in each of the 254 cities by integrating the estimated population elasticity of housing costs. Figs. A1(a), A1(b) and A1(c) use population elasticity from estimations that control for the city land area, whereas Figs. A1(d), A1(e) and A1(f) use those that do not. Housing costs are normalised with respect to their average across all cities, allowing for a reading in percentage deviation relative to the mean. Each circle represents a city, with the circle's size proportional to the mean city population between 2007 and 2019. The largest 6 cities are labelled. The solid line corresponds to a spline fit.

Figure A2: Predicted nominal income across Chinese cities



Notes: This figure displays the predicted nominal income, separately for high-skilled, low-skilled, and rural migrant households, in each of the 254 cities, by integrating the estimated population elasticity of nominal income. Figs. A2(a), A2(b) and A2(c) use population elasticities from estimations controlling for the city land area and share of migrants. Figs. A2(d), A2(e) and A2(f) use population elasticities encompassing indirect effects from the city land area but not the share migrants. Figs. A2(g), A2(h) and A2(i) use population elasticities encompassing indirect effects from both the city land area and the share of migrants. The nominal income is normalised with respect to its average across all cities, allowing for a reading in percentage deviation relative to the mean. Each circle represents a city, with the circle's size proportional to the mean city population between 2007 and 2019. The largest 6 cities are labelled. The solid line corresponds to a spline fit.

D Estimation variants

D.1 First-step estimates for residential land prices

Several issues regarding the first-step estimation for the price of residential land parcels need to be discussed. 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 centre is estimated, as we do in our baseline estimation. However, this is an approximation, and there is no theoretical justification for assuming that the relationship is log-linear. Instead, the mono-centric city model predicts a negative but convex relationship between land price and distance to the city centre (Fujita and Thisse, 2013), which may be due to an increase in housing consumption as the distance from the city centre increases or to some congestion on the transport network. We caution that the structure of land transaction data may exacerbate this issue. In many large cities, there has been a discernible trend in which a greater number of land parcels located farther from the city centre are being sold in the primary land market. This phenomenon may lead to a downward bias in the gradient estimates towards zero if we continue to rely on the linear model. To explore these issues, we re-estimate Eq. (6) adding a quadratic term for the logarithm of distance to city centre into the specifications of Columns 3 and 8 in Table 2. Results are reported in Columns 1 and 2 of Table A2. The unchanged R^2 suggests that augmenting the specification does not substantially improve the fit of the model and that the log-linear model appears to be reasonable.

There may also be concerns about the geography we impose with urban areas having a single centre. To address this, we re-estimate Eq. (6) allowing for up to three centres. Specifically, we define the brightest night light as the primary centre and consider the second and third brightest as additional centres if their light value exceeds 80% of the brightest. The shortest distance between these three centres is used as a control variable. Results are reported in Columns 3 and 4 of Table A2. It is also worth noting that there are more land parcel transactions far from the city centres and that the distance to the city centre can probably present larger measurement error for shorter distances. To investigate this possibility, we also report the results in Columns 5 and 6 after eliminating the 10% of observations closest to the centre in each urban area, both for the rudimentary and for our preferred estimation. The results are robust to variations in the definition of centres and sample restrictions.

Finally, our analytical focus is on 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 A2, remain stable. The impact of these first-step estimation variants on the second-step estimations is presented in Section D.2.

Table A2: 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 and 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 and 4 take into account the polycentric urban structure and use the distance to the nearest city centres (centre and subcentre, whereby subcentres are defined as the grid cells whose pixel value exceeds 80% of the centre, the brightest grid cell’s). Columns 5 and 6 exclude the 10% of observations of land parcels that are closest to the CBD in each city. Columns 7 and 8 reintroduce observations of land parcels transacted through non-market-based method (bilateral agreements).

D.2 Second-step estimates for residential land prices

Table A3: City determinants of unit land price at city centre - Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)
Log population	-2.561 ^c (1.307)	-3.654 ^a (1.167)	-3.929 ^b (1.556)	-4.935 ^a (1.462)	-3.665 ^a (1.204)	-3.502 ^a (0.812)
Log population squared	0.109 ^b (0.047)	0.152 ^a (0.041)	0.164 ^a (0.056)	0.197 ^a (0.052)	0.149 ^a (0.042)	0.141 ^a (0.029)
Log land area	0.498 ^c (0.276)	0.673 ^a (0.232)	0.738 ^b (0.289)	0.571 ^c (0.329)	0.795 ^a (0.237)	0.636 ^a (0.164)
Log land area squared	-0.049 ^b (0.020)	-0.062 ^a (0.016)	-0.064 ^a (0.021)	-0.054 ^b (0.023)	-0.066 ^a (0.018)	-0.056 ^a (0.014)
Log income	0.461 ^b (0.183)	0.568 ^a (0.160)	0.624 ^a (0.169)	0.771 ^a (0.173)	0.858 ^a (0.192)	0.404 ^a (0.131)
Log migrant share	0.138 (0.275)	0.268 (0.258)	0.242 (0.291)	0.442 (0.293)	0.039 (0.297)	0.018 (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 to 4 use alternative dependent variables estimated in Columns 2, 4, 6, and 8 of Table A2, respectively. Column 5 incorporates weights based on the number of observations in each city pair into our preferred specification estimates. Column 6 estimates the elasticity of land prices with respect to city characteristics in a single step rather than two consecutive steps.

Table A4: City determinants of unit land price at city centre - Cubic form

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

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

D.3 Estimates for non-housing good prices by sub-category

Table A5: City determinants of non-housing good prices by sub-category: Linear effects

Dep. Variable	Non-housing item prices (Logged)					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Food (Vegetables & fruits)	Cabbage	Tomato	Cucumber	Banana	Apple	Pear
Log population	0.0611 (0.0670)	0.0748 (0.0519)	0.00666 (0.0433)	0.167 ^b (0.0782)	0.0339 (0.0505)	0.000689 (0.0575)
Log land area	-0.0658 (0.0541)	-0.0839 ^b (0.0418)	-0.0553 (0.0349)	-0.161 ^b (0.0621)	0.0246 (0.0401)	0.0730 (0.0457)
R^2	0.39	0.51	0.34	0.43	0.31	0.23
Panel B: Food (Meats & animal products)	Pork	Beef	Fish	Chicken	Egg	Milk
Log population	-0.0380 ^c (0.0208)	-0.00400 (0.0277)	-0.0578 (0.0349)	0.118 ^a (0.0374)	0.0262 (0.0218)	-0.0525 (0.0370)
Log land area	0.0159 (0.0168)	-0.00414 (0.0226)	0.0425 (0.0281)	-0.0627 ^b (0.0301)	-0.0273 (0.0179)	0.0146 (0.0299)
R^2	0.23	0.27	0.23	0.40	0.32	0.15
Panel C: Food (Cooking condiments)	Soybean oil	Salt	Soy sauce			
Log population	-0.0107 (0.0228)	-0.0613 (0.0540)	0.0266 (0.0508)			
Log land area	0.0115 (0.0188)	0.0680 (0.0443)	-0.0642 (0.0410)			
R^2	0.19	0.22	0.12			
Panel D: Telecom. & Transportation	Mobile phone	Landline phone	Bus	Taxi		
Log population	0.0617 (0.0670)	0.0156 (0.0111)	0.0357 (0.0442)	0.0724 ^b (0.0350)		
Log land area	0.0430 (0.0525)	-0.00241 (0.00867)	-0.0547 (0.0347)	-0.0187 (0.0275)		
R^2	0.26	0.16	0.46	0.58		
Panel E: Education & medical care	High school	Hospital regis.	Outpatient	Appendectomy	Urinalysis	
Log population	0.0854 (0.103)	-0.109 (0.0994)	-0.0000190 (0.109)	0.0322 (0.0776)	-0.212 (0.167)	
Log land area	0.0473 (0.0799)	0.00767 (0.0725)	-0.108 (0.0885)	-0.0427 (0.0608)	0.202 (0.131)	
R^2	0.40	0.20	0.47	0.34	0.11	
Observations	84	84	84	84	84	84

Notes: This table replicates Table 9 but estimates linear effects only. Standard errors are reported in parentheses.

E IV estimations

Table A6: 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 (1.578)	-7.688 ^a (2.809)	-10.767 ^b (4.588)	-4.760 (3.585)	-2.640 (4.093)	-9.154 ^a (3.237)	-9.180 ^b (4.239)
Log population squared	0.207 ^a (0.056)	0.308 ^a (0.099)	0.420 ^a (0.161)	0.210 ^c (0.125)	0.140 (0.143)	0.361 ^a (0.114)	0.364 ^b (0.149)
Log land area	1.124 ^a (0.296)	2.794 ^c (1.496)	8.615 ^b (3.391)	3.095 ^c (1.718)	4.559 ^b (2.233)	4.676 ^a (1.530)	7.318 ^a (2.657)
Log land area squared	-0.093 ^a (0.021)	-0.216 ^b (0.102)	-0.609 ^a (0.230)	-0.231 ^b (0.117)	-0.328 ^b (0.152)	-0.343 ^a (0.105)	-0.520 ^a (0.181)
Overidentification p-value		0.488	0.029	0.058	0.091	0.313	0.024
First-stage statistic		3.5	3.5	4.7	4.4	5.4	4.4
Panel B. Residential land, with first- and second-step controls (3,209 obs.)							
Log population	-3.890 ^a (1.061)	-4.562 ^b (1.923)	-5.747 ^a (2.042)	-5.064 ^c (2.621)	-4.402 ^c (2.435)	-6.060 ^a (2.117)	-6.138 ^a (2.225)
Log population squared	0.161 ^a (0.037)	0.185 ^a (0.067)	0.227 ^a (0.071)	0.204 ^b (0.091)	0.182 ^b (0.084)	0.238 ^a (0.074)	0.241 ^a (0.078)
Log land area	0.703 ^a (0.227)	1.142 (1.123)	2.376 ^b (1.165)	2.029 ^c (1.154)	1.923 ^c (1.107)	2.077 ^c (1.079)	2.707 ^b (1.148)
Log land area squared	-0.063 ^a (0.016)	-0.092 (0.075)	-0.176 ^b (0.078)	-0.152 ^c (0.078)	-0.145 ^c (0.075)	-0.157 ^b (0.073)	-0.199 ^a (0.077)
Log income	0.592 ^a (0.158)	0.560 ^a (0.173)	0.517 ^a (0.172)	0.499 ^a (0.176)	0.511 ^a (0.176)	0.519 ^a (0.171)	0.504 ^a (0.173)
Log migrant share	0.293 (0.249)	0.275 (0.253)	0.237 (0.258)	0.250 (0.259)	0.265 (0.260)	0.227 (0.252)	0.223 (0.256)
Overidentification p-value		0.327	0.138	0.294	0.167	0.263	0.289
First-stage statistic		5.9	4.4	5.5	5.7	5.4	4.8
<i>Instruments</i>							
Urban population in 1982		Y2	N	Y2	Y2	Y2	Y2
Urban density in 1990		Y2	N	N	N	Y2	Y2
Urban area in 1990		Y2	Y2	Y2	Y2	Y1	Y
Urban population in 1990		N	Y2	N	N	N	N
Sunshine hours		N	Y	N	Y	N	N
# of starred hotels		N	Y2	Y	Y	N	Y
# of 5A scenic spots		N	N	Y2	Y	N	Y
Predicted migrant9500/Emp.90		N	N	N	N	Y	Y
Rural population in 1982		N	N	N	N	Y	Y

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

Table A7: 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 (0.006)	0.034 ^a (0.010)	0.035 ^a (0.010)	0.043 ^a (0.014)	0.046 ^a (0.014)	0.037 ^a (0.011)	0.035 ^a (0.011)
Log land area	-0.013 ^a (0.005)	-0.032 ^a (0.011)	-0.033 ^a (0.011)	-0.036 ^a (0.013)	-0.037 ^a (0.013)	-0.029 ^b (0.013)	-0.033 ^a (0.013)
Log income	0.055 ^b (0.021)	0.064 ^a (0.022)	0.064 ^a (0.022)	0.058 ^b (0.023)	0.057 ^b (0.023)	0.055 (0.034)	0.068 ^b (0.029)
Log migrant share	0.029 (0.023)	0.017 (0.024)	0.016 (0.024)	0.013 (0.025)	0.011 (0.026)	0.019 (0.071)	0.008 (0.066)
Overidentification p-value		0.460	0.074	0.777	0.218	0.099	0.191
First-stage statistic		15.5	14.7	8.5	8.1	4.9	5.7
<i>Instruments</i>							
Urban population in 1982		Y	N	Y	Y	Y	Y
Urban density in 1990		Y	N	N	N	Y	Y
Urban area in 1990		Y	Y	Y	Y	Y	Y
Urban population in 1990		N	Y	N	N	N	N
Sunshine hours		N	Y	N	Y	N	N
# of starred hotels		N	Y	Y	Y	N	Y
# of 5A scenic spots		N	N	Y	Y	N	Y
Predicted migrant9500/Emp.90		N	N	N	N	Y	Y
Rural population in 1982		N	N	N	N	Y	Y
Observations	1,223	1,223	1,223	1,223	1,223	1,223	1,223

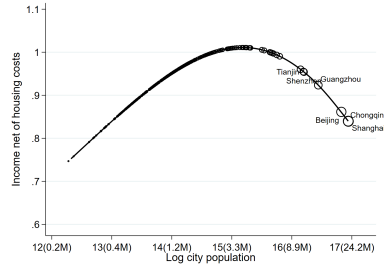
Notes: Column 1 reports OLS estimates (Column 3, Table 3) for reference. IV estimates are reported in Columns 2 to 7 using limited information maximum likelihood (LIML). Columns 2 to 5 instrument city population and land area. Columns 6 and 7 additionally instrument the migrant share. Y and N stand for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

Table A8: City determinants of housing expenditure share - IV estimates

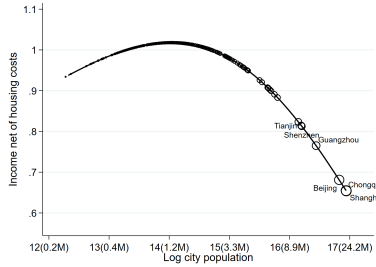
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ols	iv	iv	iv	iv	iv	iv
Panel A. High-skilled households (241 obs.)							
Log population	0.033 ^a (0.009)	0.029 ^b (0.014)	0.035 ^a (0.014)	0.034 ^b (0.014)	0.032 ^b (0.014)	0.023 (0.016)	0.045 ^a (0.018)
Log land area	0.008 (0.010)	0.004 (0.019)	-0.006 (0.018)	0.007 (0.017)	0.005 (0.017)	0.020 (0.023)	-0.028 (0.024)
Log migrant share	0.073 (0.052)	0.087 (0.055)	0.080 (0.054)	0.073 (0.058)	0.080 (0.058)	0.184 (0.125)	0.109 (0.113)
Overidentification p-value		0.442	0.046	0.084	0.006	0.140	0.487
first liml-stage statistic		17.4	14.5	15.0	12.1	4.8	3.8
Panel B. Low-skilled households (241 obs.)							
Log population	0.035 ^a (0.011)	0.018 (0.017)	0.030 ^b (0.015)	0.030 (0.018)	0.027 (0.018)	0.021 (0.021)	0.050 ^b (0.020)
Log land area	0.007 (0.012)	0.035 ^c (0.019)	0.012 (0.017)	0.025 (0.018)	0.022 (0.018)	0.021 (0.028)	-0.029 (0.023)
Log migrant share	0.098 (0.064)	0.122 (0.076)	0.106 (0.069)	0.097 (0.077)	0.107 (0.077)	0.236 (0.198)	0.149 (0.173)
Overidentification p-value		0.456	0.018	0.065	0.005	0.101	0.156
first liml-stage statistic		17.4	14.5	15.0	12.1	4.8	3.8
Panel C. Rural migrant households (1,360 obs.)							
Log population	0.022 ^a (0.005)	0.019 ^a (0.006)	0.020 ^a (0.006)	0.021 ^a (0.006)	0.020 ^a (0.006)	0.018 ^a (0.006)	0.021 ^a (0.006)
Log land area	0.001 (0.004)	0.007 (0.007)	0.006 (0.007)	0.007 (0.007)	0.008 (0.007)	0.009 (0.007)	0.004 (0.007)
Log migrant share	-0.034 (0.022)	-0.032 (0.022)	-0.033 (0.022)	-0.035 (0.022)	-0.034 (0.022)	-0.031 (0.062)	-0.035 (0.060)
Overidentification p-value		0.610	0.284	0.212	0.188	0.121	0.266
first liml-stage statistic		56.4	41.8	45.3	36.1	9.5	9.7
<i>Instruments</i>							
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

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

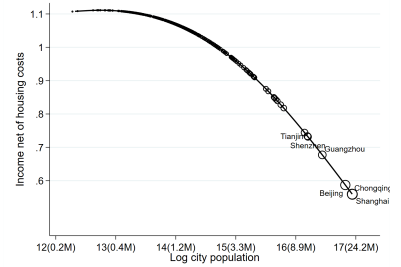
Figure A3: Predicted real income across Chinese cities with IV



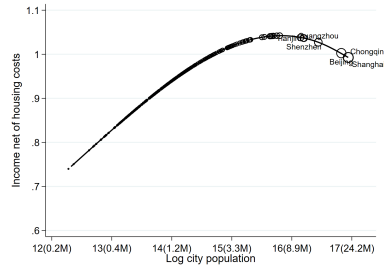
(a) High-skilled - Population only



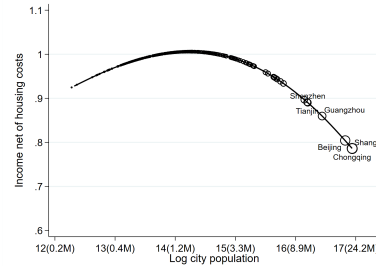
(b) Low-skilled - Population only



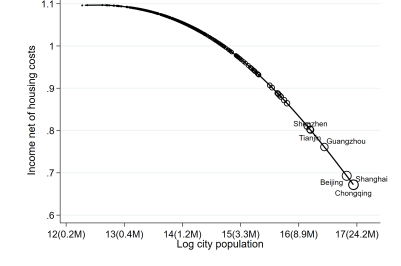
(c) Rural migrants - Population only



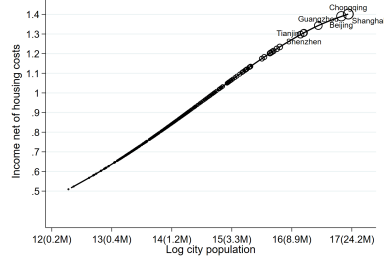
(d) High-skilled - Population and area



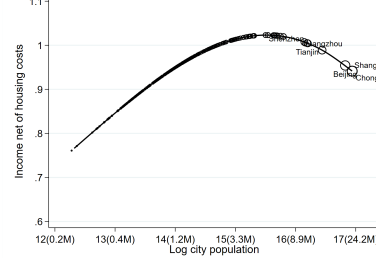
(e) Low-skilled - Population and area



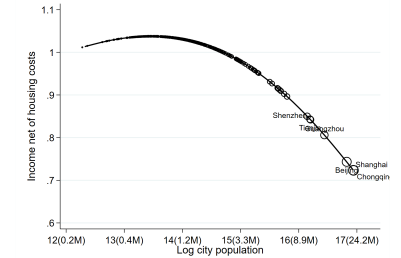
(f) Rural migrants - Population and area



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



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



(i) Rural migrants - Population, area and migration

Notes: This figure displays the predicted real income for for high-skilled households (Figs. A3(a), A3(d), and A3(g)), low-skilled households (Figs. A3(b), A3(e), and A3(h)), and rural migrant households (Figs. A3(c), A3(f), and A3(i)), respectively. Figs. A3(a), A3(b) and A3(c) use population elasticities from estimations controlling for the city land area and share of migrants. Figs. A3(d), A3(e) and A3(f) use population elasticities encompassing indirect effects from the city land area but not the share migrants. Figs. A3(g), A3(h) and A3(i) use population elasticities encompassing indirect effects from both the city land area and the share of migrants. IV estimates of housing costs and nominal income are used in the predictions. Each gray triangle symbolizes a representative high-skilled household, while a black circle denotes a representative low-skilled household in one of the 254 cities. The solid line depicts a quadratic fit. For ease of comparison across figures, note that the vertical axis is at 1.1 in all figures except Fig. A3(g), where this limit could not be applied.