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Local public service provision and spatial inequality in Chinese cities: The role of residential income sorting and land-use conditions

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Local Public Service Provision and Spatial Inequality in Chinese Cities: the Role of Residential Income Sorting and Land-Use Conditions

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Abstract

Spatial inequality refers to unequal access to local public services between high-income and low-income households in relation to their residential locations. We examine two hypotheses regarding the role of income sorting and land-use conditions in shaping spatial inequality in Chinese cities, where residents have little direct influence on local public service provision. First, in the presence of resource indivisibility, travel cost, and location-based rationing, scarcity of public-service resources in a city makes access to public services more uneven across neighborhoods, thus exacerbating income sorting and spatial inequality in the city. Second, the exacerbating effect of resource scarcity is mitigated by land-use conditions that limit income sorting. Estimates of willingness to pay by households of different income levels for public-service resources across cities corroborate both the exacerbating effect of resource scarcity and the mitigating effect of inclusive land-use conditions.

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1. Introduction

Income inequality is one of the biggest challenges for policy makers globally in recent years (Schwab, 2014). The unequal access to opportunities that often accompanies income inequality reduces intergenerational mobility (Corak, 2013) and makes economic growth unsustainable (World Economic Forum, 2014). Improving low-income households' access to local public services, such as education, healthcare and transportation, is among the most effective policy instruments to promote equal opportunities and inclusive economic growth. The present paper studies unequal access to local public services between high-income and low-income households in relation to their residential locations, which we refer to as spatial inequality. We focus on how interactions between resource provision for local public services and residential market shape spatial inequality in cities. The resource provision affects disparity in access to public services across neighborhoods. The residential market, in turn, influences income sorting in response to uneven access to public services across neighborhoods.

We examine two hypotheses. First, resource scarcity for local public services in a city will intensify income sorting across neighborhoods to exacerbate spatial inequality.. Travel cost and location-based access regulations (e.g. school catchment zone policy) make access to local public services dependent on residential location. Due to resource indivisibility, meager resources entail greater variation in public-service quality across locations—when the budget for school teachers is low, fewer schools can have teachers with specialized expertise; when the budget for doctors is low, fewer hospitals can have doctors with specialized skills; and less road space and fewer public buses per resident means more uneven coverage of public transport services across neighborhoods. Resource scarcity for local public services, therefore, makes access to these services uneven across neighborhoods. The uneven access, then, incentivize high-income households to sort themselves into the few neighborhoods that have favorable access, making these neighborhoods more exclusive and thus exacerbating spatial inequality. Second, land-use conditions that limit income sorting will mitigate the exacerbating effect of resource scarcity on spatial inequality. Such land-use conditions are inclusive in that they promote equal access to local public services.

Using recent data from more than 200 cities in China, we test these two hypotheses in two steps. In the first step, we investigate how resource provision for local public services in a city affects income sorting across neighborhoods and identify land-use conditions that limit income sorting. We regress a city-specific income sorting measure on city-level resource provision for local public services, land-

use conditions that may constrain market-driven residential redevelopment and hence income sorting, and other relevant urban attributes. The regression reveals the response of income sorting to the resource provision and the contribution of the land-use conditions to income sorting. We define the latter as excess income sorting.

In the second step, we examine the role of income sorting and land-use conditions in shaping spatial inequality by comparing households' willingness to pay for public-service resources across cities at different household income levels. The willingness to pay for each income level is revealed by compensating differences in housing expense and wage income across cities in relation to public-service resource provision. The two hypotheses above yield two predictions about the willingness-to-pay estimates for households of different income levels. First, the exacerbating effect of resource scarcity on spatial inequality implies that higher resource provision for local public services would benefit low-income households more than high-income households due to diminished spatial inequality. In other words, endogenous spatial inequality in response to public-service resource provision makes the access to local public services by high-income households less dependent, but the access by low-income households more dependent, on the level of resource provision in the city. Thus we expect the willingness to pay estimates to decline with household income level.

Second, if land-use conditions that limit income sorting mitigate spatial inequality as predicted by the second hypothesis, then the excess income sorting would raise the willingness to pay for public-service resources by high-income households, who benefit from spatial inequality, but reduce the willingness to pay by low-income households, who are harmed by spatial inequality. Our findings are supportive of the two hypotheses.

Income disparity across neighborhoods within metropolitan areas is widely documented in the literature (see Rosenthal and Ross, 2014). Davidoff (2005) highlights the wide variation in intra-city income sorting across US metropolitan areas; measured by the fraction of income dispersion explained by neighborhood fixed effects, the extent of income sorting varies from less than one percent to approximately 33 percent. There is a long-standing literature on mechanisms of intra-city income sorting in relation to local public good provision. Banzhaf and Walsh (2008), for example, show evidence that households "vote with their feet" for local public goods and neighborhoods with better public goods (air quality in their case) attract more high-income households, consistent with Tiebout (1956) hypothesis. Income sorting arising from bidding for access to local amenities would be moderated by location choice incentives with respect to spatially heterogeneous employment opportunities (e.g., De Bartolome and Ross, 2007; Hanushek and Yilmaz, 2013; Bayer and McMillan,

2012). Recent studies show that income sorting with respect to local amenities is also moderated by sorting incentives associated with demographic preferences. Banzhaf and Walsh (2013), for example, show that diminished disparity in public good quality across neighborhoods, while reducing income sorting incentives, can encourage residential segregation by race.

The adverse effect that income segregation can have on the equality of opportunities is also extensively studied. Income segregation is found to reduce learning, employment and other social opportunities for the poor (*e.g.*, Glaeser, Resseger and Tobio, 2008; Ioannides and Loury, 2004; Bayer, Ross and Topa, 2008; Glaeser, Laibson and Sacerdote, 2002; Glaeser and Mare, 2001; Glaeser and Sacerdote, 2000; Glaeser, Sacerdote and Scheinkman, 1996). It thus reinforces income inequality by reducing intergenerational mobility (Chetty *et al.*, 2014).

Empirical studies of income sorting in the context of developing economy cities are relatively few, although income segregation there is often highly visible (Kilroy, 2008). Since early 1990s Chinese cities have experienced rapid growth not only in income and population size but also in income inequality. The income Gini coefficient for the nation rose from 0.38 in 1988, to 0.45 in 1999, and to 0.49 in 2007 (Knight, 2013), reflecting increasing reward to skills and disparity in opportunities associated with different social and occupational background (Appleton, Song and Xia, 2013). The Gini coefficient varies considerably across Chinese cities, ranging from 0.246 to 0.483 according to 2007 Urban Household Survey (UHS) data (Zheng, *et al.* 2013). Using the same data, we find that, in a typical Chinese city, approximately 17 percent of income variation among households can be explained by differences across residential neighborhoods. This measure of income sorting varies from less than 2 percent to about 73 percent in our sample of over 200 Chinese cities.¹

The provision of local public services varies considerably across Chinese cities, as a result of large disparity in fiscal capacity between the rich coastal cities and the less developed interior cities. The fiscal disparity increased after the introduction of the tax-sharing system between the local and central governments in 1994. Much of the public spending responsibility has been devolved to sub-provincial local governments. In 2003, the sub-provincial local governments received 34% of public revenue but were responsible for 51% of public expenditure. Between 1990 and 2003, the ratio of per capita GDP between China's richest province and the poorest rose from 7.3 to 13; in 2003, the richest province had more than 8 times as much in per capita public spending as did the poorest province (Dollar and Hofman, 2008). Among the city and county level jurisdictions, which are most important for the

¹ Because of the difference in the neighborhood scale used in computation, the measured level of income sorting in our sample of Chinese cities and that for US cities reported by Davidoff (2005) are not strictly comparable. The higher measure for Chinese cities is partly due to the more disaggregated neighborhood units used for our computation.

delivery of local public services, including school education, health and public transportation, the disparity in per capita public spending is even larger—the richest jurisdiction had about 48 times the level of per capita spending than the poorest one (World Bank, 2006). These sub-provincial governments are accountable to the central government mostly for local GDP growth but have little accountability for spending on public services, either to the central government or to their local residents (Dollar and Hofman, 2008).

The present study contributes to the literature by showing that the disparity in resource provision for local public services across cities affects low-income households more than high-income households. The differential impact arises from residential market response in terms of income sorting to differences in public-service resource provision across cities. Our findings also show the importance of inclusive land-use planning in promoting equal access to local public services, especially in cities where public-service resources are more constrained.

We provide additional background of urban development and local public service provision in Chinese cities in section 2. Section 3 discusses the methodology and data for measuring income sorting, resource provision for local public services, and land-use conditions that affect residential development in individual Chinese cities. Section 4 reports the cross-city regression results regarding the impact of resource provision on income sorting and spatial inequality. We conclude in Section 5.

2. Urban development and local public service provision in Chinese cities

Urbanization in China was very slow in the 40 years of the centrally planned economy prior to 1990. The limited new housing construction in cities during that period was largely undertaken by state enterprises on land allocated to them. In early 1990s real estate market was re-introduced in Chinese cities as part of economic reform, allowing city governments to grant state land—all urban land in China is state owned—for private development via public land leases. Between 1993 and 2006, Chinese cities on average doubled their built-up area. Under the central planning, urban homes were provided by the state, usually through employers (work units), as welfare according to workers' family need and seniority. The welfare housing system was abolished in 1998, around which time the existing housing stock was also privatized through work-unit sale of homes to sitting tenants at subsidized prices (Fu, Tse and Zhou, 2000). Private residential construction took off and housing prices in Chinese cities rose steadily with household income in the following decade. Despite the rapid urban expansion since the early 1990s, Chinese cities remain largely monocentric with high population density. Even though private car ownership rose considerably, the majority of workers still

commute by public transportation. Central locations in cities are always more highly valued compared to peripheral locations, especially by high-income households, as the quality of schools, hospitals and public transport services are better there (Zheng, Fu and Liu, 2006). The expansion of these services often lagged behind the physical expansion of Chinese cities in the 1990s and early 2000s (Zheng, Hu and Wang, 2015).

After the liberalization of housing market at the end of the 1990s, land rent differential rose both across cities and across locations within individual cities to capitalize heterogeneous location qualities (see, *e.g.*, Zheng, Fu and Liu, 2009; Zheng, Sun and Wang, 2014; Zheng, Hu and Wang, 2015), reflecting competitive allocation of land and housing in residential markets. Zheng, Fu and Liu (2006) show that residents in Chinese cities were largely able to choose their residential location according to their willingness to pay for location qualities, although their location choices were subject to the constraints of available housing types at different locations and access to housing finance.

Chinese cities have a 3-tier sub-municipal administrative structure: the first tier is district, or *Qu*, the second tier is street precinct, or *Jiedao* (*JD*), and the third tier is residential neighbourhood, or *Juweihui* (*JWH*). A *JWH* typically has 500 to 1,000 households. Beijing, for example has 18 *Qus*, 130 *JDs* and 2,625 *JWHs* in 2006. The municipal government controls the budget of local public services, including school education, healthcare, and public transportation. It also controls the overall planning of the public infrastructure and facilities. The lower tier governments may be assigned responsibilities to run and maintain some of the public facilities and services.

The city government is largely financed by a tax-sharing system introduced in 1994 (Dollar and Hofman, 2008), which also made cities responsible for most of the local public service budget and delivery. In 2003, the sub-provincial governments accounted for over 75% of the public expenditure on education and health (Martinez-Vazquez *et al.*, 2008). But, with no *ad valorem* property tax in Chinese cities, no democratic election of municipal and sub-municipal government officials, and little public participation in local budgeting (He, 2011), there was little accountability in municipal spending on local public services and the urban residents' influence on resource provision for local public services was very limited. Large disparity in the resource provision for local public services across cities results from uneven economic development across regions and from the priority given to local GDP growth, for which local governments were accountable to the central government.

The expenditure on basic local public services, such as education and healthcare, has been low compared to the practice in other developed and developing economies. The Chinese government

spent less than 3% of GDP on education in the early 2000s; in comparison, the public education expenditure as percentage of GDP in U.S., U.K., and India are, respectively, 5.7%, 5.3%, and 4.1% (Dahlman, Zeng and Wang, 2008). The public spending on school education in China was even less adequate, since much of the public education expenditure went to supporting tertiary education. Between 1998 and 2003, the share of public education expenditure for primary education fell from 34.5% to 33.6%. In OECD countries, more than 90% of primary and secondary education expenses are funded publicly; in China less than 70% are paid for by the government. The inadequate public spending on school education contributed to strong competition for access to good schools in Chinese cities. The public spending on school education also varies considerably across cities. In 2006, for instance, the public expenditure for primary school education was Rmb9,410 Yuan (about USD1,176 according to 2006 market exchange rate) per pupil in Shanghai (one of the richest provinces) but only Rmb948 Yuan per pupil in Henan (one of the poorest provinces). The junior high school education expenditure per pupil in these two regions were 10,055 Yuan and 1,223 Yuan, respectively. China's public health expenditure in terms of share of GDP in the early 2000s was less than 1%, even less adequate than public education expenditure. In 2003, the difference in public health expenditure per capita between the highest and lowest provinces was 13 times (Martinez-Vazquez *et al.*, 2008).

Within individual cities, the distribution of public school resources can be highly uneven across locations, as the city government often targets their limited resources to selected flagship schools to boost their performance in the highly competitive national university admission examinations. School access is rationed through school catchment zone policies. Zheng, Hu and Wang (2015) provide evidence that differences in school quality across school catchment zones in Beijing are capitalized in housing prices. Public hospitals are open to all residents regardless of their residential location, although the healthcare benefits may vary across individuals based on their employment and Hukou status.² Spatial disparity in access to public healthcare services arises mainly from differential travel cost required to take advantage of specialized healthcare facilities.

² Hukou is individuals' official residential registration in China, differentiated in terms of the place of registration and rural vs. urban status. At birth, individuals' Hukou place and status follow those of their parents. Although people are free to change their employment and place of residence, the destination government may not grant Hukou modification entitling migrant workers to receive local welfare benefits.

3. Measuring income sorting, resource provision for local public services, and land-use conditions affecting residential redevelopment

The extent of income sorting in a city is measured as the ratio of the between-neighborhood variation in household total income over the population variation in household total income within the city.³ When the variation is measured by variance, the ratio can be interpreted as the R^2 in a regression of the income measure on a full set of dummy variables indicating residence in each of the neighborhoods (see Kremer and Maskin, 1996; Davidoff, 2005). Indexing households by h and neighborhoods by k , the R^2 measure of income sorting is given by:

$$R^2 \equiv \frac{\sum_{k=1}^K \frac{H_k}{H} (\bar{x}_k - \bar{x})^2}{\frac{1}{H} \sum_{h=1}^H (x_h - \bar{x})^2} = \frac{\sum_{k=1}^K \frac{H_k}{H} (\bar{x}_k - \bar{x})^2}{\frac{1}{H} \sum_{k=1}^K \left(\sum_{h=1}^{H_k} (x_h - \bar{x}_k)^2 + H_k (\bar{x}_k - \bar{x})^2 \right)} \quad (1)$$

where x_h is the logarithm of total income of household h , \bar{x}_k is mean logarithm of household income in neighborhood k , \bar{x} is mean log household income in the city, and K and H are respectively the total number of neighborhoods and total number of households included in the estimation sample. According to this measure, income sorting is high if the income dispersion among the city residents can be largely explained by the variation in neighborhood means.

We employ the data from 2007 Urban Household Survey (UHS) to estimate income sorting in Chinese cities. UHS is a regular nationwide sample survey conducted by the National Bureau of Statistics of China (NBSC). The 2007 UHS covers 255 prefecture-level cities in China (as shown in the map in Figure 1) and has a sample size of 300 thousand households. The 2007 UHS employed a 3-stage stratified sampling method. For each city, street precincts, or *JDs*, are sorted by their identification numbers (ID) and sampled at fixed distances; next, residential neighborhoods, *JWHs*, in each selected *JD* are sorted by their ID and sampled at fixed distances. 7 to 566 *JWHs* are sampled randomly in each city according to city size, to represent about 20 percent of the *JWHs* in each city. The number of *JWHs* selected in each city depends on the city size and other criteria (e.g. the political status of the city) set by NBSC; the average number is 49. About 4 percent of the households in each *JWH* are randomly sampled for the survey.

*** Insert Figure 1 about here ***

We estimate the R^2 sorting index based on *JWH* neighborhoods. *JWH* boundaries are significant for

³ Reardon *et al* (2006) provide a critical review of various approaches to measuring spatial inequality and of the variation-ratio approach based on different variation measures.

heterogeneity in local public service accessibility. School catchment zones, for example, are often delineated by *JWH* boundaries (Zheng, Hu and Wang, 2015). For the final sample of 207 cities (cities with missing value for some of the key variables are dropped), the R^2 sorting index has a mean value of 0.221 and a standard deviation of 0.073; it ranges from 4.2 percent to 46.2 percent.⁴ Figure 2 plots the city-specific R^2 sorting index against the 2006 city population size, ranging from 150,000 to over 15 million.

*** Insert Figure 2 about here ***

The resource provision for local public education services is measured by the number of primary and secondary school teachers per 10 thousand city residents, denoted *TEACHER*.⁵ The resource provision for public health is measured by the number of medical doctors and number of hospital beds per 10 thousand city residents, denoted *DOCTOR* and *H_BED* respectively. For public transportation, the resource provision is measured by road space per capita, denoted by *ROAD*, and the number of public buses per 10 thousand city residents, denoted by *BUS*. We define $PUB_ED = \log(TEACHER)$, $PUB_HL = \log(DOCTOR \times H_BED)/2$ and $PUB_TS = \log(ROAD \times BUS)/2$, respectively, as indicators of resource provision for public education, health care and transport services in a city. In addition, we define a composite indicator, $PUB_SERVICE = (PUB_ED + PUB_HL + PUB_TS)/3$, to measure the overall resource provision for local public services by a city. In computing these measures, we include residential population in urban areas regardless of their Hukou status but exclude rural jurisdictions under each city. Given that the local government has little accountability for local public service provision to local residents, these city-level measures of resource provision for local public services are unlikely endogenous to income sorting in the city. Nevertheless, we compute these measures using data in year 2002, five years prior to the observed income sorting outcome measured by R^2 , to minimize any potential endogeneity problem.

Table 1 provides the sample statistics of the resource provision measures. The value of *TEACHER* among the 207 cities in our final sample averages about 86 (per 10 thousand residents in 2002); it ranges from 37 to 185. The number of doctors (*DOCTOR*) and hospital beds (*H_BED*) ranges from 6 to 91 and from 14 to 175, per 10 thousand residents, respectively. *ROAD* value varies between 0.4 and 34 square meters per resident and the number of public buses (*BUS*), between 0.9 and 30 per 10

⁴ Davidoff (2005) scales up his R^2 estimates to account for errors in income measurement. Our R^2 estimates are not adjusted. His estimation is based on reported income bins. Ours is based on reported actual income, which would have smaller measurement error compared to income-bin measure. Nevertheless, our R^2 estimates likely understate the actual income sorting due to errors in income measurement.

⁵ Nearly all schools in Chinese cities were run by the government. Even in Beijing, only 2% of all schools were private in 2010, according to Beijing Municipal Commission of Education.

thousand people. The composite public service level indicator, *PUB_SERVICE*, has a mean 3.8 and a standard deviation of 0.40.

*** Insert Table 1 about here ***

Three variables are used to measure land-use conditions that may affect residential redevelopment opportunities and hence income sorting in individual cities. In the past state enterprises (SOEs) built free homes for their employees, often in central urban districts, and sold them to their employee-tenants during housing privatization in the 1990s. These SOE housing projects were seldom redeveloped for sale at market prices due to land-use right restrictions. Hence, cities having a high employment share in SOEs historically would have a lesser degree of income sorting. The SOE employment share in 1998, denoted by *SOE_SHARE*, is used to measure the presence of SOE housing projects in each city. It averages 0.593 across our city sample and has a standard deviation of 0.259.

Residential redevelopment opportunities in a city were often correlated with the growth of urban built-up area, as households displaced by private redevelopment in central urban districts were often relocated to new homes built by government in urban periphery. We use the ratio of the urban built-up area of 1998 over that of 2004, *OLD_BUILT-UP*, an indicator of slow urban expansion, as another measure of residential redevelopment constraints; it has a mean value of 0.612 and standard deviation of 0.304. The 1998 built up area generally represents the central core area of the city today with high concentration of quality schools, hospitals and public transport networks, whereas newly developed urban areas often lacks these amenities in the 1990s and early 2000s (Zheng, Hu and Wang, 2015). As a result, a lower *OLD_BUILT-UP* ratio would indicate both greater spatial disparity in local public service quality in the city and more opportunities for high-income households to displace low-income households in city center through residential redevelopment.

The third variable to indicate redevelopment constraint is the share of land with gradient smaller than 15 degrees, denoted by *LOW_GRADIENT*. This geographic feature is widely used in the literature to measure housing supply elasticity (Saiz, 2010). It has a mean value of 0.749 and a standard deviation of 0.203 across the cities in our sample. A higher *LOW_GRADIENT* means lower construction cost, which would encourage residential (re)development in the city.

Besides the resource provision and residential development constraints, additional control variables will be included to account for cross-city variations in income sorting. They include income dispersion among residents in the city, measured by the coefficient of variation of household income, *HI_CV*; mean household annual income, *HI_mean*; and urban population density, measured by

population per square kilometer of built-up area in 2000, *POP_DESITY2000*. *HI_CV* is computed using 2007 UHS data and has a mean value of 0.901 and ranges from 0.572 to 1.285. *HI_mean* averages 32,340 Yuan. *POP_DESITY2000* has a mean value of 20,875 and ranges from 3,989 to 84,687.

4. Estimating the impact of resource provision on income sorting and spatial inequality

Our two empirical hypotheses, stated in the introduction section, are: (1) resource scarcity for local public services in a city will cause greater income sorting in the city, exacerbating spatial inequality; and (2) given the resource provision for local public services, spatial inequality is greater in cities where land-use conditions are more favorable to residential redevelopment to facilitate income sorting. These two hypotheses are tested in two steps. In the first step, we estimate the respective influences on income sorting due to city-level resource provision for local public services and due to land-use conditions that affect residential redevelopment opportunities. We compute a measure of excess income sorting to represent the latter influence. In the second step, we examine the spatial inequality implications of resource provision and land-use conditions through their interaction with income sorting.

In the second step, we evaluate the spatial inequality impact of public-service resource provision and inclusive land-use conditions. Since we do not observe spatial inequality directly in the absence of detailed spatial information of household income and local public service quality, we rely on a revealed-preference approach, according to Roback (1982), to evaluate spatial inequality. Local public services are amenities, the benefit of which to households would be revealed, under the assumption of perfect labor mobility across cities, by the households' willingness to pay, in terms of compensating land-rent differential relative to wage-rate differential across cities, for the resources deployed by individual cities to produce such amenities.⁶ We separately measure the willingness to pay of low-income, middle-income, and high-income households for the same city-level resource provision for local public services. These willingness to pay estimates are expected to vary by household income level because the variation in spatial inequality in relation to public-service resource provision and land-use conditions would affect the access to local public services by low-income households more than the access by high-income households.

⁶ Fu and Gabriel (2012) find inter-province labor mobility in China in the early 1990s to be responsive to differences in wage rates, cost of living, and learning opportunities. Zheng, Fu and Liu (2009) find land rent differential across Chinese cities to be increasingly correlated with quality of living as a result of rising income and labor mobility.

Under our hypothesis that resource scarcity for local public services in a city will exacerbate income sorting and spatial inequality, the willingness to pay for the resource provision should be greater for low-income households than for high-income households, because additional resource provision would improve the access to local public services by low-income households relative to high-income households due to reduced spatial inequality. Furthermore, excess income sorting due to land-use conditions more favorable to market-driven residential redevelopment, which according to our second hypothesis help to widen spatial inequality, can be expected to reduce the benefit of resource provision to low-income households but increase it to high-income households.

Impact of public-service resource provision and land-use conditions on income sorting

Table 2 reports the OLS estimates of the cross-city regression of income sorting as measure by the R^2 index. The baseline regression in column (1) shows that income sorting increases with income dispersion in the city measured by HI_CV . The income sorting is somewhat mitigated in cities with higher average household income HI_mean , but the effect is very marginal. Urban population density, $POP_DENSITY2000$, has no significant effect on income sorting, consistent with the finding in Wheeler (2008). We further control for the number of JWH neighborhood units sampled by UHS, N_JWH , to account for both the potential influence of city size and for possible statistical bias in the income-sorting estimate—the R^2 index can be biased upward when more neighborhoods are included in estimation (Davidoff, 2005). N_JWH does have a positive effect on the R^2 index.

Results in columns (2) through (7) examine the impact of pre-determined resource provision for local public services on income sorting. As shown in column (2), more adequate resource provision reduces income sorting: one standard deviation increase in the overall measure of resource provision, $PUB_SERVICE$, reduces the R^2 income sorting measure by 0.25 standard deviation. Column (3) further shows that the negative effect of resource provision on income sorting is greater in cities with greater income dispersion among households, as shown by the negative coefficient of the interaction between $PUB_SERVICE$ and a binary variable indicating cities with above average income dispersion, HI_CV_H .

*** Insert Table 2 about here ***

Column (4) reports the additional influence on income sorting from land-use conditions affecting residential redevelopment opportunities, namely SOE_SHARE , $OLD_BUILT-UP$, and $LOW_GRADIENT$. The SOE employment share (SOE_SHARE), indicating the extent of old housing stock resistant to market-driven redevelopment, reduces income sorting. $OLD_BUILT-UP$, indicating a lack of urban

expansion (and displacement of residents from redevelopment of old residential communities), also dampens income sorting. Lastly, *LOW_GRADIENT*, the share of urban area with a gradient less than 15 degree and hence easy for residential development, has a positive effect on income sorting. These results are consistent with the notion that market-driven residential development facilitates income sorting.

Columns (5), (6) and (7) report estimation results with disaggregated measure of resource provision for different local public services, including schools (*PUB_ED*), healthcare (*PUB_HL*), and road and public transit (*PUB_TS*). The resource provision for schools and urban transportation reduces income sorting but the difference in public-health resource provision does not. The weak effect of *PUB_HL* on income sorting is consistent with the absence of location-based rationing for public hospital services; residential location makes little difference to the access to public hospital services apart from transportation convenience, which is accounted for by the effect of *PUB_TS*. The effects on income sorting due to land-use conditions affecting residential redevelopment opportunities are largely unchanged when the resource provision is disaggregated with respect to different local public services.

We use the estimates in column (4) and (7), respectively, to compute two excess sorting indexes, *EX_SORTING1* and *EX_SORTING2*, to represent the variation in income sorting across cities due to different land-use conditions affecting residential redevelopment opportunities as indicated by *SOE_SHARE*, *OLD_BUILT-UP*, and *LOW_GRADIENT*. These two indexes are demeaned and have a standard deviation of 0.029 and 0.035, respectively, which represent 40% to 50% of the standard deviation of the R^2 income sorting index (see Table 1).

One potential concern is reverse causality, in that income sorting may influence the resource provision for local public services by the city. Even though the resource provision measures are pre-determined, they may still be influenced by income sorting due to the persistence of income sorting pattern. To test the validity of the assumption that income sorting is unlikely to influence the resource provision due to the lack of accountability of local governments to residents with respect to local budgeting, we run a regression of *PUB_SERVICE* on city attributes, including city mean household annual income, urban population density, the number of *JHW* neighborhood units represented in 2007 UHS, as well as the three land-use conditions influencing the excess income sorting. The estimates are reported in Table 3. We find the resource provision, on per capita basis, decrease with urban density, consistent agglomeration economies. Cities with a larger number of *JHW* represented in UHS, being politically more powerful, have greater resource provision per resident. The land-use conditions, namely *SOE_SHARE*, *OLD_BUILT-UP*, and *LOW_GRADIENT*, show little influence on the resource

provision. The F test fails to reject the null hypothesis that the estimates of these three variables are jointly zero. Thus the possibility of resource provision being endogenous with respect to income sorting can be reasonably excluded.

*** Insert Table 3 about here ***

Impact of public-service resource provision and land-use conditions on spatial inequality

To evaluate spatial inequality, we construct indexes of willingness to pay for local amenities, denoted by *AMENITY*, for representative households of low income, middle income and high income, respectively. For a representative household, the index is defined by:

$$AMENITY_j \equiv \frac{1-\beta}{1+\eta} \ln(P_j Q_H) - \left(1 + \frac{1-\beta}{1+\eta}\right) \ln W_j \quad (2)$$

where P_j and W_j are respectively housing price and wage in city j ; Q_H is housing quantity demanded and $P_j Q_H$, home value, for the representative household; $1-\beta$ is the housing expenditure share of household income, and η the price elasticity of demand for housing. This definition is derived from Roback (1982) principle of compensating land-rent differential and the constraint that we observe home value but not housing price (see Appendix for the derivation). For simplicity, we will suppress the city index j where there is no confusion. We choose $1-\beta = 1/3$ and $\eta = -0.8$ (see Chow and Niu, 2015) to compute the *AMENITY* index using household data from 2007 UHS. We define a low-income household of a city as the one with 25th percentile home value HV_{25} and 25th percentile household income HI_{25} in the city. Similarly a middle income household is defined as the one with 50th percentile home value and household income, HV_{50} and HI_{50} , respectively; and a high-income household, the one with 90th percentile home value and household income HV_{90} and HI_{90} . Thus the amenity index for these representative households are $AMENITY_L = \frac{5}{3} \ln HV_{25} - \frac{8}{3} \ln HI_{25}$,

$$AMENITY_M = \frac{5}{3} \ln HV_{50} - \frac{8}{3} \ln HI_{50}, \text{ and } AMENITY_H = \frac{5}{3} \ln HV_{90} - \frac{8}{3} \ln HI_{90}, \text{ respectively.}$$

To isolate the contribution of local public services and spatial inequality to households' willingness to pay, we control for several observable amenity attributes, including air quality (measured by PM10 concentration), population density, geography, and climate. The climatic amenities are measured by variables *RAIN_INDEX* and *TEMP_INDEX*; the former represent the annual rainfall in 2000 and the

latter is the distance of annual seasonal temperature variation (relative to the mildest winter and summer temperature of all cities in our sample):

$$TEMP_INDEX_j = \sqrt{\left(TW_j - \max_j TW_j\right)^2 + \left(TS_j - \min_j TS_j\right)^2} \quad (3)$$

where TW_j stands for winter (January average) temperature for city j and TS_j , for summer (July average) temperature. A higher $TEMP_INDEX$ value indicates more extreme winter or summer temperature in the city and hence a lower thermal comfort level. Both $TEMP_INDEX$ and $RAIN_INDEX$ are standardized (so that they have zero mean and unit standard deviation across our city sample). To mitigate the high-correlation between $TEMP_INDEX$ and $RAIN_INDEX$, we construct two orthogonal climate indexes, defined below:

$$CLIMATE_INDEX1_j = \sqrt{2} / 2 \cdot (-TEMP_INDEX_j + RAIN_INDEX_j), \quad (4)$$

$$CLIMATE_INDEX2_j = \sqrt{2} / 2 \cdot (TEMP_INDEX_j + RAIN_INDEX_j). \quad (5)$$

The summary statistics of these variables are reported in Table 1.

*** Insert Table 4 about here ***

Table 4 reports the evaluation of spatial inequality based on joint estimation of $AMENITY_L$, $AMENITY_M$ and $AMENITY_H$ using GMM method. Columns (1) to (3) evaluate the impact of overall resource provision for local public services, $PUB_SERVICE$, on spatial inequality. The willingness-to-pay estimates for $PUB_SERVICE$ are 0.605, 0.368, and 0.343, respectively, for low-income, middle-income, and high-income households. The statistical significance of the estimates is also highest for the low-income households and lowest for the high-income households. The pattern is consistent with the prediction of our first hypothesis that increased resource provision for local public services not only raises the quality of these services for all residents but also improves access to local public services by low-income households relative to high-income households. We further note that the willingness-to-pay estimates for $PUB_SERVICE$ depend on the variation in income sorting across cities due to land-use conditions as measured by $EX_SORTING1$. Greater income sorting due to more market-driven residential redevelopment appears to reduce the access to public-service resources by low-income households but somewhat improve the access by top-income households.

The same concern for reverse causality pertaining to Table 2 can be applied to Table 4: households' willingness to pay could influence the resource provision by individual cities. We mitigate possible reverse causality by using lagged measures of public-service provision as independent variables.

Moreover, such potential reverse causality should not affect our results for three reasons. First, the evidence for spatial inequality hinges on the difference in willingness-to-pay estimates for *PUB_SERVICE* between low-income and high-income households, not on the magnitude of these estimates. Second, households are mobile across cities; hence, to the extent that their valuation of local public services influences the resource provision, such influence would apply equally to all cities. The cross-city variation in the resource provision is primarily due to supply factors, such as urban density and the city's political status, as demonstrated by the results in Table 3. Notably, Table 3 shows that mean household income has insignificant correlation with *PUB_SERVICE*. Third, to the extent that local residents may politically influence the public-service resource provision, even though such influence is unlikely given the political system in Chinese cities, it is more likely for high-income households to influence the resource provision to their advantage; such a possibility, therefore, would bias against the spatial inequality evidence.⁷

Columns (4) to (6) of Table 4 evaluate the impact of resource provision for education, healthcare, and urban transportation, respectively, on spatial inequality. The results show that the willingness to pay for public education and transportation resource provision, *PUB_ED* and *PUB_TS* respectively, are significantly more positive for low-income households than for high-income households, consistent with the results pertaining to the overall resource provision. The finding that low-income households benefit more from public transport resource provision is also consistent with the finding in Glaeser, Kahn and Rappaport (2008) that the poor choose to live in central cities because they are more dependent on public transport services provided there. The willingness to pay for public healthcare resources, *PUB_HL*, however, appears somewhat higher for high-income households than for low-income households. As noted earlier, access to public hospitals does not depend on residential location apart from transportation cost; thus, the result that public health resource provision has little impact on spatial inequality is expected. The effect of variation in income sorting across cities due to different land-use conditions affecting residential redevelopment opportunities, indicated by the estimates for the interaction between *PUB_SERVICE* and *EX_SORTING2*, remain qualitatively

⁷ The difference in the willingness to pay between low-income and high-income households could be influenced by the presence of migrant workers among low-income households. These migrant workers have no *hukou* in the city and hence no access to some of the local public services, such as public schools. In our UHS sample, the share of household without *hukou* is small (about 5%). Even if *hukou* affected low-income households' access to local public services, these households' willingness to pay for public-service resources would be insensitive to income sorting (since they would be denied local public services regardless of their residential location). Thus the difference in willingness to pay for public-service resources between low-income households and high-income households would understate the impact of spatial inequality due to income sorting for residents with *hukou*.

unchanged: the excess sorting harms access to local public service by low-income households relative to high-income households.

The willingness-to-pay estimates for other urban amenity variables are largely consistent with expectations. Urban density, measured by $\log(POP_DENSITY2000)$, which has a slightly negative effect on income sorting in Table 2, has a slightly more positive effect on the willingness to pay of low-income households relative to high-income households; but the effect is statistically insignificant. Air pollution, indicated by $PM10$ concentration, has a significant negative effect on the willingness to pay of all households; but the effect is greater in magnitude for low-income households, as they are less able to afford self-protection (Zheng, Sun & Kahn, 2015). Climate amenities are important for all households. Lastly, the geography feature, in terms of land gradient in the urban area indicated by $LOW_GRADIENT$, has no direct effect on households' willingness to pay apart from its contribution to excess sorting in the city.

5 Conclusions

Promoting equal opportunities and inclusive growth in a time of rising income inequality poses a major policy challenge to cities both in developed and in developing economies. Extant studies found that reduced residential segregation can mitigate the detrimental effect of income inequality on intergenerational mobility (Chetty, et al., 2014) and that improved availability of local public goods can mitigate income segregation (Banzhaf and Walsh, 2013). The present study provides further evidence that more adequate resource provision for local public services, especially for education and urban transportation, can be effective in reducing income sorting in cities. Moreover, reduced income sorting has the effect of mitigating spatial inequality, improving low-income households' access to public-service resources. In addition, our findings indicate that market-driven residential redevelopment tends to facilitate income sorting and exacerbate spatial inequality. Thus both adequate resource provision for local public services and inclusive land-use policies (e.g. providing space for low-income housing in neighborhoods with good access to public services) are important for promoting equal opportunities in cities. The adoption of such policies, however, would depend on broader civic participation in local governance. Village elections in China have brought about more pro-poor public investment in those villages with elected government officials (Shen and Yao, 2008). Reforms to local public finance and governance can also help Chinese cities to become more equal in opportunities for all households.

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Appendix

To derive an amenity index representing a household's willingness to pay for amenities in city j , which has a housing price P_j and offers a wage W_j and an amenity index θ_j , we assume households to have a CES utility function for the consumption of a traded numeraire good Q_T and housing Q_H :

$$u = \theta_j \left(\phi \cdot Q_T^{\frac{\sigma-1}{\sigma}} + (1-\phi) Q_N^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} = \theta_j \left((1-\phi)^\sigma + \phi^\sigma P_j^{\sigma-1} \right)^{\frac{1}{\sigma-1}} \frac{W_j}{P_j}, \quad (A1)$$

where $\sigma \geq 0$ is the elasticity of substitution and $0 \leq \phi \leq 1$ a preference parameter. The expression following the second equal sign is the indirect utility, which, by Roy's identity, gives the housing demand function:

$$Q_H = \frac{(1-\phi)^\sigma}{(1-\phi)^\sigma + \phi^\sigma P_j^{\sigma-1}} \frac{W_j}{P_j} \approx (1-\beta) P_0^{(\sigma-1)\beta} \frac{W_j}{P_j^{1-(1-\sigma)\beta}}. \quad (A2)$$

The approximation follows the linearization below with respect to P_j around a baseline price P_0 :

$$\ln \frac{(1-\phi)^\sigma}{(1-\phi)^\sigma + \phi^\sigma P_j^{\sigma-1}} \approx \ln(1-\beta) + (1-\sigma)\beta \frac{P_j - P_0}{P_0} \approx \ln(1-\beta) + (1-\sigma)\beta (\ln P_j - \ln P_0), \quad (A3)$$

where $1-\beta \equiv (1-\phi)^\sigma / ((1-\phi)^\sigma + \phi^\sigma P_0^{\sigma-1})$ is the housing expenditure share of income at the baseline price. The price elasticity of housing demand in Eq. (A2) is $\eta \equiv (1-\sigma)\beta - 1$, which is less than unity for $1 > \sigma \geq 0$.

Following Roback (1982), the compensating housing price that makes the household indifferent between cities can be obtained by applying logarithm to the indirect utility in Eq. (A1) and using the linear approximation Eq. (A3):

$$(1-\beta) \ln P_j = \ln W_j + \ln \theta_j + \left(\ln \left((1-\phi)^\sigma + \phi^\sigma P_0^{\sigma-1} \right)^{\frac{1}{\sigma-1}} - \beta \ln P_0 - \ln u \right). \quad (A4)$$

Since we observe housing value $P_j Q_H$ but not housing price P_j , we make use of Eq. (A2) to obtain:

$$\ln P_j = \frac{1}{1+\eta} \ln(P_j Q_H) - \frac{1}{1+\eta} \ln W_j - \ln \left((1-\beta) P_0^{(1-\sigma)\beta} \right).$$

Thus the amenity index, representing the household's willingness to pay for the amenities offered by city j , including local public services and other amenities, can be estimated by:

$$AMENITY_j \equiv \ln \theta_j + \varphi = \frac{1-\beta}{1+\eta} \ln(P_j Q_H) - \left(1 + \frac{1-\beta}{1+\eta} \right) \ln W_j, \quad (A5)$$

where φ is a constant. Whether P_j is rental price or sale price would affect φ but not the relative $AMENITY_j$ across cities, as long as the price-rent ratio is invariant across cities. Chow and Niu (2015) find an estimate of the price elasticity of housing demand in China of about -0.8 and an estimate of the income elasticity of 0.92. The latter indicates that our homothetic utility assumption is a reasonable proximation.



Figure 1. 255 Cities of prefecture level or above in China in 2007

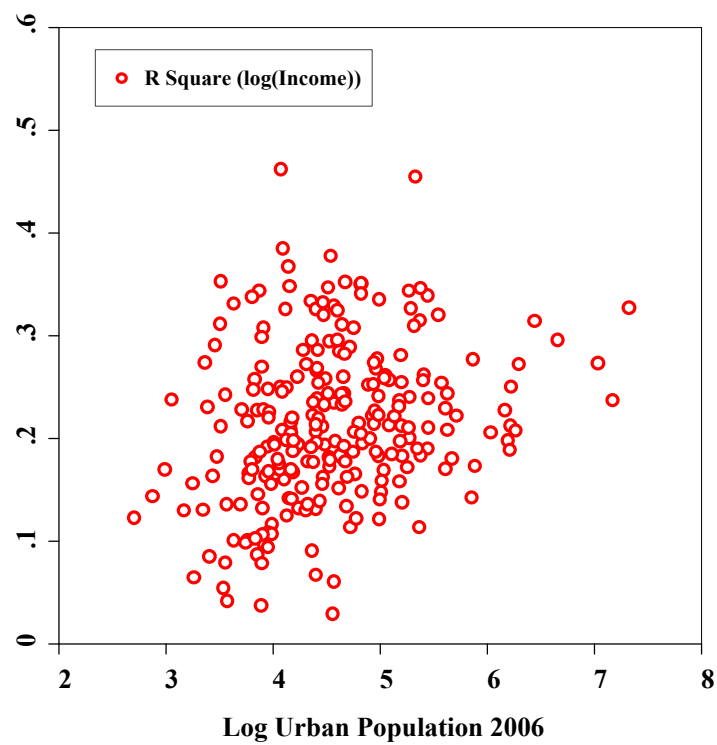


Figure 2. Distribution of the R^2 income-sorting index across 207 cities

Table 1 City-level Variable Description and Summary Statistics

Variable	Description	Obs.	Mean	Std. Dev.	Min	Max
<i>TEACHER</i>	Number of primary and secondary school teachers per 10,000 people, year 2002. [2]	207	85.960	22.267	36.845	184.694
<i>DOCTOR</i>	Number of doctors per 10,000 people, year 2002. [2]	207	25.683	10.524	6.412	91.068
<i>H_BED</i>	Number of hospital beds per 10,000 people, year 2002. [2]	207	50.745	20.049	14.270	175.436
<i>ROAD</i>	Total road space per capita (m ²), year 2002. [2]	207	6.753	4.481	0.380	34.090
<i>BUS</i>	Number of public buses per 10,000 people, year 2002. [2]	207	5.733	3.944	0.925	29.852
<i>PUB_ED</i>	log(<i>TEACHER</i>)	207	4.439	0.284	3.607	6.087
<i>PUB_HL</i>	[log(<i>DOCTOR</i>)+log(<i>H_BED</i>)]/2	207	3.498	0.409	1.746	4.839
<i>PUB_TS</i>	[log(<i>ROAD</i>)+log(<i>BUS</i>)]/2	207	1.624	0.568	0.017	3.016
<i>PUB_SERVICE</i>	1/3×(<i>PUB_ED</i> + <i>PUB_HL</i> + <i>PUB_TS</i>)	207	4.589	0.485	2.2741	6.641
<i>R</i> ²	Variance-ratio sorting index for log(household total income), defined in Eq. (1). [1]	207	0.221	0.073	0.042	0.462
<i>EX_SORTING1</i>	Excess income sorting predicted by the land-use condition variables, namely, <i>SOE_SHARE</i> , <i>OLD_BUILD_UP</i> , and <i>LOW_GRADIENT</i> , according to the estimates reported in column (4) of Table 2.	201	0	0.029	-0.258	0.054
<i>EX_SORTING2</i>	Excess income sorting predicted by the land-use condition variables, namely, <i>SOE_SHARE</i> , <i>OLD_BUILD_UP</i> , and <i>LOW_GRADIENT</i> , according to the estimates reported in column (7) of Table 2.	201	0	0.035	-0.347	0.053
<i>HI_CV</i>	Coefficient of variation in household total income. [1]	207	0.901	0.117	0.572	1.285
<i>HI_mean</i>	Mean household annual income, Rmb10 thousand yuan. [1]	207	3.234	1.045	1.497	7.437
<i>HI_CV_H</i>	Binary variable, with “1” indicating <i>HI_CV</i> is greater than cross-city mean. [1]	207	0.459	0.499	0.000	1.000
<i>N_JWH</i>	Number of residential neighbourhoods, or <i>JWH</i> s, sampled. [1]	207	44.3	59.1	8	566
<i>POP_DENSITY2000</i>	2000 urban population per sqkm of built-up area. [2][4]	207	20,875	11,301	3,989	84,687
<i>SOE_SHARE</i>	Share of SOE employment in total industrial enterprises in 1998. [5]	201	0.593	0.259	0.000	1.000
<i>OLD_BUILT-UP</i>	Urban built-up area of 1998/ Urban built-up area of 2004. [2]	201	0.612	0.304	0.000	1.000
<i>LOW_GRADIENT</i>	The share of land with slope smaller than 15 degrees. [6]	207	0.749	0.203	0.204	0.999
<i>PM10</i>	PM10 concentration (μg/m ³), year 2002. [2][3]	207	0.116	0.040	0.030	0.251
<i>TEMP_INDEX</i>	Average annual thermal uncomfot index, 1999-2006: $\text{sqrt} \left(TW_{j \max} TW_j \right)^2 + \left(TS_{j \min} TS_j \right)^2$, standardized. [3]	207	0	1	-1.880	2.571
<i>RAIN_INDEX</i>	Average annual rainfall 1999-2006 (m), standardized. [3]	207	0	1	-1.583	1.990

<i>CLIMATE_INDEX1</i>	$\sqrt{2} / 2 (TEMP_INDEX_j + RAIN_INDEX_j)$	207	0	1.317	-2.475	2.306
<i>CLIMATE_INDEX2</i>	$\sqrt{2} / 2 (TEMP_INDEX_j + RAIN_INDEX_j)$	207	0	0.515	-1.166	1.161
<i>AMENITY_L</i>	Amenity Index for low income: $(5/3) \times \ln(HV_{p25}) - (8/3) \times \ln(HI_{p25})$. [1]	207	-12.772	0.830	-15.185	-10.812
<i>AMENITY_M</i>	Amenity Index for middle income: $(5/3) \times \ln(HV_{p50}) - (8/3) \times \ln(HI_{p50})$. [1]	207	-14.764	0.627	-16.430	-11.751
<i>AMENITY_H</i>	Amenity Index for high income: $(5/3) \times \ln(HV_{p90}) - (8/3) \times \ln(HI_{p90})$. [1]	207	-15.527	0.673	-18.396	-13.961

Note: The number in bracket indicate data sources: [1] calculation based on 2007 UHS; [2] *City Statistical Yearbooks of China*; [3] *China Statistical Yearbook*; [4] China's fifth census; [5] *Annual Survey of Industrial Firms* (ASIF). TW_j and TS_j denote, respectively, the 1999-2006 average January and July mean temperatures in city j . $HV_{q\#}$ and $HI_{q\#}$ denote #th percentile home value and household income, respectively, in a city; [6] calculation based on ASTER Global Digital Elevation Model (ASTER GDEM) Version 2 released in 2011.

Table 2. OLS estimates of the effect of resource provision for local public services on income sorting

Columns:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
<i>HI_CV</i>	0.132*** (3.30)	0.145*** (3.39)	0.198*** (3.13)	0.180*** (3.30)	0.077** (2.16)	0.158*** (3.00)	0.154*** (2.82)
<i>PUB_SERVICE</i>		-0.0370** (-2.05)	-0.0453** (-2.34)	-0.0411** (-2.30)			
<i>PUB_ED</i>					-0.032** (-1.98)	-0.027* (-1.70)	-0.031** (-2.01)
<i>PUB_HL</i>					-0.006 (-0.40)	-0.000 (-0.00)	0.032** (2.31)
<i>PUB_TS</i>					-0.029** (-2.15)	-0.030** (-2.26)	-0.036*** (-2.68)
<i>PUB_SERVICE</i> × <i>HI_CV_H</i>			-0.009** (-2.00)	-0.008** (-2.00)		-0.008** (-2.02)	-0.008** (-2.09)
<i>HI_mean</i>	-0.007* (-1.69)	-0.007* (-1.73)	-0.006 (-1.42)	-0.009** (-2.04)	-0.001 (-0.32)	-0.000 (-0.09)	0.001 (0.20)
$\log(\text{POP_DENSITY2000})$	-0.007 (-0.83)	-0.008 (-0.72)	-0.002 (-0.18)	0.004 (0.30)	-0.010 (-0.91)	-0.006 (-0.50)	-0.008 (-0.63)
$\log(N_JWH)$	0.026*** (4.24)	0.024*** (3.63)	0.022*** (3.33)	0.027*** (3.50)	0.030*** (4.60)	0.032*** (5.06)	0.029*** (4.17)
<i>SOE_SHARE</i>				-0.050** (-2.10)			-0.037* (-1.67)
<i>OLD_BUILT-UP</i>				-0.031* (-1.96)			-0.045** (-2.26)
<i>LOW_GRADIENT</i>				0.050** (2.24)			0.043* (1.77)
Constant	0.101 (1.07)	0.228 (1.55)	0.167 (0.91)	0.106 (0.55)	0.343*** (2.62)	0.193 (1.21)	0.155 (0.81)
Observations	207	207	207	201	207	207	201
R^2	0.111	0.109	0.123	0.273	0.205	0.227	0.328

Note: The dependent variable is the R^2 income-sorting index. Robust t-statistics are in brackets. ***, **, and * denote respectively statistical significance at 1%, 5% and 10% level.

Table 3 OLS estimates of resource provision for local public services

Dependent variable:	(1) <i>PUB_SERVICE</i>
<i>HI_mean</i>	0.034 (1.13)
$\log(\text{POP_DENSITY2000})$	-0.417*** (-9.29)
$\log(\text{N_JWH})$	0.085** (2.58)
<i>SOE_SHARE</i>	-0.096 (-1.40)
<i>OLD_BUILT-UP</i>	-0.018 (-1.07)
<i>LOW_GRADIENT</i>	0.010 (0.10)
Constant	6.94*** (14.0)
Joint F test for the estimates of the three excess-sorting variables to be zero	1.07 (Probability = 0.36)
Observations	225
R^2	0.427

Note: Robust t-statistics are in brackets. ***, **, and * denote respectively statistical significance at 1%, 5% and 10% level.

Table 4 GMM estimates of the willingness to pay for urban amenities by households with low, median, and high income

Columns:	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	<i>AMENITY_L</i>	<i>AMENITY_M</i>	<i>AMENITY_H</i>	<i>AMENITY_L</i>	<i>AMENITY_M</i>	<i>AMENITY_H</i>
<i>PUB_SERVICE</i>	0.605*** (2.92)	0.368** (2.50)	0.343* (1.95)			
<i>PUB_SERVICE</i> × <i>EX_SORTING1</i>	-2.452*** (-2.61)	-1.943** (-2.30)	0.309 (0.39)			
<i>PUB_ED</i>				0.386** (2.04)	0.299** (1.98)	-0.277 (-1.62)
<i>PUB_HL</i>				0.0176 (0.10)	0.0278 (0.21)	0.270* (1.95)
<i>PUB_TS</i>				0.279** (2.00)	0.197** (2.02)	0.179* (1.91)
<i>PUB_SERVICE</i> × <i>EX_SORTING2</i>				-2.863** (-2.61)	-1.456* (-1.73)	0.0381 (0.05)
log(<i>POP_DENSITY2000</i>)	0.115 (0.67)	0.0528 (0.35)	-0.0289 (-0.21)	0.234 (1.32)	0.0903 (0.64)	-0.0255 (-0.18)
<i>PM10</i>	-5.586*** (-5.03)	-4.547*** (-3.10)	-4.331*** (-5.60)	-5.554*** (-3.01)	-2.810** (-2.08)	-1.514 (-1.20)
<i>CLIMATE_INDEX1</i>	-0.241*** (-5.15)	-0.190*** (-4.38)	-0.211*** (-4.96)	-0.253*** (-5.05)	-0.160*** (-3.78)	-0.135*** (-3.24)
<i>CLIMATE_INDEX2</i>	-0.241** (-2.15)	-0.110 (-1.23)	-0.237** (-2.47)	-0.370*** (-3.26)	-0.0657 (-0.75)	-0.182** (-2.01)
<i>LOW_GRADIENT</i>	-0.0358 (-0.13)	0.00499 (0.02)	0.0230 (0.10)	-0.327 (-1.10)	-0.211 (-1.00)	0.166 (0.76)
Constant	-15.24*** (-6.93)	-15.94*** (-8.69)	-15.81*** (-8.49)	-16.07*** (-7.64)	-16.56*** (-9.15)	-15.12*** (-8.12)
Observations	201	201	201	201	201	201
<i>R</i> ²	0.231	0.193	0.209	0.279	0.178	0.240

Note: Equations (1), (2) and (3) and equations (4), (5) and (6), respectively, are estimated jointly using GMM method to take into account the cross-equation covariance of errors, which minimizes the equation weighted sum of squared errors. Robust t-statistics are in brackets. ***, **, and * denote respectively statistical significance at 1%, 5% and 10% level.