The Spatial Distribution of Income in Cities: Cross-Country Evidence and Theory

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Abstract

We draw on new granular data from 133 cities from 26 countries to study how the spatial distribution of income within cities varies with economic development. We document that in less-developed countries, average incomes of urban residents decline monotonically in distance to the city center, whereas income-distance gradients are flat or increasing in developed economies. Neighborhoods with natural amenities – in particular hills and proximity to a river – are poorer than average in less-developed countries and richer than average in developed ones. We explain these patterns in a spatial model where preferences are non-homothetic in both housing and neighborhood amenities. In cities with low average income levels, the primary consideration of households is job access, and relatively richer households locate closer to city centers, where earning opportunities are better. As income rises, richer urban residents put more weight on amenities and locate in neighborhoods with better ones, further from city centers. When estimated to match our data for U.S. cities, the model predicts that gaps in income levels and commuting costs can explain a large fraction of the difference in urban income distributions between less- and more-developed countries.

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1. Introduction

How are cities in low-income countries different from those in the developed world? To what extent does the development process shape the internal structure of cities and the spatial distribution of income in urban areas? In this paper, we take up these questions from an empirical and theoretical perspective, drawing on new disaggregated data from within cities of all income levels. A growing literature on urban economics in the less-developed country has begun to systematically document differences in developing-world cities, such as higher population density (Chauvin, Glaeser, Ma, and Tobio, 2017), slower transport speeds (Akbar, Couture, Duranton, and Storeygard, 2023a,b), and lack of availability of public transit (Gonzalez-Navarro and Turner, 2018). Yet research on these topics has been limited by a lack of spatially granular and internationally comparable data on household income, commuting flows, and transportation infrastructure within cities.

Our paper contributes by building and analyzing a new dataset with granular information covering 146,000 neighborhoods in 133 cities around the world. To do so, we draw on travel surveys collected in 26 cities from 22 developing countries by Japan's International Cooperation Agency (JICA) for use in planning urban infrastructure projects. The travel surveys record the residential location, employment location, income, demographic characteristics, transportation modes for commuting, and daily travel activities of representative households in each city. We complement these data sets with similar administrative data from cities in developed countries (USA, France, Spain, Japan) and an additional developing country (Brazil) to construct our final data sets. To the extent possible, we harmonize the data across different cities to make the data sets comparable at the neighborhood level in all our countries.

We document several prominent ways in which the income distribution in cities varies between developed and developing countries. First, we show that in less-developed countries, average residential income in cities declines steadily with distance to city centers. Taking an average across our less-developed cities, incomes in the city center are around the 60^{th} percentile relative to the rest of the city. This falls to the 35^{th} percentile in neighborhoods at 25 kilometers from the city center. In contrast, in the United States, income gradients are mostly U-shaped, with incomes declining sharply as one moves away from the city centers and then rising steadily as one moves into suburban areas. European cities generally have flatter gradients, with less variation in average income percentiles across space than in U.S. cities. Nonetheless, in either case, there is no significant decline in income as one moves away from city centers, in stark contrast to cities in less-developed countries.

We next ask how incomes in urban areas vary with the presence of natural amenities. Our data show that in less-developed cities, average incomes are significantly lower than average in hilly areas or in close proximity to rivers. Urban households living on hills in poorer countries have incomes about 8 percentile points *lower* on average than households in non-hilly areas. Average incomes are about 5 percentile points lower next to rivers than further from them. The opposite is true in developed cities, where average incomes are substantially *higher* in both hilly areas and near rivers. The income premium is about 15 percentile points for hilly areas in developed cities, and 8 percentile points for proximity to rivers.

We find that these patterns cut across continents and hold for different measures of household income, distances to city centers, and natural amenities. Moreover, these patterns are present in several cities where we have repeated surveys over time over periods of income per capita growth.

What explains these stark differences between cities in less-developed and developed countries? There is an abundance of theories to explain the spatial distribution of spatial income distribution for cities in developed countries. However, these frameworks have limitations in simultaneously explaining why cities in less-developed countries exhibit *opposite* patterns. We develop a new spatial model to theoretically and quantitatively show that non-homotheticity in *both* housing and neighborhood amenities, as well as the differences in commuting costs, can explain the gap.

In our model, ex-ante heterogeneous households with different earning potential decide residential locations based on job access, housing costs, and the demand for neighborhood amenity (e.g., natural amenities around hills and rivers and open spaces available in suburban areas). If housing is a subsistence good, richer households dominate in "attractive" neighborhoods, raising housing costs and pushing out poorer residents. At the same time, the non-homotheticity in neighborhood amenity implies that which neighborhoods are "attractive" depends on the residents' overall income levels. In cities where the overall income is low, households' primary consideration is access to jobs. When income rises, residents start to value neighborhood amenities. Therefore, which neighborhoods are more "attractive" flips as the city's overall income level rises.

Another important aspect that determines the spatial distribution of income is commuting cost. Due to the lack of transportation infrastructure or the penetration of private cars, less-developed cities may face higher commuting costs. This disadvantage disproportionately lowers commuting access for residents in suburban areas and neighborhoods with challenging geographic features, such as hills and rivers. If households' value job access for their residential

choice, this effect facilitates the sorting of richer households toward the urban core, and poorer households toward the periphery.

We combine our theory with our data to quantify the relevance of these channels in explaining the gap in spatial income distribution between developed and less-developed cities. We start by measuring the commuting costs city by city. We do so by estimating our model's commuting gravity equation, which predicts that the commuting flows depend on the bilateral commuting costs and the destinations' wages. We find a significant heterogeneity in commuting costs across cities. In contrast to the semi-elasticity of commuting with road distances (km) of 0.08 in USA cities and 0.14 in Tokyo, those in less-developed cities range from 0.2 to 0.4. We also show that the cross-city heterogeneity leads to disproportionately lower commuting access in suburban, hilly, and river areas in less-developed cities relative to developed cities. We also estimate these commuting costs by income groups within each city and show that the heterogeneity in commuting costs are by an order of magnitude larger across cities than within cities across income groups.

In the final section, we use our equilibrium model to quantify how much the commuting costs and nonhomothetic preferences explain the gap in equilibrium spatial income distribution. To do so, we first calibrate our model to USA cities. Next, we run counterfactual simulations of (1) lowering the overall city income (productivity) to the level of less-developed cities and (2) increasing the commuting costs to the estimated level of less-developed cities.

We find that *both* the overall city income *and* commuting costs are quantitatively important in explaining the gap in spatial income distribution. When we lower the overall city income, the residential income premium in suburban, hills, and river areas in the USA cities almost disappears. When we further increase the commuting costs, those areas become poorer than other parts of the city, comparable in magnitude to those in less developed cities. Interestingly, we find that raising commuting costs while setting the overall income to the USA level *increases* the relative income in suburban, hills, and river areas. Therefore, commuting cost *alone* is completely unable to explain the spatial income gap. This happens because, when overall income is high, commuting access matters disproportionately more for lower-income residents. On the other hand, when we lower the income levels simultaneously, even relatively higher-income residents within the city are affected by commuting access. This induces the sorting of higher-income residents toward neighborhoods with higher commuting access.

Related Literature Our paper builds on a growing body of work studying how cities in developed and developing countries systematically differ. Existing research has recognized

that cities in developing countries differ from developed countries in aggregate characteristics, such as city size, density, and relative population size. However, research on these topics has been limited by a lack of granular and internationally comparable data on the incomes, commuting, and infrastructure within cities (see Henderson and Turner (2020), Bryan, Glaeser, and Tsivanidis (2020), and Bryan, Frye, and Morten (2025) for recent surveys). Some existing research provides cross-city comparisons of internal city structure within a developing country. Harari (2024) provides cross-city comparisons of residential income segregation and its impacts on local public goods focusing on Brazilian cities. Adukia, Asher, Jha, Novosad, and Tan (2022) documents residential segregation and access to public services in Indian cities using detailed geocoded censuses. Our contribution is preparing rich neighborhood-level geocoded data of income, commuting, and neighborhood characteristics ranging across 133 cities in 26 countries; using this data to document systematic differences in spatial income distribution and commuting patterns between developed and less developed cities; and developing a quantitative theory to explain these differences.

We also contribute to the empirical and theoretical literature on the spatial distribution of income within cities. This literature has exclusively focused on the patterns in developed country cities, in particular, USA. Existing work seeks to rationalize those patterns by the non-homotheticity in demand for housing or land (Alonso, 1964; Becker, 1965; Margo, 1992; Hoelzlein, 2019; Finlay and Williams, 2022; Couture, Gaubert, Handbury, and Hurst, 2024), transportation infrastructure (LeRoy and Sonstelie, 1983; Glaeser, Kahn, and Rappaport, 2008), and natural amenities (Lee and Lin, 2018). Some authors study differences between USA and other developed countries and seek the explanations in nonhomotheticity in amenities (Brueckner, Thisse, and Zenou (1999) and Almagro and Domínguez-Iino (2024) for European cities and Tabuchi (2019) for Tokyo). Our contribution is to provide new evidence from less-developed country cities that mark a sharp contrast to USA and other developed country cities; and show that *all* of the non-homotheticity in housing, non-homotheticity in neighborhood amenities, and the gap in commuting costs, are crucial to explain the differences between less- and more-developed country cities.

We also contribute to the literature on the structural transformation and how it affects the spatial organization of economic activity. Existing work has primarily focused on how the shift of industrial structure (i.e., agriculture, manufacturing, and services) affects the spatial concentration of population and economic activity across cities (Eckert and Peters, 2022; Chatterjee, Giannone, and Kuno, 2021; Bohr, Mestieri, and Robert-Nicoud, 2024; Lebrand and Kleineberg, 2024) or within cities (Coeurdacier, Oswald, and Teignier, 2022). While related in

its focus on the non-homothetic preferences, we focus instead on how it shapes the spatial distribution of residential income within a city.

2. Data

In this section, we describe how we assemble various data sources to construct our database of household income, neighborhood characteristics, and commuting flows for 133 cities from 26 countries.

2.1. Travel Surveys from Developing Countries

Our key data source for developing countries is a collection of micro-data of travel surveys that cover 26 cities in developing countries. Travel surveys, a key resource for urban and transportation planning, typically collect information about the residential and workplace locations, demographic characteristics (e.g., age, household size), income, employment, and daily travel activities (time, geolocation, purpose, transportation mode) of representative households in each city. In developed countries, these surveys are typically conducted in major metropolitan areas at a regular frequency. In developing countries, these surveys are often only conducted by city governments before or after major urban and transportation infrastructure projects or when writing city master plans, and with the help of international aid agencies.

We compile household-level travel surveys conducted or supervised by the Japan International Cooperation Agency (JICA) for the purpose of designing urban transportation improvements. We have access to the microdata from 27 cities in 21 countries. Panel (a) of Table 1 summarizes the list of cities covered in this data set. The data set covers developing country cities across the continents, including 3 cities in South America (Lima, Managua, and Belem), 3 cities in South Asia (e.g., Dhaka and Karachi), 12 cities in East Asia (e.g., Hanoi and Viangchan), 1 city in East Europe (Bucharest), 2 cities from Middle East (Cairo and Damascus), and 7 cities in Africa (e.g., Nairobi and Maputo). The surveys were conducted between 1996 and 2015, with varying questionnaires, sampling strategies, and local enumeration firms. Sample sizes in the JICA survey range from 5,000 to 300,000 respondents, with an average of 70,000. In five cities (Dhaka, Ho Chi Minh, Hanoi, Nairobi, and Phnom Penh), we have access to multiple surveys across different years.

Our travel surveys are particularly useful for our purpose because of their fine spatial resolution. The surveys segment the city into many different neighborhoods (survey zones).

Table 1: List of Cities Covered in Our Analysis

	South America	Asia, E. Europe	Africa, M. East
Number of City-Years	3	20	8
Number of Cities	3	16	7
Number of Countries	3	12	6
Avg Number of Respondents	70469	67359	42873
Avg Number of Neighborhoods	190	203	166
List of Cities	Belem (00), Lima (03), Managua (98)	Bucharest (98), Cebu (14), Chengdu (00), Colombo (13), Da Nang (08), Dhaka (09), Dhaka (14), Hanoi (05), Hanoi (14), Ho Chi Minh (03), Ho Chi Minh (14), Jakarta (18), Karachi (11), Kuala Lumpur (99), Lahore (10), Manila (96), Phnom Penh (00), Phnom Penh (12), Viang Chan (07), Yangon (13)	Abidjan (13), Cairo (01), Damascus (98), Dar es Salaam (07), Kinshasa (18), Mombasa (15), Nairobi (05), Nairobi (13)

(a) Less developed cities surveyed by JICA, by continent

	USA	W. Europe, Japan	South America	Asia, E. Europe	Africa, M. East
Number of Cities	48	24	33	20	8
Number of Countries	1	4	3	12	6
Total Number of Neighborhoods	27655	18005	94447	4079	1334
List of Countries	United States	France, Japan, Spain, United Kingdom	Brazil, Nicaragua, Peru	Bangladesh, Cambodia, China, Indonesia, Lao People's DR, Malaysia, Myanmar, Pakistan, Philippines, Romania, Sri Lanka, Viet Nam	Côte d'Ivoire, D.R. of the Congo, Egypt, Kenya, Syrian Arab Republic, U.R. of Tanzania: Mainland

(b) All cities in neighborhood-level income dataset, by continent

The respondents' residential and work locations, along with the origin and destination of trips in a respondent's travel itinerary, are coded at the neighborhood level. Oftentimes, these survey zones are only available in the form of non-geo-located maps (i.e., an image).

In response, we manually geo-coded these surveys. In our sample, there are, on average, 193 survey zones in a city, and the average size of each neighborhood is 8km^2 in area.

For all surveys, we observe income at the household level across all sources, either through reported household income or individual income aggregated to the household level. To obtain the average residential income, we aggregate the household income to the neighborhood-level.

For employed individuals, our surveys report where that individual lives and works, allowing us to construct pairwise commuting flows.

2.2. Additional Data on Income, Commuting Flows, and Rents

Residential Neighborhood Income from USA, France, Spain, UK, Brazil We collect average residential neighborhood income from census and tax data for four developed countries (USA, Spain, France, UK) and a developing country (Brazil).

Information from the United States stems from the 2008-2012 aggregated American Community Survey and is available at the level of census tract. For French cities, income is derived from tax returns maintained by *Institut national de la statistique et des études économiques*. In France, mean income is unavailable, and a neighborhood's income corresponds to the median income of its households. The spatial unit for French cities is the "IRIS", with an average size one quarter that of a census block. In the UK, income is measured at the "Small Area" level, which is slightly larger than a census block, and is derived from the Office of Tax Statistics. In Spain, income is measured at an extremely fine spatial resolution, the *Sección*, with income measures also derived from tax information. Brazilian cities contain the smallest neighborhoods (*Setores*) with an average size one-tenth that of a US census block. Income represents average household income as elicited by the households in the 2010 census.

Travel Survey from Tokyo, Japan For Tokyo, Japan, we have access to the microdata of 2018 Tokyo Person Trip Survey (Tokyo Metropolitan Area Transportation Planning Council, 2018). The data shares a similar structure as the JICA surveys discussed above—an individual-level survey reporting household income, demographic information, discrete neighborhoods, home and work location, and trips throughout the day. As with the travel surveys from developing countries, we aggregate income at the neighborhood level and generate commuting flows at the neighborhood-pair level.

Commuting Flows in USA We obtain commuting flow information in the USA from the Longitudinal Employer-Household Dynamics Origin Destination Employment Statistics (LODES) dataset from the year 2015. The LODES data reports the aggregate number of

workers living and working in any given pair of census tracks, as well as living-working flows disaggregated by a coarse measure of income: workers earning $0-$30k, $60-$90k, and $90+.

Rents in USA We obtain median rents for USA cities from the 2008-2012 aggregated American Community Survey at the level of census tract. We use this information primarily for calibrating our quantitative model in Section 6.

2.3. Geographic data

City Boundaries To create a consistent definition of city boundaries for all cities and exclude neighborhoods that lie in rural areas, we use the World Settlement Footprint's "Built Up Areas" data set (Florczyk et al., 2019). This data set uses satellite images to categorize land use at a fine-grained spatial level defines cities as large contiguous swaths of land which are "built-up," i.e. full of buildings, roads, and pavement, in contrast to agriculture or forest cover. For our analysis, we only include neighborhoods that intersect with the Human Settlements-defined city area.

City Centers We use Open Street Maps (OSM) to define city centers. OSM provides the latitudes and longitudes of each locality (cities, towns, and villages) across the world, and we choose these coordinates as the city center. In some cases, there are multiple OSM localities within our city boundaries. In this case, we choose the coordinates of the OSM localities with the largest population to define the city center.[1]

Bilateral Travel Distance To calculate the distance between pairs of neighborhoods in our pairwise commuting flow data set, we use the OSM Routing Service, an open source algorithm for finding the shortest path between two locations along OSM's road network.

Hills, Rivers and Coastlines To determine whether a neighborhood is "hilly", we use 30m×30m elevation estimates as part of Amazon Web Services Terrain Tiles global datasets (Larrick, Tian, Rogers, Acosta, and Shen, 2020). Slope is calculated through the average change in elevation across 4 adjacent 30m by 30m grids (Hijmans, 2024). A neighborhood is "hilly" if its average slope is greater than 5 degrees.

To determine whether a neighborhood is near a river, we rely on OSM's outlines of river banks and canals. We categorize a neighborhood as close to a river if any part of the neighborhood is

[1]The coordinates of OSM localities are manually coded by volunteer contributors across the world. In private correspondence with a contributor who is particularly prolific at codifying city locations, they report looking for city halls or central plazas to define the point-wise city location. For instance, Cebu City's location is at the city hall. London's city center is at Trafalger Square.

within 100m of a riverbank. Coastlines were also downloaded from OSM, and the Great Lakes are classified as coastal areas. Similarly, a neighborhood is coastal if it is within 100m from a coastline.

Development status We define "Developed" cities as those in the USA, Spain, France, UK, and Japan. We define "less-developed" cities as those surveyed by JICA and Brazil. The average income of developing cities is $3,500 2017 international PPP adjusted dollars, while the average income of developed cities $29,000. Kuala Lumpur is the richest "developing" city: in 1999 Malaysia's GDP per capita was 14,000 USD in 2017 PPP adjusted dollars. The poorest is Damascus, Syria, in 1998, with a GDP per capita of 1,350 USD.

Neighborhood Population Sampling strategies differ across JICA surveys, making it difficult to derive neighborhood-level population estimates from the household survey data alone. Consequently, we construct a standardized measure of population size for each neighborhood using the 2015 LandScan population distributions (Bright, Rose, and Urban, 2016). Population estimates from the US, UK, Spain, France, and Brazil are derived from the underlying administrative data source directly.

2.4. Final Data Sets

Our final neighborhood-level income dataset includes 146,000 neighborhoods across 133 cities in 26 countries. 72 cities are classified as "developed" and 61 are classified as "less-developed". For each neighborhood, we observe average household income, distance to the city center, and its geographic features. Panel (b) of Table 1 lists all the cities in our analysis. Appendix Figure A.1 shows a map of all cities in our data across the world.

Our final pairwise commuting flow dataset includes all 27 JICA cities, all 48 cities in the USA, and Tokyo. For each home-work pair, we observe the proportion of the working population living and working in that pair. We also disaggregate pairwise commuting flows by coarse measures of income.

3. Spatial Distribution of Income

In this section, we document the distinguishing patterns of the spatial distribution of income between developed and less-developed cities.

3.1. A First Look from Examples: Los Angeles and Lima

Before proceeding with statistical analysis, we start by comparing two cities as an illuminating example: Los Angeles, USA, a "developed" city, and Lima, Peru, a "less-developed" city. The cities make a useful comparison: both cities are located between the Pacific Ocean and large mountain ranges and have similar climates.

Figure 1 map income and geographic features for the two cities. Panels (a) and (b) map the average neighborhood residential income, defined as each neighborhood's percentile rank of income within the city. Higher values and lighter colors indicate higher income. The dot in each image represents the center of the city. Panels (c) and (d) demonstrate which neighborhoods are hilly and near waterways.

Focusing first on Panels (a) and (b), it is clear that the two cities exhibit opposite relationships between average income and distance to the city center. In Los Angeles, the city center is surrounded by poorer neighborhoods, except for a few blocks at the very center. As one goes away from the city center, in particular toward northern (Pasadena) or western (Santa Monica) directions. In contrast, in Lima, the city center is surrounded by neighborhoods that are richer on average. As one goes away from the city center, the average income tends to decrease.

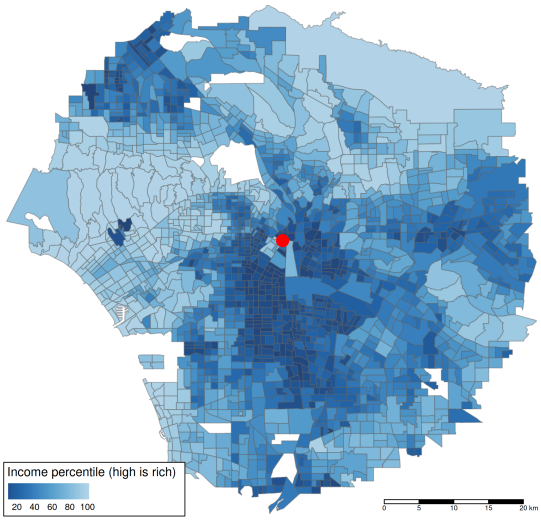
Turning to Panels (c) and (d), we show the two cities also exhibit opposite patterns between the average income and hilly areas. In Los Angeles, the hilly areas of Laurel Canyon and Beverly Hills, to the northwest of the city center, report high incomes. In Lima, Los Olivos, corresponding to the lighter blue area to the northwest of the center, is a middle-class area contained in the valley between two poor hillsides on either side.

Lima and Los Angeles are two cities that make a sharp contrast. To what extent do these observations generalize between developed and less-developed cities at large? In the following section, we formalize this analysis and expand our scope to include developed cities in the USA, Western Europe, and Japan, and less-developed cities across South America, Asia, and Africa. While there is heterogeneity in the patterns within developed and less-developed cities, we nonetheless show that the two groups of cities display systematically different trends that persist across a range of specifications.

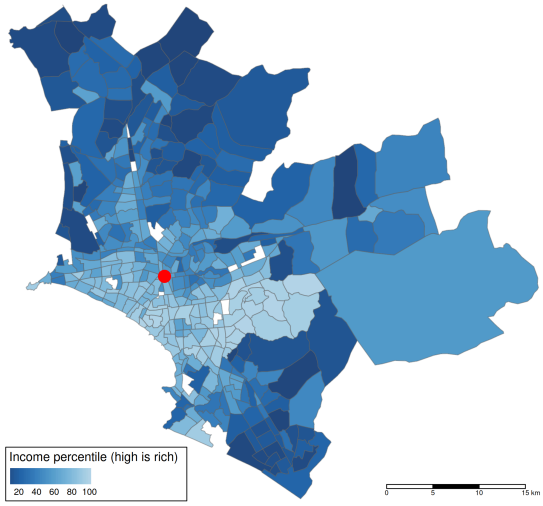
3.2. Residential Income and Distance to City Center

We first focus on the residential income and distance to the city center. Figure 2 shows the relationship between distance from the city center and average neighborhood residential income percentiles for developed cities (Panel a) and less-developed cities (Panel b) up to 25

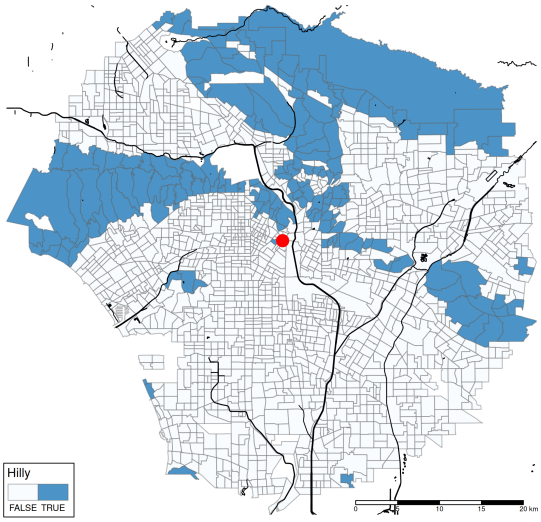
Figure 1: Residential Income and Hilly Areas in Los Angeles and Lima



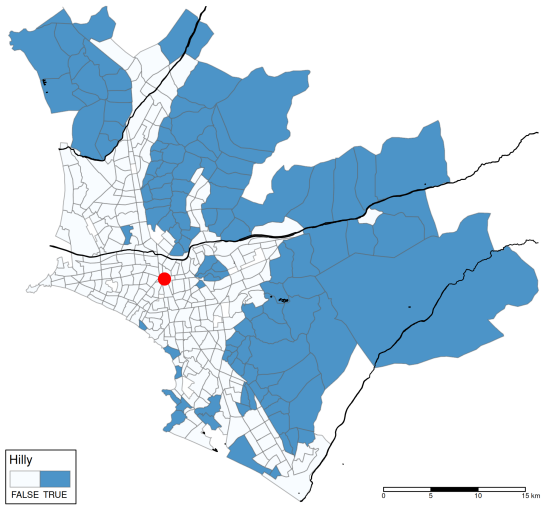
(a) Residential Income (Los Angeles)



(b) Residential Income (Lima)



(c) Hills and Rivers (Los Angeles)

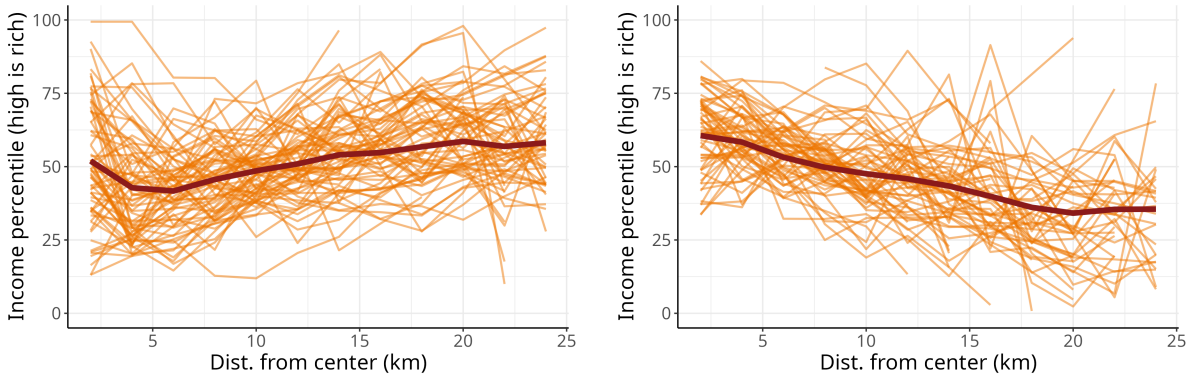


(d) Hills and Rivers (Lima)

Note: Dots in each image represent the center of the city. Neighborhoods further than 30km from the city center are omitted. Figures (a) and (b) show the percentiles of average neighborhood residential income ranking within each city (from 0 to 100, with higher value and lighter color indicating higher income). White areas indicate neighborhoods where residential income is missing or not available. Figures (c) and (d) show a binary measure for hilliness (blue is hilly) along with the path of waterways in black.

kilometers from the city center. Each light line represents a single city, while averages are highlighted in bold.

Figure 2: Residential Income and Distance from City Center



(a) Developed Cities

(b) Less Developed Cities

Note: Distance from the city center and average neighborhood residential income percentile for developed cities (Panel a) and less-developed cities (Panel b) up to 25 kilometers from the city center. Each light line represents a single city, and averages are highlighted in bold.

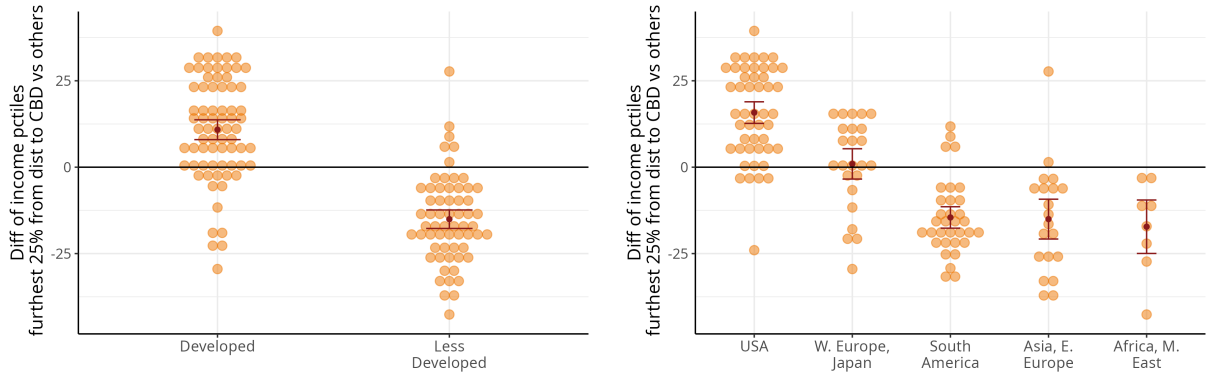
Panel (a) shows that, in developed cities, income follows a slight U-shape with distance to the city center. On average, city centers are relatively wealthy (slightly above the 50 percentile points), but income quickly declines within a short distance from the CBD. After reaching its nadir at around 5 kilometers from the city center, income climbs from around 40 percentile points to around 60 percentile points. Overall, there is a positive gradient from the city center to the periphery of the city.

In contrast, Panel (b) shows that, in less-developed countries, income has a strong negative monotone relationship with distance to the city center. Areas close to the city center have an average income percentile of approximately 60 percentile points, and it falls to approximately 35 percentile points at 25 kilometers from the city center. Appendix Figure B.2 shows that this pattern persists when using normalized log income, defined as the difference between log income for a neighborhood and the log of average income for the city at large.

In Figure 3, we further study the income-distance relationship across cities. For each city in our data set, we compute the "suburban-urban income gap," defined by the difference between the income percentiles of neighborhoods that accommodate 25 percent of the city population that live furthest from the city center (which covers approximately 52 percent of the geographic area of the city) relative that of the remaining neighborhoods.[2] Panel (a) compares developed and less-developed cities, where each dot represents a city in each category. We also plot the

[2]The patterns are similar by defining suburban areas using 50 percent as the cut-off to define suburban areas (covering approximately 75 percent of the geographic area of each city) and by using alternative distance proxies (Appendix Figure B.4 and Table B.8, respectively).

Figure 3: Suburban-Urban Income Gap



(a) By Development Status

(b) By Continents

Note: The "suburban-urban income gap" of each city. Suburban neighborhoods are those containing the 25 percent of the population furthest from the city center. Each dot represents a city. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

mean and its 95 percent confidence interval within each category.

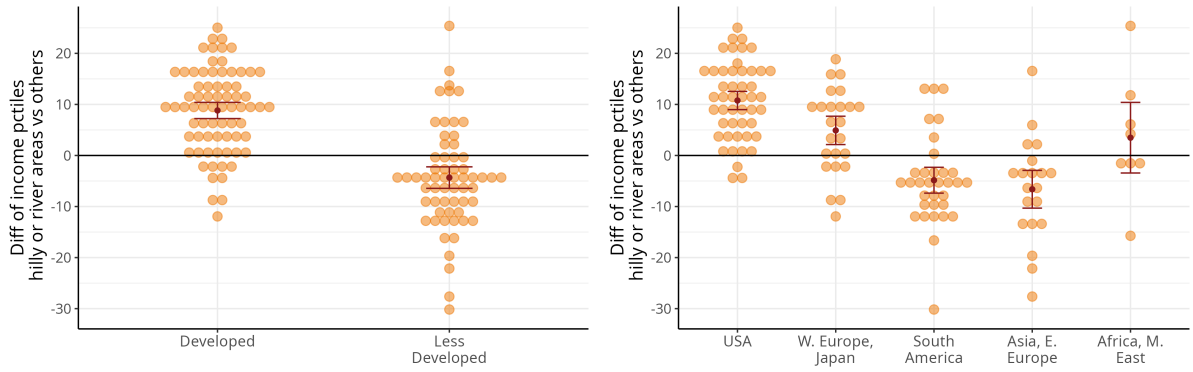
Panel (a) shows that the suburban-urban income gap is positive at approximately 10 percentile points for developed cities, while it is negative at approximately 15 percentile points for less-developed cities. While there are large dispersions across cities, the mean of the statistics is significantly different from one. Appendix Figure B.3 shows the difference in log income, rather than the difference in income percentiles, between suburban and urban neighborhoods, revealing 20 log points higher income in suburban areas in developed cities and 30 log points lower income in less-developed cities.

Panel (b) shows the heterogeneity of these patterns across continents. For developed cities, the suburban-urban income gap is highest in the USA at approximately 15 percentile points. In contrast, it is zero on average for W. Europe and Japan, suggesting on average flat relationships between income and distance to the center (see Appendix Figure B.1 for line graphs akin to Figure 2). The bottom outlier is Tokyo, Japan, with a gap of -31.8 percentile points. Within European cities, France is negative with -3.73 percentile points, while they are small but positive for Spain (2.66) and UK (6.64); See Appendix Table B.1 and B.2 for the suburban-urban income gaps for each city and country. The contrasts between US and other developed-world cities have been remarked upon before (Brueckner et al., 1999; Tabuchi, 2019). Suburban-urban differences in income are consistently negative across South America, Asia and E. Europe, and Africa and M. East.

3.3. Residential Income and Hills/Rivers

We next focus on the residential income and natural geographic features, focusing on hills and rivers. In the United States, Lee and Lin (2018) document that these geographic features are key determinants of the affluence of the neighborhood: areas near hills and in rivers are richer than average. Figure 4 shows that developing cities do not share this pattern. Instead, areas near hills and rivers are poorer than average. We plot the differences in average income percentiles between hilly or river areas and other areas for each city. For ease of exposition, we combine hilly and river areas, however the patterns we document are broadly similar if we look at hills and rivers independently, with somewhat smaller magnitudes of differences for rivers (Appendix Figures B.5 and B.6; see also Table 2 for the regression analysis including hills and rivers independently).

Figure 4: Residential Income and Hills/Rivers: By City



(a) By Development Status

(b) By Continents

Note: Differences in average income percentile between neighborhoods that are hilly or near a river and those that are not. "River neighborhoods" are those within 100 meters of a natural waterway. Hilly neighborhoods are those with an average slope greater than 5 degrees. Each dot represents a city. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

Panel (a) shows that the income percentiles of hilly or river neighborhoods are higher by approximately 10 percentile points in developed cities and lower by approximately 5 percentile points in less-developed cities, both statistically significantly different from zero. In Panel (b), we again see heterogeneity within developed cities. Income differences are larger in the USA than W. Europe and Japan (see Appendix B.3 and B.4 for the value for each city and country). However, unlike the suburban-urban income gap in Figure 3, the average difference is positive and statistically different from zero for W. Europe and Japan. In developing cities, average

income differences in hilly or river neighborhoods are negative and statistically significantly different from zero for South America and Asia and E. Europe. For Africa and M. East, the difference is positive but statistically insignificant due to small sample sizes.

3.4. Regression Results and Robustness

We now show that the patterns of the distance to the city center in Section 3.2 and hills and rivers in Section 3.3 hold using a multiple regression framework in which we jointly regress all geographic factors. Specifically, we run the following regression:

$$\text{Income Percentile}_{nc} = \beta' X_{nc} \times \text{Developed}_c + \gamma' X_{nc} \times \text{Less Developed}_c + \nu_c + \epsilon_{nc}, \qquad (1)$$

where c indexes a city, n indexes a neighborhood, X_{nc} are vectors of dummies including the suburban areas (neighborhoods with the furthest distance from CBD that accommodate 25 percent of city population), hilly, and river areas as defined in Section 2, ν_c indicates the city fixed effects, and ϵ_{nc} are idiosyncratic neighborhood errors. In our baseline sample, we weight this regression by the inverse of the number of neighborhoods in each city c, such that the regression puts an equal weight for each city. We show below that our results are robust to alternatively weighting by the neighborhood population size.

Table 2 reports the results. The top panel reports the results of the regression (1), and the bottom panel reports the differences in the regression coefficients between developed and less-developed cities. In Columns (1)-(3), we start from simple regressions for the suburban areas, hilly areas, and river areas independently. Across the board, the regression coefficients are positive and statistically significant for developed cities, and they are negative and statistically significant for less-developed cities. The income percentile gaps are also large in magnitude, consistent with the findings outlined in Sections 3.2 and 3.3, while the gap is somewhat smaller for rivers (Column 3) relative to suburban areas and hilly areas (Columns 1 and 2). Finally, Column (4) shows that these patterns are similar by simultaneously regressing all three proxies. Therefore, these patterns hold true when controlling for each other.

In Appendix B.3, we show that our regression results are robust to various alternative specifications. Appendix Table B.5 shows a similar pattern of the results by using log income instead of income percentiles within each city as the independent variable. Appendix Table B.6 shows the robustness of including additional neighborhood controls (area size and the quadrants), restricting the neighborhoods to within 25 or 15 kilometers from the city center, and weighting neighborhoods by their residential population. Appendix Table B.7 shows how

Table 2: Regression Results of Neighborhood Residential Income

Dependent Variable:	Income percentile (high is rich)			
Model:	(1)	(2)	(3)	(4)
Variables				
Developed × Top 25% distance from center	10.3***			9.16***
	(1.79)			(1.78)
Less Developed × Top 25% distance from center	-16.2***			-15.9***
	(1.75)			(1.71)
Developed × Hilly		15.0***		14.0***
		(3.09)		(3.19)
Less Developed × Hilly		-8.02***		-7.17***
		(1.63)		(1.58)
Developed × < 100m from river			7.58***	6.25***
			(0.946)	(0.906)
Less Developed × < 100m from river			-4.68***	-3.77***
			(1.25)	(1.12)
Difference in slopes: Developed vs Less Developed				
Top 25% distance from center	-26.5***			-25.0***
	(2.50)			(2.47)
Hilly		-23.0***		-21.2***
		(3.49)		(3.55)
< 100m from river			-12.3***	-10.0***
			(1.57)	(1.44)
Weight	City	City	City	City
Subset	Full	Full	Full	Full
Fixed-effects				
City	Yes	Yes	Yes	Yes
Fit statistics				
Observations	145,520	145,520	145,520	145,520

*Note: Top panel reports the results of the regression (1). Bottom reports the results of the regression where we replace $X_{nc} \times Developed_c$ with X_{nc} to assess the differences in the coefficients between developed and less-developed cities. Unit of observation is a neighborhood and weights are the inverse number of neighborhoods in each city c. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.*

results change when we eliminate each continent one by one. We find robust differences

between developed and less-developed cities, though the differences are slightly attenuated when omitting the USA. Appendix Table B.8 shows that our results on the difference in incomes between urban and suburban areas are robust to alternative definitions of the distance to city centers.

In Appendix Table B.9, we also consider an additional geographic structure: coastlines. Interestingly, we find that the average income tends to be higher for both developed and less-developed cities. However, the coefficients for the developed cities are still larger, and the difference is significant for simple regressions (though significance disappears for multiple regressions). Appendix Figure B.7 replicates the dot plot analysis of Figure 4 examine the ratio of income between coastal and non-coastal areas, showing the same pattern.

In Appendix Table B.10, we report the results of regression (1) by replacing the independent variable with log population density (see Figures B.8, B.9, and B.10 for the corresponding dot plots across continents). We find that the population density declines in suburban, hilly, and river areas, both for developed and less-developed cities. The decline in population density in suburban areas is larger for less-developed cities, while that in hilly areas is smaller for less-developed cities. The coefficients for rivers are similar between developed and less-developed cities and not statistically different from each other.

4. Theoretical Framework

In this section, we develop a theory to explain the gap in the spatial distribution of income between developed and less-developed country cities.

At the heart of our theory is the non-homotheticity of residential location choice. It is, of course, the central element of existing theories of spatial income distribution. Existing work seeks to rationalize the spatial income distribution of cities in developed countries (primarily the USA) by the non-homotheticity in demand for housing, space, amenities, or transportation infrastructure. However, these frameworks have limitations in simultaneously explaining why cities in less-developed countries exhibit *opposite* patterns.

We show that incorporating *multiple* sources of non-homotheticity in residential location choice – one for housing and one for amenity/space – can coherently explain the patterns in both developed and less-developed cities. If housing is a subsistence good, households with higher potential earnings dominate in "attractive" neighborhoods, raising local housing costs and pushing out those with lower potential earnings. At the same time, the non-homotheticity in amenity/space implies that which neighborhoods are "attractive" depends

on the residents' overall income levels. In cities where the overall income is low, households' primary consideration is access to jobs. Their income levels can be so low that they do not value natural amenities (hills or rivers) or large spaces available in suburban areas. When income rises, residents start to value those aspects. This induces the movement of richer residents toward those areas in sacrifice for better job access in urban core areas.

Another important aspect that determines the spatial distribution of income is commuting costs. Due to the differences in transportation infrastructure or the penetration of private cars, the spatial heterogeneity of access to jobs may differ greatly across developed and less-developed cities. Our theory builds on recent quantitative urban literature (e.g., Ahlfeldt, Redding, Sturm, and Wolf, 2015; Tsivanidis, 2023) to accommodate rich geographic heterogeneity in commuting costs and neighborhood fundamentals. This feature allows us to calibrate our model to these cities and quantify the relevance of non-homotheticity and spatial frictions in the spatial income distribution. We seek this exercise in Sections 5 and 6.

4.1. Environment

Consider a city c that consists of $j \in \mathcal{J}_c$ neighborhoods. Each neighborhood j is endowed with exogenous amenity B_{jc}, the productivity of final goods A_{jc}, and the supply shifter of housing S_{jc}. Furthermore, each pair of locations $i, j \in \mathcal{J}_c$ is endowed with commuting costs τ_{ijc}. For notational brevity, we omit subscripts c in this section and reintroduce them in the next section for the quantitative analysis.

There is a unit measure of households $\omega \in \chi$. Households are heterogeneous with respect to idiosyncratic preferences for residential location choice $\epsilon(\omega) \equiv \{\epsilon_j(\omega)\}_j$ and with respect to efficiency unit of labor $s(\omega)$, which we call "earning potential" for short. Each household decides sequentially where to reside, where and how much to supply labor, and how much to consume housing and freely traded final goods (numéraire).

4.2. Households' Preferences and Residential Location Decisions

We specify households' preferences over final goods and housing using non-homothetic constant elasticity of demand (NH-CES) preferences (Comin, Lashkari, and Mestieri, 2021). This preference class provides well-defined demand functions over any positive value of

income and prices.[3] Specifically, given the consumption amount of final goods y and housing h, the sub-utility of households U_j derived from this consumption is implicitly determined by the following equation:

$$1 = \left(\frac{y}{U_j}\right)^{\frac{\sigma-1}{\sigma}} + \chi^{\frac{1}{\sigma}} \left(\frac{h}{U_j^{\varepsilon}}\right)^{\frac{\sigma-1}{\sigma}}, \tag{2}$$

where $\varepsilon(>0)$ is the parameter that governs the degree of non-homotheticity in housing. If $1 > \varepsilon > 0$, housing is a subsistence good (e.g., housing expenditure share decreases as income rises, fixing prices), and if $\varepsilon > 1$, it is a luxury good. If $\varepsilon = 1$, Equation (2) becomes a standard CES preference. σ determines the elasticity of substitution between housing and final goods. χ regulates the relative demand for housing.

Given this sub-utility from consumption U_j, household ω's utility by residing in j is given by:

$$\left(U_j^{\rho} + B_j^{\rho}\right)^{\frac{1}{\rho}} + \epsilon_j(\omega), \tag{3}$$

where B_j is an exogenous amenity in location j, capturing factors such as the natural amenities available in hills or rivers or the open space available in suburban areas. ρ regulates the non-homotheticity of residential location choice with respect to B_j, which we explain in detail in the next subsection.

We now describe households' decisions. First, conditional on residential locations, they decide how much to consume housing h and final goods y subject to budget constraint by solving the following problem:

$$\begin{aligned} U_j(s(\omega)) \equiv \arg\max_{\{h,y\}} \quad & U_j \\ \text{s.t.} \quad & P_j h + y \leq \overline{w}_j s(\omega) \quad \text{and Equation (2)} \end{aligned} \tag{4}$$

where P_j is the housing price; $s(\omega)$ is the earning potential of household ω; and $\overline{w}_j$ is the wage rate per efficiency unit of labor for residents in j, which is determined by the labor supply decision as we discuss in Section 4.4. Given the indirect sub-utility $U_j(s)$, the housing and final

[3] Alternative classes of non-homothetic preferences used to study a specific city or a country, such as Stone-Geary preferences (Tsivanidis, 2023) or unit-demand preferences (Couture et al., 2024), impose restrictions on income and prices, which make it unsuitable in our applications that involve large dispersion of income and prices within and across cities. Finlay and Williams (2022) apply NH-CES preferences to study spatial income sorting in the USA and show that it can capture observed heterogeneity in housing expenditure.

goods consumptions are given by:

$$h_j(s) = U_j(s)^{-\epsilon(\sigma-1)} \left[\frac{P_j}{\overline{w}_j s}\right]^{-\sigma} \chi, \tag{5}$$

$$y_j(s) = U_j(s)^{-(\sigma-1)} \left[\frac{1}{\overline{w}_j s}\right]^{-\sigma}. \tag{6}$$

Equations (2), (5), and (6) implicitly determine $U_j(s)$.

Anticipating this decision, household ω chooses the residential location that maximizes the utility (3)

$$j(\omega) \equiv \arg\max_j V_j(s(\omega)) + \epsilon_j(\omega), \qquad V_j(s) \equiv \left(U_j(s)^\rho + B_j^\rho\right)^{\frac{1}{\rho}} \tag{7}$$

Following the literature, we assume that $\epsilon_j(\omega)$ is independently drawn from the Gumbel distribution with shape parameter ν. Then, the probability that households with earning potential s reside in location j is given by

$$\pi_j(s) = \frac{\exp\left(\nu V_j(s)\right)}{\sum_\ell \exp\left(\nu V_\ell(s)\right)}. \tag{8}$$

4.3. Non-homotheticity in Residential Location Choice

We now discuss how the residential location choice depends on households' income levels. Equation (8) shows that location choice probability is summarized by $V_j(s)$, which are increasing in amenity B_j and wage rates $\overline{w}_j$ and decreasing in housing price P_j. The partial derivatives are given by

$$\frac{\partial \ln V_j(s)}{\partial \ln B_j} = \frac{B_j^\rho}{U_j(s)^\rho + B_j^\rho} > 0, \tag{9}$$

$$\frac{\partial \ln V_j(s)}{\partial \ln \overline{w}_j} = \frac{U_j(s)^\rho}{U_j(s)^\rho + B_j^\rho} \lambda_j(s) > 0, \tag{10}$$

$$\frac{\partial \ln V_j(s)}{\partial \ln P_j} = \frac{U_j(s)^\rho}{U_j(s)^\rho + B_j^\rho} \lambda_j(s) \xi_j(s) < 0, \tag{11}$$

where $\lambda_j(s) \equiv \frac{\partial \ln U_j(s)}{\partial \ln s}$ is the elasticity of utility with income, and $\xi_j(s) \equiv h_j(s) P_j / s\overline{w}_j$ is the housing expenditure share. We study how these partial derivatives depend on earning potential s to reveal the patterns of non-homotheticity in residential location choice.

First, the non-homotheticity with respect to B_j crucially depends on the sign of ρ.

Proposition 1. *For any* $\{s, B_j, \overline{w}_j, P_j\}$, $\rho < 0$ *if and only if*

$$\frac{\partial}{\partial s}\left|\frac{\partial \ln V_j(s)}{\partial \ln B_j}\right| > 0. \tag{12}$$

If $\rho < 0$, households with higher earning potential s are more responsive to B_j. Therefore, in this case, B_j is interpreted as a "luxury good." On the other hand, with $\rho > 0$, B_j can be interpreted as a "subsistence good." In the limit of $\rho \to 0$, $\left(U_j(s)^\rho + B_j^\rho\right)^{\frac{1}{\rho}} \to U_j(s)B_j$. In this case, the elasticity of residential location choice with amenities does not depend on income levels, holding wage rates and house prices fixed, as considered, for example, by Tsivanidis (2023), Finlay and Williams (2022), and Couture et al. (2024).

Second, the non-homotheticity of residential location choice with respect to wage rates $\overline{w}_j$ tends to depend on ρ in an opposite way from that to amenity B_j.

Proposition 2. *For any* $\{s, B_j, \overline{w}_j, P_j\}$, *there exists* $\eta \leq 0$ *such that for all* $\rho < \eta$,

$$\frac{\partial}{\partial s}\left|\frac{\partial \ln V_j(s)}{\partial \ln \overline{w}_j}\right| < 0. \tag{13}$$

Hence, if ρ is negative and takes a sufficiently large value, households with higher earning potential tend to be less responsive to wage rates $\overline{w}_j$ in their location choice decision. If $\rho < 0$, households with higher earning potential s are more responsive to B_j, and hence, less responsive to U_j. The proposition requires a larger negative value for ρ than before because the elasticity of utility $\lambda_j(s) \equiv \frac{\partial \ln U_j(s)}{\partial \ln s}$ may rise with income.

Finally, the non-homotheticity of residential location choice with respect to P_j depends on the degree of non-homotheticity of housing ε.

Proposition 3. *Suppose* ρ *and* $\{s, B_j, \overline{w}_j, P_j\}$ *satisfy the conditions of Proposition 2. If* $1 > \varepsilon > 0$,

$$\frac{\partial}{\partial s}\left|\frac{\partial \ln V_j(s)}{\partial \ln P_j}\right| < 0. \tag{14}$$

If housing is a subsistence good ($1 > \varepsilon > 0$), the housing expenditure share decreases in income. Therefore, households with higher earnings tend to be less responsive to housing costs.

Proposition 3 is crucial for the equilibrium property of spatial income sorting. If housing prices rise in demand (as we assume in the general equilibrium conditions below), "attractive" neighborhoods tend to have high housing prices. Under the condition of Proposition 3,

households with lower earning potential are disproportionately disincentivised to live in those neighborhoods, inducing income sorting.

At the same time, Proposition 1 and 2 imply that which neighborhoods are "attractive" depends on the residents' income levels. In cities where the overall income level is low, households' primary consideration is access to jobs. Their income levels can be so low that they do not value natural amenities (hills or rivers) or large spaces available in suburban areas. When income rises, residents start to value those aspects in sacrifice for access to jobs. Therefore, cities with different levels of overall income may exhibit different patterns of spatial income sorting.

4.4. Commuting (Labor Supply) Decisions

We assume that each household ω has a continuum of members with a unit measure, each endowed with $s(\omega)$ efficiency unit of labor supply. Each member chooses her work location. If a member v decides to commute to work location $n = n(v)$, she earns income at wage rate $w_n \epsilon_n^W(v)$ per efficiency unit of labor, where $\epsilon_n^W(v)$ captures the idiosyncratic factor that affects the productivity of the member at a particular workplace. In addition, she faces commuting costs in the form of iceberg costs $\tau_{jn} \geq 1$ in the earnings, where j is household ω's residential location. This cost captures the cost of traveling to further distances as well as the heterogeneity in transportation infrastructure (such as the availability of paved roads in suburban, hilly, or river areas). Together, the labor supply decision of a member v is given by

$$n(v) = \arg\max_n \tau_{jn}^{-1} w_n \epsilon_n^W(v). \tag{15}$$

We assume that $\epsilon_n^W(v)$ is drawn from an i.i.d. Frechet distribution with shape parameter θ. Then, the probability that a household member residing in location j commuting to location n is given by

$$\pi_{jn}^W = \frac{\left(\tau_{jn}^{-1} w_n\right)^\theta}{\sum_\ell \left(\tau_{j\ell}^{-1} w_\ell\right)^\theta}. \tag{16}$$

Furthermore, applying the law of large numbers, the wage rate per efficiency unit of labor for residents in j is given by

$$\overline{w}_j = \varrho \sum_\ell \left(\tau_{j\ell}^{-1} w_\ell\right)^\theta, \tag{17}$$

where $\varrho \equiv \Gamma\left(\frac{\theta-1}{\theta}\right)$, where $\Gamma(\cdot)$ is the Gamma function. Equation (17) indicates that the wage rates per efficiency unit of labor for residents in neighborhood j is proportional to the

geometric average of the wage rates at various work destinations weighted by the commuting cost, often called "commuting access" in the literature (e.g., Tsivanidis, 2023).

4.5. Production, Market Clearing, and Equilibrium

Final goods are produced in each location n by perfectly competitive firms with linear production technology using labor with productivity A_n. Perfect competition implies that

$$w_n = A_n. \tag{18}$$

Housing is supplied by perfectly competitive developers using land, owned by the absentee landlord, and the final goods. Furthermore, the efficiency of housing supply S_j could depend on location j, reflecting the heterogeneity of geological features of the neighborhood. We assume that the inverse supply function of housing is given by

$$P_j = \frac{1}{S_j} H_j^{\mu}, \tag{19}$$

where H_j is the aggregate supply of housing.

The market clearing of housing in location j is given by

$$H_j = \int_s h(s)\pi_j(s)dG(s), \tag{20}$$

where $G(\cdot)$ is the cumulative distribution function of earning potential $s(\omega)$ across households.

The equilibrium is defined by households' consumption $\{h(s), y(s)\}$, residential choice probabilities $\{\pi_j(s)\}$, labor supply probabilities $\{\pi_{jn}^W\}$, wages $\{w_j\}$, and house prices $\{P_j\}$, that satisfy households' optimal consumption decision (4), residential location decision (7) and (8), labor supply decision (15) and (16), final goods producers' optimality condition (18), and housing supply and market clearing conditions (19) and (20).

4.6. Spatial Income Distribution

The average residential income in neighborhood j is given by

$$I_j = \overline{w}_j \frac{\int_s s\pi_j(s)dG(s)}{\int_s \pi_j(s)dG(s)}, \tag{21}$$

Therefore, the equilibrium residential income in neighborhood j is affected by two components. First, it depends on the wage rates per efficiency unit of labor in residential location $\overline{w}_j$, determined by Equation (17). This term is higher if neighborhood j is surrounded by neighborhoods that offer higher wages, or equivalently, higher productivity $w_n = A_n$. Notice that the variation of $\overline{w}_j$ is lower for cities with lower commuting costs on average $\{\tau_{jn}\}$. In an extreme case, if $\tau_{jn} = 1$ for all j, n, then $\overline{w}_j$ does not vary across locations.

Second, the residential income is affected by the average earning potential of households residing in the neighborhood j, $\int_s s\pi_j(s)dG(s)/\int_s \pi_j(s)dG(s)$. As we discussed in Section 4.3, this component is determined by $\{B_j, \overline{w}_j, P_j\}$ and the non-homotheticity in preferences. In particular, if housing is a subsistence good $1 > \varepsilon > 0$, households with higher earning potential tend to sort into "attractive," high house price locations (Proposition 3). At the same time, which locations are "attractive" depends on the overall income levels depending on the non-homotheticity in amenity. With $\rho < 0$, i.e., if amenity is a luxury good, households in cities with overall low income tend to find high-wage, low-amenity locations as attractive, and households in cities with overall high income tend to find low-wage, high-amenity locations as attractive (Propositions 1 and 2). This differential sorting can explain the opposite patterns of the observed gap in spatial income distribution as we document in Section 3.

5. Quantifying the Gap in Commuting Costs

The previous section showed that commuting costs and nonhomothetic preferences could explain the gap in observed spatial income distribution between developed and less-developed cities. In this section and next, we use our model to quantify the relevance of these channels. In this section, we focus on commuting (labor supply) decisions and show that there is a major gap in commuting costs between developed and less-developed cities. In Section 6, we quantify how much these commuting costs and nonhomothetic preferences explain the gap of equilibrium spatial income distribution between developed and less-developed cities.

5.1. Estimating Commuting Gravity Equations for Each City

We use our model's commuting (labor supply) decisions in Section 4.4 to quantify the commuting costs for each city. Recall that our model predicts the probability of commuting by residents (household members) in residential location j to workplace location n by

$$\pi^W_{jn} = \frac{\left(\tau^{-1}_{jnc} w_{nc}\right)^\theta}{\sum_\ell \left(\tau^{-1}_{j\ell c} w_{\ell c}\right)^\theta}, \tag{22}$$

where c indicates a city. We introduce a parametric assumption that the commuting cost τ_{jnc} is a power function of road distance between neighborhoods j to n such that

$$\log \tau_{jnc} = \kappa_c \text{RoadDistance}_{jnc} + \epsilon_{jnc}, \tag{23}$$

where we allow κ_c to vary by city, and ϵ_{jnc} is additional idiosyncratic travel costs for a pair of neighborhoods that are not captured by road distance.

Combining the two equations and taking logs,

$$\log \pi^W_{jnc} = \theta \log w_{nc} - \kappa_c \theta \text{RoadDistance}_{ijc} - \log \sum_{\ell} \left(\tau^{-1}_{j\ell c} w_{\ell c}\right)^{\theta} + \epsilon_{jnc}. \tag{24}$$

We estimate an empirical analog of this equation using a Pseudo-Poisson Maximum Likelihood (PPML) estimator to handle the presence of many pairs of zero commuters. Specifically, we estimate the following two-way fixed model

$$\log \mathbb{E}\left[\pi^W_{jnc}\right] = \psi_{nc} - \tilde{\kappa}_c \text{RoadDistance}_{ijc} + \eta_{nc}, \tag{25}$$

where $\psi_{nc} \equiv \theta \log w_{nc}$ is the workplace fixed effects, $\tilde{\kappa}_c \equiv \kappa_c \theta$, and $\eta_{nc} \equiv -\log \sum_{\ell} \left(\tau^{-1}_{j\ell c} w_{\ell c}\right)^{\theta}$ is the origin fixed effects.

The estimates of Equation (25) provide three useful information about the nature of commuting costs for each city. First, a comparison of the semi-elasticity of commuting with road distance, $\tilde{\kappa}_c$, reveals the differences in the severity of commuting costs across cities. Second, once we assume a value for θ, the workplace fixed effects ψ_{nc} will provide an estimate of the wage rate, or equivalently productivity, of the workplace location $w_{nc} = A_{nc} \propto \exp(\psi_{nc}/\theta)$ up to scale (Kreindler and Miyauchi, 2023). Third, the origin fixed effects η_{nc} is proportional to the wage rates at the residential location $\overline{w}_{jc} \propto \exp(-\eta_{nc}/\theta)$ (Equation 17).[4] The final information is particularly important, as it is one component that determines the equilibrium residential income according to Equation (21).

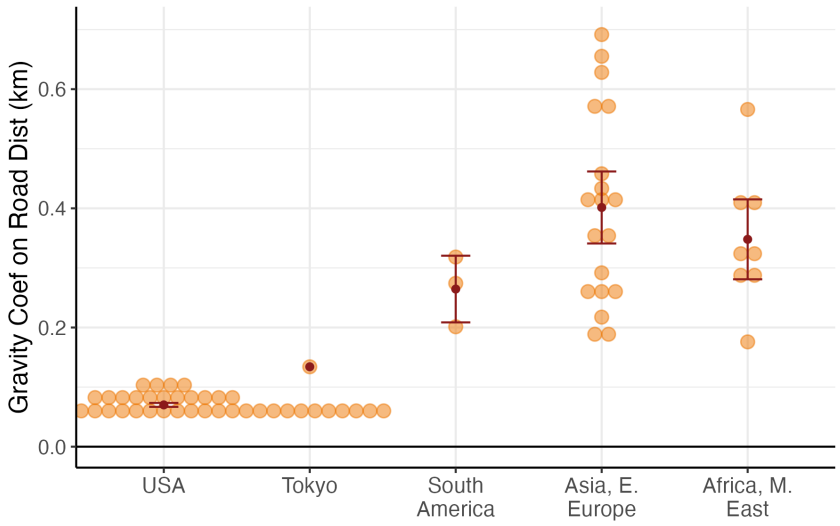
5.2. Estimation Results

In Figure 5, we present the point estimates of $\tilde{\kappa}_c \equiv \kappa_c \theta$ from estimating equation (25) for each city. We estimate these equations for the U.S. cities, Tokyo, and less-developed cities from JICA

[4] With PPML specification, the estimates of the origin fixed effects $\hat{\eta}_{nc}$ is numerically identical to the geometric sum of the estimated workplace fixed effects with estimated coefficients on the covariates $\sum_{\ell} \exp\left(\hat{\tilde{\kappa}}_c \text{RoadDistance}_{ijc} + \hat{\psi}_{jc}\right)$ up to scale (Fally, 2015).

travel survey data. From this exercise, we exclude cities from UK, France, Spain, and Brazil, where we do not have bilateral commuting flow data.[5]

Figure 5: Estimated Semi-Elasticity of Commuting to Road Distance ($\tilde{\kappa}_c$)



Note: Results of the $\tilde{\kappa}_c \equiv \kappa_c \theta$ from estimating equation (25) for each city.

The figure presents the striking heterogeneity in the commuting costs. For USA cities, the mean of the estimated semi-elasticities is approximately 0.08, indicating that an increase in commuting distance by one-kilometer results in a drop in commuting by 8%, conditional on the origin and workplace fixed effects. In Tokyo, this number is approximately 0.14. The difference between the USA and Japan (Tokyo) may come from the differences in typical transportation modes for commuting; in the USA, the most common transportation modes are private cars, while in Tokyo, it is public transit.

In contrast to these developed cities, the semi-elasticity of commuting is significantly negative and larger. For South American cities, the mean is 0.27, for Asia and E. European cities, it is 0.40, and for Africa and M. East, it is 0.35. The differences from the developed cities may reflect the lack of availability of private cars, fast and smooth road infrastructure, and efficient public transit systems.

[5] In Appendix Figure C.1 and Table C.1, we present the results by alternatively specifying Equation (23) as an isoelastic function of road distance (i.e., $\log \text{RoadDistance}_{jnc}$ for the right-hand side) to measure the commuting elasticity to road distance (instead of semi-elasticity). We find a similar pattern of results, except that the commuting elasticity of Tokyo is similar to those of developing countries, consistent with the relatively large geographic scale of Tokyo relative to other cities.

We next focus on our estimates of productivity at workplaces $A_{nc} \propto \exp(\psi_{nc}/\theta)$ and wage rates at residential location $\overline{w}_{jc} \propto \exp(\eta_{nc}/\theta)$. For the estimates of productivity at workplaces, we first subtract the log area size from the workplace fixed effects ψ_{nc} to adjust the mechanical one-to-one relationship between the area size and the fixed effects (Kreindler and Miyauchi, 2023). In Table 3, we report the results of the regression of these estimates on the suburban, hilly, and river dummies interacted with developed and less-developed city dummies, following the same regression specification for our income regression (Table 2; Equation 1). For the values of θ, we assume a value of $\theta = 5$, which is a median estimate found in the literature ranging over developed and less-developed cities.

In Column (1), we find that the productivity at workplaces is significantly lower in suburban, hilly, and river areas in both developed and less-developed cities, consistent with the interpretation that the productivity of city centers tends to be higher in most cities. However, the magnitudes are different between developed and less-developed cities. In less-developed cities, the productivity disadvantage in suburban and river areas is significantly higher in less-developed cities relative to developed cities.

In Column (2), we find that the wage rates at workplaces also tend to be lower in suburban, hilly, and river areas in both developed and less-developed cities. This pattern is again consistent with the idea that places away from the city centers tend to have lower productivity, and due to the commuting costs, wage rates at residential locations tend to be affected by this spatial productivity distribution. However, again, we find substantial differences between developed and less-developed cities. This is in part driven by the larger commuting costs in less-developed cities (Figure 5) and in part because of the steeper productivity gradient (Column 1 of Table 3).

In our theory, these wage rates are one key determinant of the residential income distribution (Equation 21). In the equilibrium, the residential income is additionally affected by the sorting of workers across different earning potential. In Section 6, we use the general equilibrium structure of our model to quantify the relevance of this commuting costs on the equilibrium residential sorting, and hence, the observed spatial income distribution.

5.3. Heterogeneity of Commuting Costs by Income Groups

One important aspect of commuting costs is that it may depend on workers across different income groups. In the USA, the use of different transportation modes across income groups is pointed out as one potential reason behind the spatial income distribution (Glaeser et al., 2008). In developed cities, the heterogeneous access to private cars drives the heterogeneous

Table 3: Regression Results of Estimated A_j and $\overline{w}_j$

Dependent Variables:	$\log A_j (= \tilde{\psi}_j/\theta)$	$\log \overline{w}_j = (-\eta_j/\theta)$
Model:	(1)	(2)
Variables		
Developed × Top 25% distance from center	-0.130***	-0.105***
	(0.015)	(0.009)
Less Developed × Top 25% distance from center	-0.352***	-0.368***
	(0.033)	(0.036)
Developed × Hilly	-0.261***	-0.024***
	(0.034)	(0.007)
Less Developed × Hilly	-0.233***	-0.173***
	(0.035)	(0.041)
Developed × < 100m from river	-0.024***	-0.015***
	(0.007)	(0.002)
Less Developed × < 100m from river	-0.171***	-0.100***
	(0.021)	(0.020)
Difference in slopes: Developed vs Less Developed		
Top 25% distance from center	-0.222***	-0.263***
	(0.0360)	(0.0375)
Hilly	0.0281	-0.149***
	(0.0490)	(0.0412)
< 100m from river	-0.147***	-0.0843***
	(0.0228)	(0.0198)
Weight	City	City
Subset	USA, Tokyo, JICA Cities	USA, Tokyo, JICA Cities
Fixed-effects		
City	Yes	Yes
Fit statistics		
Observations	33,453	33,560

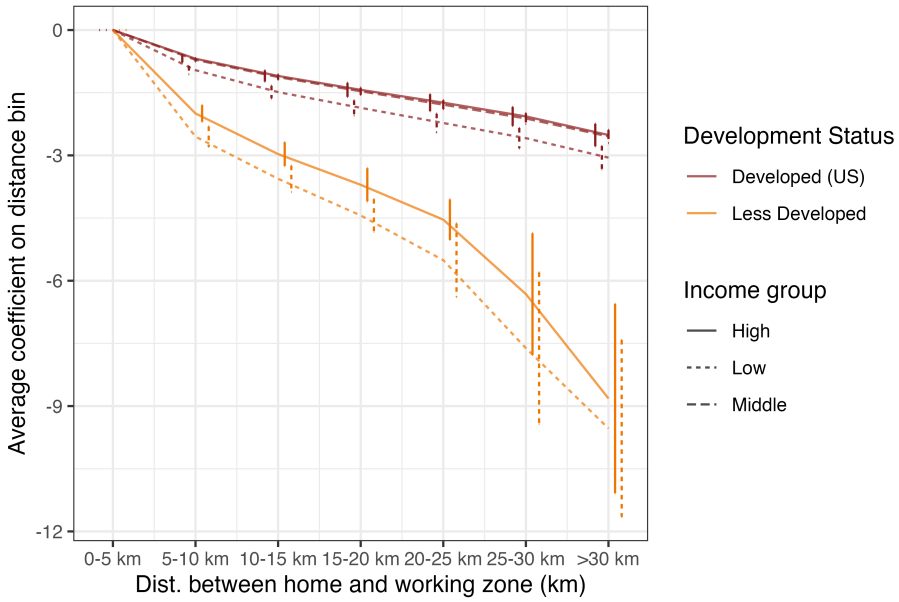
Note: Estimates based on $\theta = 5$. $\tilde{\psi}_{nc} \equiv \psi_{nc} - \log Area_{nc}$.

gains from urban transportation infrastructure (Tsivanidis, 2023; Zárate, 2021; Balboni, Bryan, Morten, and Siddiqi, 2020).

To investigate the relevance of this issue, in Figure 6, we report the results of the nonparametric commuting gravity equations for developed cities (USA) and for less-developed cities (JICA), separately for low and high-income groups within each city group. In both

types of cities, we find that the spatial decay of commuting tends to be steeper for lower-income groups. However, the variations of commuting groups across income groups within cities are significantly smaller than those across cities. Of course, it does not indicate that the heterogeneity of commuting costs across income groups within a city is not an important driver to explain the spatial income distribution. However, it does indicate that the differences in commuting costs between developed and less-developed cities apply similarly to all income groups.

Figure 6: Commuting Costs by Income Groups



6. Quantifying the Gap in Equilibrium Spatial Income Distribution

In this section, we use the full general equilibrium structure of our model to quantify how the commuting costs and nonhomothetic preferences explain the gap in equilibrium spatial income distribution. To do so, we first calibrate our model to USA cities. Next, we run a counterfactual simulation of (1) lowering the overall city income (productivity) to the level of less-developed cities and (2) increasing the commuting costs to the level of less-developed cities, as estimated in the previous section.

6.1. Calibrating the Model to USA Cities

We assume that amenity B_{jc} is a function that depends on the observed suburban areas (where open spaces are available) and the hills and rivers (where natural amenities are available). Specifically,

$$\log B_{jc} = \beta_0 + \beta_1 \text{Suburban}_{jc} + \beta_2 \text{Hills}_{jc} + \beta_3 \text{Rivers}_{jc}, \tag{26}$$

where Suburban_{jc}, Hills_{jc}, and Rivers_{jc} indicate the dummies for the suburban areas (neighborhoods with the furthest distance from CBD that accommodate 25 percent of city population), hilly, and river, as defined for our income regression equation (1). Notice that we assume common parameters for $\{\beta_0, \beta_1, \beta_2, \beta_3\}$ across all cities as common preference parameters.

Together, our structural parameters common across cities are household preference parameters $\{\sigma, \chi, \rho, \nu\}$, preference parameters for amenities $\{\beta_0, \beta_1, \beta_2, \beta_3, \}$, dispersion of productivity draws for commuting decisions θ, and inverse housing supply elasticity μ, and the distribution of earning potential $G(\cdot)$. Our city-specific parameters are productivity distribution $\{A_{jc}\}_j$, bilateral commuting costs $\{\tau_{jnc}\}_{j,n}$, housing supply shifters $\{S_{jc}\}_j$. In the previous section, we have calibrated θ, $\{A_{jc}\}_j$, and $\{\tau_{jnc}\}_{j,n}$.[6] We now discuss our calibration of the remaining parameters, as summarized in Table 4.

Table 4: Calibrated Parameters

	Value	Description	Source
σ	0.52	Elasticity of substitution for housing	Finlay and Williams (2022)
ε	0.36	Elasticity of nonhomotheticity in housing	Finlay and Williams (2022)
χ	0.1	Preference shifter for housing	Target housing expenditure share
ρ	-2	Elasticity of nonhomotheticity in amenity	TENTATIVE
ν	10	Residential location choice elasticity	TENTATIVE
$G(\cdot)$	{3,1} wp 0.5	Earning potential distribution	Variance of income distribution
β_0	6.37	Amenity level	Target USA income distribution
β_1	0.44	Amenity for suburban areas	Target USA income distribution
β_2	0.56	Amenity for hilly areas	Target USA income distribution
β_3	0.33	Amenity for river areas	Target USA income distribution
μ	0.5	Inverse housing supply elasticity	Literature
S_{jc}	–	Housing supply shifter	Rationalize rents distribution

We calibrate the elasticity of substitution between housing and final goods $\sigma = 0.52$ and the elasticity of nonhomotheticity in housing $\varepsilon = 0.36$ from Finlay and Williams (2022), who

[6] The procedure in the previous section only reveals the relative $\{A_{jc}\}_j$ within the city, but not its scale. We estimate the scale targeting the observed mean income of USA cities.

estimated these parameters for USA cities. The value of $0 < \varepsilon < 1$ indicate that housing is a subsistence goods, consistent with the empirical observation in USA cities. We set the preference shifter for housing χ such that the housing expenditure share in our sample USA cities coincides with the observed counterpart given σ, ε observed income and rents across neighborhoods for USA cities.

The elasticity of nonhomotheticiy in amenity ρ and the elasticity of residential location choice ν are key parameters for our model. We tentatively set them to -2 and 10, correspondingly. The value $\rho < 0$ indicates that amenity is luxury goods, i.e., the relative importance of amenity for residential increase as income level increases, as explained in Section 4.3.

We assume that the earning potential distribution $G(\cdot)$ follows a bimodal distribution with a mass point with 3 and 1 (normalization), each of which is associated with probability 0.5. This earning potential generates a similar degree of income variance as we observe in the USA economy reported by Heathcote, Perri, and Violante (2010).

We set the preference parameters for amenities $\{\beta_0, \beta_1, \beta_2, \beta_3, \}$ using the indirect inference approach. Specifically, we look for the values of these parameters such that the regression coefficients of model-predicted residential log income on the dummies for suburban, hilly, and river areas with those as observed in Table 2. We find positive values for all β_1, β_2, and β_3, consistent with an interpretation that these natural amenities are luxury goods (given $\rho < 0$). Appendix Table C.2 shows that our calibrated model can indeed rationalize the observed coefficients.

Finally, we calibrate the housing supply elasticity $\mu = 0.5$ based on a typical value estimated in the literature. We set the housing supply shifter S_{jc} for each location to be consistent with the observed rents P_j, given the observed population size and income using housing equilibrium conditions (Equations 19 and 20).

6.2. Can Income Levels and Commuting Costs Explain Income Distribution Gaps?

In Section 4, we discussed two key channels driving the spatial distribution of income within cities. The first channel is the nonhomothetic preferences in housing and amenities. Where rich and poor reside within a city is determined by the relative "attractiveness" of the neighborhoods. Furthermore, which neighborhoods are more "attractive" (i.e., the trade-off between wage rates or amenities) may be affected by the city's overall income. The second channel is commuting costs. As highlighted in Section 5, access to jobs for residents in suburbs and hills and rivers are lower than in the urban core, and disproportionately so in

less-developed cities.

We now use our model calibrated to the USA cities to quantify these two channels through a series of counterfactual simulations. In our first counterfactual simulation, we lower the overall city income (productivity) to the mean value of less-developed cities. This counterfactual quantifies the importance of nonhomothetic preferences in explaining the gap in spatial income distribution. In our second counterfactual simulation, we increase the commuting costs to the average levels for those in less-developed cities. This counterfactual quantifies the importance of commuting costs in explaining the gap in spatial income distribution. Finally, we feed in both changes simultaneously. This counterfactual assesses to what extent the two channels alone can explain the observed gap in spatial income distribution.

Table 5 presents the results. For our baseline specification (Column 1) and for our counterfactual equilibrium (Columns 2-4), we run the regression of log mean residential income on the suburban, hilly, and river dummies, following the same regression specification as Equation (1). Since we calibrate $\{\beta_0, \beta_1, \beta_2, \beta_3\}$ so that the model-predicted regression coefficients coincide with the ones using actual data from USA, the patterns in Column (1) coincide with that from actual data. Consistent with the findings in Section 3, all regression coefficients from the USA are positive (Column 1), and all regression coefficients from less-developed cities are negative (Column 5).

In Column (2), we report the results under the counterfactual simulation to lower the average productivity $\{A_{jc}\}_j$ by 190 log points, which is the average mean real income difference between USA cities and less-developed cities in our sample. We find that all regression coefficients decrease. While the regression coefficients still do not go down as much as those in less-developed cities (Column 5), some regression coefficients turn negative. This pattern indicates that non-homothetic preferences and differences in overall income levels alone have a sizable contribution to the spatial income distribution gap.[7]

In Column (3), we report the results under the counterfactual simulation to increase the commuting semi-elasticity $\tilde{\kappa}_c$ by 0.30, which is the differences of the mean estimates of $\tilde{\kappa}_c$ between USA cities and less-developed cities (Figure 5). Interestingly, we find that the regression coefficients do not change, or even increase, relative to our baseline specification (Column 1). This pattern arises because of the differential incentives for residential

[7] In Appendix Table C.3, we report the results of the regression with the fraction of high-earning-potential households as the dependent variable, isolating the effects of sorting, and find consistent patterns with the above explanations.

Table 5: Counterfactual Simulation: Residential Income

	Dependent variable:				
	log Residential Income				
	(1)	(2)	(3)	(4)	(5)
Suburban	0.248^{***}	-0.042^{***}	0.289^{***}	-0.300^{***}	-0.302^{***}
	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)
Hilly	0.338^{***}	-0.066^{***}	0.321^{***}	-0.330^{***}	-0.181^{***}
	(0.003)	(0.005)	(0.005)	(0.006)	(0.010)
River	0.140^{***}	0.005^{***}	0.204^{***}	-0.144^{***}	-0.052^{***}
	(0.001)	(0.002)	(0.002)	(0.002)	(0.007)
Cities	US	US	US	US	Less Developed
Spec	Data	Lower Income	Increase Comm Costs	Lower Income & Increase Comm Costs	Data
Observations	27,129	27,129	27,129	27,129	99,840
R^2	0.705	0.062	0.588	0.493	0.347
Adjusted R^2	0.704	0.061	0.587	0.492	0.347

Note: Results of the regression (1) using log mean residential income as an outcome variable. For outcome variables, Column (1) uses the prediction in our calibrated model to the USA, where the regression coefficients coincide with those using actual data due to our calibration strategy (Section 6.1); Column (2) uses the prediction from the counterfactual to lower $\{A_{jc}\}_j$ by 190 log points; Column (3) uses the prediction from the counterfactual to increase $\tilde{\kappa}_c$ by 0.30; Column (4) uses the prediction from changing $\{A_{jc}\}_j$ and $\tilde{\kappa}_c$ simultaneously; and Column (5) uses the data from less-developed cities.

location choice across income groups within USA cities. An increase in commuting costs makes commuting access in suburban, hilly, and river areas relatively worse. This change disproportionately disincentivises lower-earning-potential residents in the USA cities to live in those areas relatively more than higher-earning-potential residents, who are not sensitive to commuting access in their residential location choice. Therefore, this counterfactual increases the sorting of higher-earning-potential residents toward suburban, hilly, and river areas. This finding suggests that the differences in commuting costs *alone* cannot explain any observed gap in spatial income distribution.

In Columns (4), we report the results under the counterfactual simulation to simultaneously decrease $\{A_{jc}\}_j$ and increase $\tilde{\kappa}_c$. In this counterfactual, we find negative regression coefficients on all suburban, hilly, and river dummies, comparable in magnitudes with the ones from

less-developed cities (Column 5). Interestingly, while the increase in commuting costs $\tilde{\kappa}_c$ *increases* the regression coefficients when we set overall productivity levels $\{A_{jc}\}_j$ at the level of USA (Columns 1 vs 3), it instead *decreases* the regression coefficients when we set overall productivity levels at the level of less-developed cities (Column 2 vs 4). This is because, when overall income is low, peoples' primary consideration for residential locations is the access to jobs. Therefore, when we increase the commuting costs, and hence make commuting access in suburban, hilly, and river areas relatively worse, high-earning-potential residents are disproportionately incentivised to move away from those areas.

These findings suggest that *both* overall income or productivity levels *and* commuting costs are important to explain the observed gap in spatial income distribution between developed and less-developed cities. These findings also suggest that the impacts of reducing commuting costs (such as through transportation infrastructure improvements) may have vastly different effects on the spatial income distribution between developed and less-developed cities.

7. Conclusion

We draw on new granular data from 133 cities in 26 countries to study how the spatial distribution of income within cities varies with economic development. We document that in less-developed countries, average incomes of urban residents decline monotonically in distance to the city center, whereas income-distance gradients are flat or increasing in developed economies. Neighborhoods with natural amenities – in particular hills and proximity to a river – are poorer than average in less-developed countries and richer than average in developed ones.

We explain these patterns in a spatial model with heterogeneous locations and households where preferences are non-homothetic in both housing and neighborhood amenities. In cities with low average income levels, the primary consideration of households is job access, and relatively richer households locate closer to city centers, where earning opportunities are better. As income rises, richer urban residents put more weight on amenities and locate in neighborhoods with better ones, further from city centers. When estimated to match our data for U.S. cities, the model predicts that gaps in income levels and commuting costs can explain a large fraction of the difference in urban income distributions between less- and more-developed countries.

References

Adukia, A., S. Asher, K. Jha, P. Novosad, and B. Tan (2022): "Residential Segregation and Unequal Access to Local Public Services in India: Evidence from 1.5 m Neighborhoods," Tech. rep., Working Paper.

Ahlfeldt, G. M., S. J. Redding, D. M. Sturm, and N. Wolf (2015): "The Economics of Density: Evidence from the Berlin Wall," *Econometrica*.

Akbar, P., V. Couture, G. Duranton, and A. Storeygard (2023a): "Mobility and congestion in urban India," *American Economic Review*, 113, 1083–1111.

Akbar, P. A., V. Couture, G. Duranton, and A. Storeygard (2023b): "The fast, the slow, and the congested: Urban transportation in rich and poor countries," Tech. rep., National Bureau of Economic Research.

Almagro, M. and T. Domínguez-Iino (2024): "Location sorting and endogenous amenities: Evidence from amsterdam," Tech. rep., National Bureau of Economic Research.

Alonso, W. (1964): *Location and Land Use: Toward a General Theory of Land Rent*, Cambridge, MA: Harvard University Press.

Balboni, C., G. Bryan, M. Morten, and B. Siddiqi (2020): "Transportation, Gentrification, and Urban Mobility: The Inequality Effects of Place-Based Policies," *Working paper*.

Becker, G. S. (1965): "A Theory of the Allocation of Time," *The economic journal*, 75, 493–517.

Bohr, C. E., M. Mestieri, and F. Robert-Nicoud (2024): "Economic Geography and Structural Change," *arXiv preprint arXiv:2412.03755*.

Bright, E., A. Rose, and M. Urban (2016): "LandScan Global 2015," .

Brueckner, J. K., J.-F. Thisse, and Y. Zenou (1999): "Why is central Paris rich and downtown Detroit poor?: An amenity-based theory," *European economic review*, 43, 91–107.

Bryan, G., E. Glaeser, and N. Tsivanidis (2020): "Cities in the developing world," *Annual Review of Economics*, 12, 273–297.

Bryan, G. T., K. Frye, and M. Morten (2025): "Spatial economics for low-and middle-income countries," Tech. rep., National Bureau of Economic Research.

Chatterjee, S., E. Giannone, and K. Kuno (2021): "Unequal global convergence," Tech. rep., Mimeo, Pennsylvania State University.

Chauvin, J. P., E. L. Glaeser, Y. Ma, and K. Tobio (2017): "What is Different about Urbanization in Rich and Poor Countries? Cities in Brazil, China, India and the United States," *Journal of Urban Economics*, 98, 17–49.

Coeurdacier, N., F. Oswald, and M. Teignier (2022): "Structural change, land use and urban expansion," .

Comin, D., D. Lashkari, and M. Mestieri (2021): "Structural change with long-run income and price effects," *Econometrica*, 89, 311–374.

Couture, V., C. Gaubert, J. Handbury, and E. Hurst (2024): "Income growth and the distributional effects of urban spatial sorting," *Review of Economic Studies*, 91, 858–898.

Eckert, F. and M. Peters (2022): "Spatial structural change," Tech. rep., National Bureau of Economic Research.

Fally, T. (2015): "Structural gravity and fixed effects," *Journal of international economics*, 97, 76–85.

Finlay, J. and T. Williams (2022): "Housing demand, inequality, and spatial sorting," *Inequality, and Spatial Sorting (April 28, 2022)*.

Florczyk, A., M. Melchiorri, C. Corbane, M. Schiavina, M. Maffenini, M. Pesaresi, P. Politis, S. Sabo, S. Freire, D. Ehrlich, T. Kemper, P. Tommasi, D. Airaghi, and L. Zanchetta (2019): "Description of the GHS Urban Centre Database 2015," *Publications Office of the European Union*.

Glaeser, E. L., M. E. Kahn, and J. Rappaport (2008): "Why do the poor live in cities? The role of public transportation," *Journal of urban Economics*, 63, 1–24.

Gonzalez-Navarro, M. and M. A. Turner (2018): "Subways and Urban Growth: Evidence from Earth," *Journal of Urban Economics*, 108, 85–106.

Harari, M. (2024): "Residential Patterns and Local Public Goods in Urban Brazil," .

Heathcote, J., F. Perri, and G. L. Violante (2010): "Unequal we stand: An empirical analysis of economic inequality in the United States, 1967–2006," *Review of Economic dynamics*, 13, 15–51.

Henderson, J. V. and M. A. Turner (2020): "Urbanization in the Developing World: Too Early or Too Slow?" *Journal of Economic Perspectives*, 34, 150–173.

Hijmans, R. J. (2024): *terra: Spatial Data Analysis*, r package version 1.7-73, https://rspatial.github.io/terra/.

Hoelzlein, M. (2019): "Two-sided sorting and spatial inequality in cities," *Working Paper*.

Kreindler, G. E. and Y. Miyauchi (2023): "Measuring commuting and economic activity inside cities with cell phone records," *Review of Economics and Statistics*, 105, 899–909.

Larrick, G., Y. Tian, U. Rogers, H. Acosta, and F. Shen (2020): "Interactive Visualization of 3D Terrain Data Stored in the Cloud," in *2020 11th IEEE Annual Ubiquitous Computing, Electronics and Mobile Communication Conference (UEMCON)*, 0063–0070.

Lebrand, M. and T. Kleineberg (2024): "The Distribution of Economic Activity across Cities: A Global Perspective," .

Lee, S. and J. Lin (2018): "Natural Amenities, Neighbourhood Dynamics, and Persistence in the Spatial Distribution of Income," *Review of Economic Studies*, 85, 663–694.

LeRoy, S. F. and J. Sonstelie (1983): "Paradise lost and regained: Transportation innovation, income, and residential location," *Journal of urban economics*, 13, 67–89.

Margo, R. A. (1992): "Explaining the Postwar Suburbanization of Population in the United States: The Role of income," *Journal of Urban Economics*.

Tabuchi, T. (2019): "Do the rich and poor colocate in large cities?" *Journal of Urban Economics*, 113, 103186.

Tokyo Metropolitan Area Transportation Planning Council (2018): .

Tsivanidis, N. (2023): "Evaluating the Impact of Urban Transit Infrastructure: Evidence from Bogota's TransMilenio," Unpublished Working Paper, U.C. Berkeley.

Zárate, R. D. (2021): "Spatial Misallocation, Informality, and Transit Improvements: Evidence from Mexico City," *Working paper*.

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A. Data Appendix

Table A.1: List of Cities From JICA Surveys (South America)

City Name	Year	Country	Number of respondents	Number of survey zones	Total geographic area (km^2)	Maximum distance to city center (km)
Belem	2000	Brazil	29835	91	420.1	21.8
Lima	2003	Peru	144490	388	2101.0	40.6
Managua	1998	Nicaragua	37082	92	257.6	13.8

Table A.2: List of Cities From JICA Surveys (Africa, M. East)

City Name	Year	Country	Number of respondents	Number of survey zones	Total geographic area (km^2)	Maximum distance to city center (km)
Abidjan	2013	Côte d'Ivoire	50619	129	873.5	25.7
Cairo	2001	Egypt	137513	429	2111.8	36.5
Damascus	1998	Syrian Arab Republic	38280	74	1941.1	22.8
Dar es Salaam	2007	U.R. of Tanzania: Mainland	26687	159	1176.7	29.0
Kinshasa	2018	D.R. of the Congo	42031	321	545.6	21.4
Mombasa	2015	Kenya	10868	32	190.2	10.5
Nairobi	2005	Kenya	20199	88	564.3	20.4
Nairobi	2013	Kenya	16794	102	594.9	20.1

Table A.3: List of Cities From JICA Surveys (Asia, E. Europe)

City Name	Year	Country	Number of respondents	Number of survey zones	Total geographic area (km^2)	Maximum distance to city center (km)
Bucharest	1998	Romania	92784	75	1110.4	13.1
Cebu	2014	Philippines	28806	229	465.5	38.7
Chengdu	2000	China	31130	125	800.0	17.0
Colombo	2013	Sri Lanka	124673	367	1633.9	49.3
Da Nang	2008	Viet Nam	18171	50	401.1	14.3
Dhaka	2009	Bangladesh	70456	86	1090.2	22.4
Dhaka	2014	Bangladesh	118026	140	1844.5	29.7
Hanoi	2005	Viet Nam	63716	250	1131.0	31.9
Hanoi	2014	Viet Nam	21485	205	1422.4	31.7
Ho Chi Minh	2003	Viet Nam	102407	247	3967.2	40.5
Ho Chi Minh	2014	Viet Nam	42908	210	1877.5	35.5
Jakarta	2018	Indonesia	5000	487	1750.4	49.9
Karachi	2011	Pakistan	96507	170	1673.5	30.3
Kuala Lumpur	1999	Malaysia	80545	222	2562.2	46.9
Lahore	2010	Pakistan	89414	188	2583.9	43.1
Manila	1996	Philippines	231838	220	1671.1	37.4
Phnom Penh	2000	Cambodia	17398	70	351.3	14.3
Phnom Penh	2012	Cambodia	42074	85	536.0	17.5
Viang Chan	2007	Lao People's DR	27630	33	330.7	11.0
Yangon	2013	Myanmar	42224	620	782.4	29.7

Table A.4: List of Cities Other Than JICA Surveys

Country	Number of Cities	Total number of survey zones	List of Cities
Brazil	30	93876	Aracaju, Belo Horizonte, Belém, Campinas, Ceilândia, Cuiabá, Curitiba, Florianópolis, Fortaleza, Goiânia, João Pessoa, Londrina, Maceió, Manaus, Natal, Novo Hamburgo, Porto Alegre, Recife, Ribeirao Preto, Rio de Janeiro, Salvador, Santos, Sao Goncalo, Sao Jose dos Campos, Sorocaba, São Luís, São Paulo, Teresina, Uberlândia, Vila Velha
France	7	5419	Bordeaux, Lille, Lyon, Marseille, Nice, Paris, Toulouse
Japan	1	168	Tokyo
Spain	7	9889	Barcelona, Bilbao, Madrid, Málaga, Seville, Valencia, Zaragoza
United Kingdom	9	2529	Birmingham, Bristol, Leeds, Liverpool, London, Manchester, Newcastle upon Tyne, Nottingham, Sheffield
United States	48	27655	Albuquerque, Atlanta, Austin, Bakersfield, Baltimore, Boston, Bradenton, Bridgeport, Buffalo, Chicago, Cincinnati, Cleveland, Columbus, Concord, Dallas, Denver, Detroit, Fresno, Honolulu, Houston, Indianapolis, Kansas City, Las Vegas, Los Angeles, Louisville, Miami, Milwaukee, Minneapolis, New Orleans, New York, Oklahoma City, Omaha, Orlando, Philadelphia, Phoenix, Pittsburgh, Portland, Providence, Sacramento, Salt Lake City, San Antonio, San Jose, Seattle, St. Louis, Tampa, Tucson, Virginia Beach, Washington D.C.

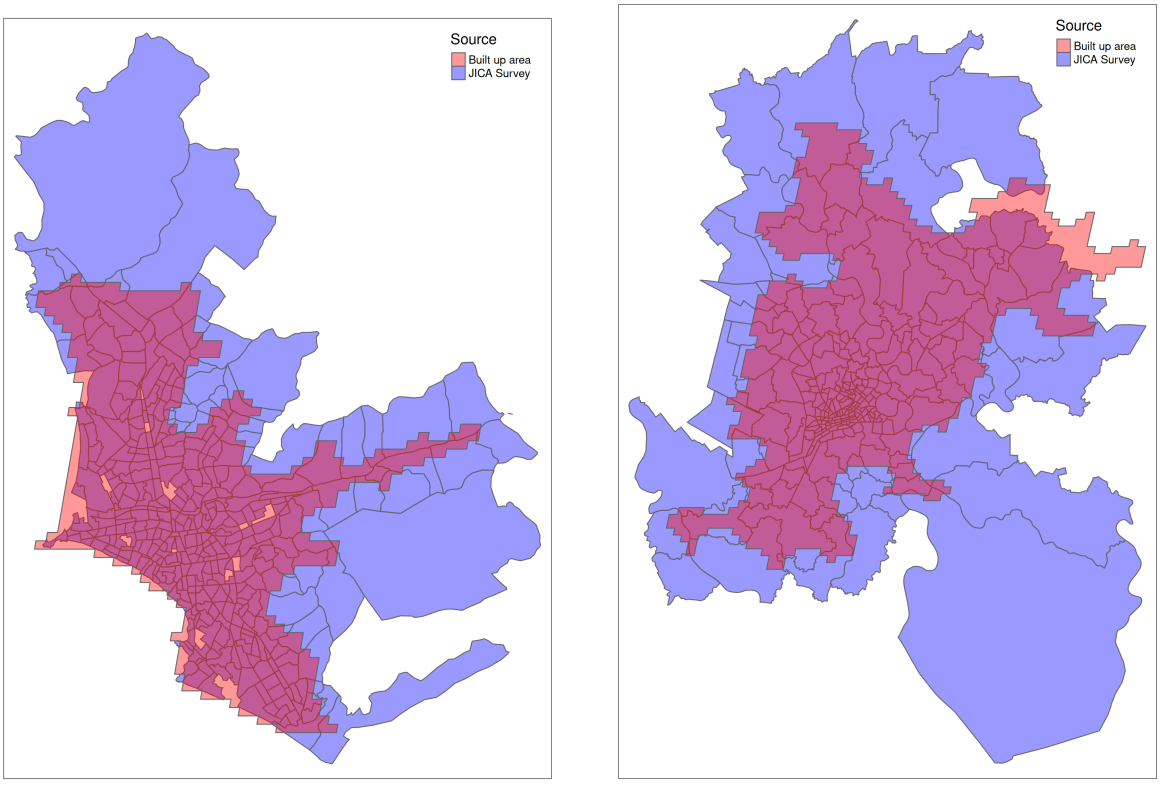
Note: A list of all countries which appear in our neighborhood-level income dataset described in Section 2, along with the number of cities from each country.

Figure A.1: Locations of Cities in our Data Set



Note: A map of all cities included in the neighborhood-level income dataset described in Section 2 .

Figure A.2: Built-up area (red) and Neighborhoods (blue) in Lima and Ho Chi Minh City



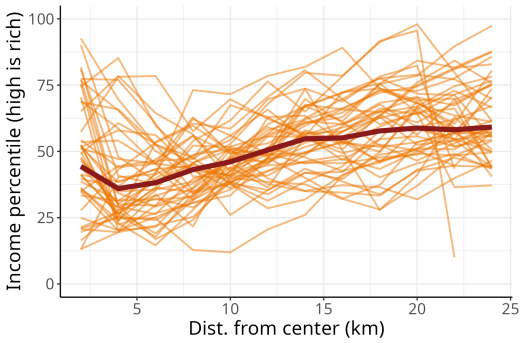
(a) Lima, Peru (b) Ho Chi Minh City, Vietnam

Note: "Built-up Area", in red, represents shape of a city as defined by the Un Human Settlements Project (Bright et al., 2016). "JICA Survey", blue, shows the neighborhoods surveyed by JICA in their surveys across the world. With a few, small, deviations, the area spanned by JICA surveys encompasses the entire "built-up area".

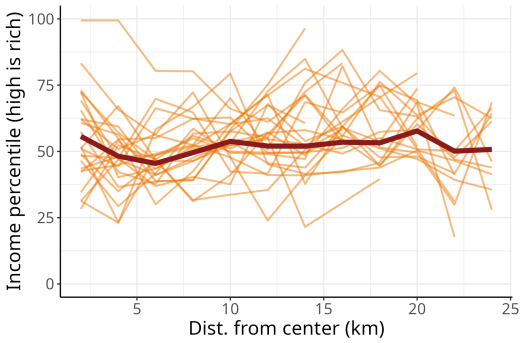
B. Additional Figures and Tables describing Income Patterns

B.1. Residential Income and Distance to City Center

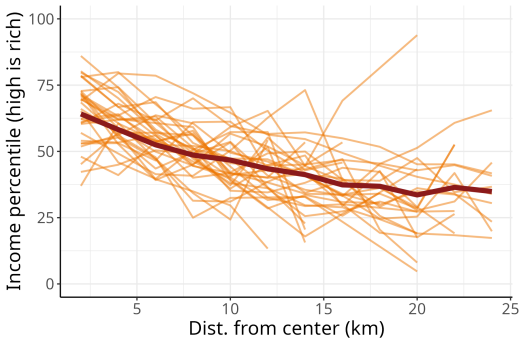
Figure B.1: Residential Income and Distance to City Center: Nonparametric Plots, by Continent



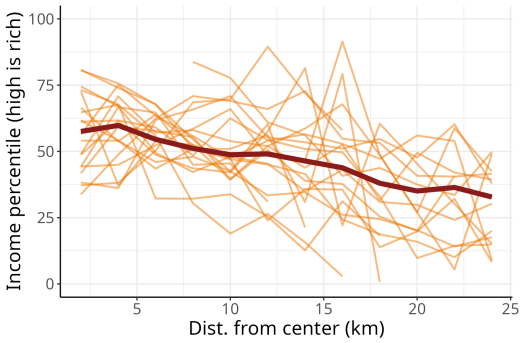
(a) USA



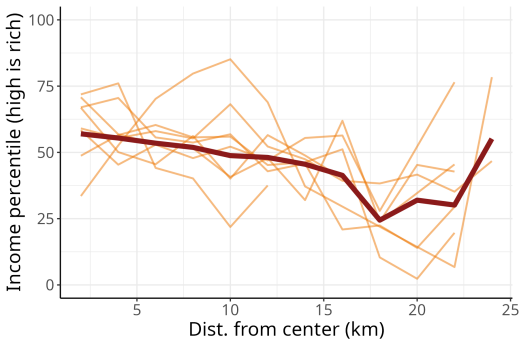
(b) W. Europe or Japan



(c) South America



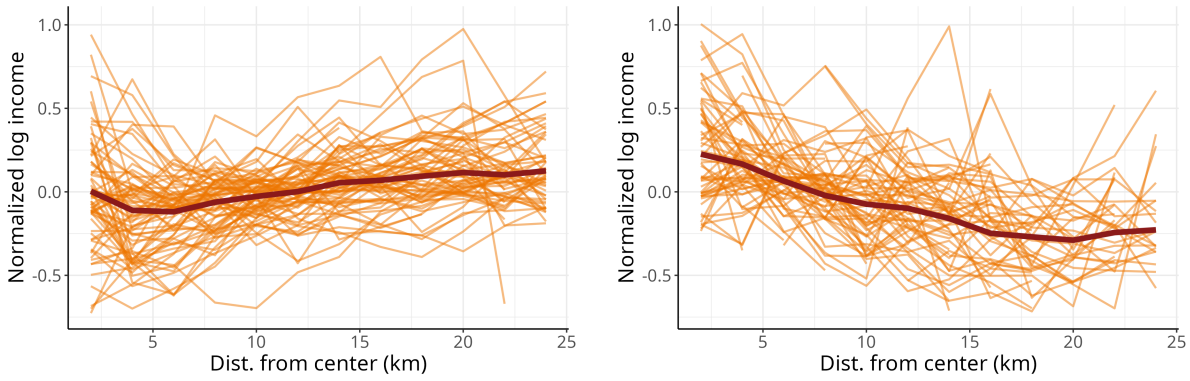
(d) Asia, E. Europe



(e) Africa, M. East

Note: Distance from the city center and average neighborhood residential income percentile. Emulates Figure B.1, grouping by continent rather than development status. Each light line represents a single city, and averages are highlighted in bold.

Figure B.2: Residential Income and Distance from City Center: Normalized Log Income

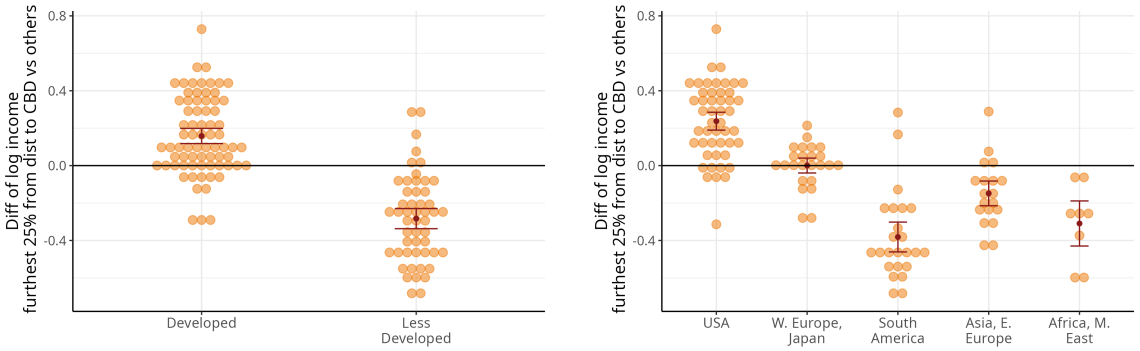


(a) Developed Cities

(b) Less Developed Cities

Note: Distance from the city center and income. Emulates Figure B.1, except using normalized log income on the y-axis. Each light line represents a single city, and averages are highlighted in bold.

Figure B.3: Suburban-Urban Income Gap: log Income

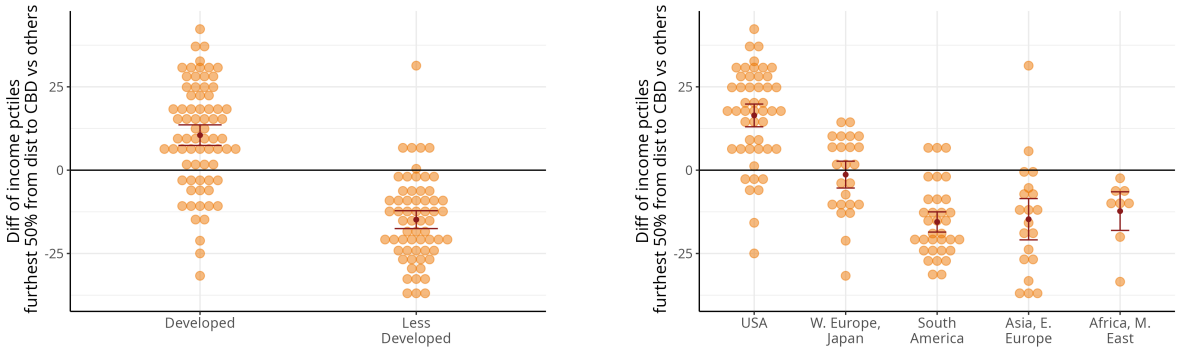


(a) By Development Status

(b) By Continents

Note: Distance from the city center and income. Emulates Figure B.1, except using normalized log income on the y-axis, and with cities grouped by continent rather than development status. Each light line represents a single city, and averages are highlighted in bold

Figure B.4: Suburban-Urban Income Gap: By City, 50 percent as cut-off of ratio of income percentiles



(a) By Development Status

(b) By Continents

Note: The "suburban-urban income gap" of each city. Emulates Figure 3, except suburban neighborhoods are those with the outer 50 percent of the population, as opposed to the outer 25 percent. Each dot represents a city. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

Table B.1: Suburban-Urban Income Gap: Top and Bottom 20 Cities

City	Country	Ratio	Continent	Development status
Damascus	Syrian Arab Republic	-42.63	Africa, M. East	Less Developed
Phnom Penh	Cambodia	-37.23	Asia, E. Europe	Less Developed
Hanoi	Viet Nam	-36.99	Asia, E. Europe	Less Developed
Ho Chi Minh City	Viet Nam	-34.27	Asia, E. Europe	Less Developed
Lima	Peru	-32.61	South America	Less Developed
Phnom Penh	Cambodia	-31.63	Asia, E. Europe	Less Developed
Uberlândia	Brazil	-30.71	South America	Less Developed
Tokyo	Japan	-29.47	W. Europe, Japan	Developed
Goiânia	Brazil	-29.23	South America	Less Developed
Kinshasa	D.R. of the Congo	-27.31	Africa, M. East	Less Developed
Lahore	Pakistan	-26.76	Asia, E. Europe	Less Developed
Curitiba	Brazil	-25.96	South America	Less Developed
Dhaka	Bangladesh	-25.53	Asia, E. Europe	Less Developed
Ho Chi Minh City	Viet Nam	-25.00	Asia, E. Europe	Less Developed
Belém	Brazil	-24.50	South America	Less Developed
Seattle	United States	-24.02	USA	Developed
Porto Alegre	Brazil	-23.10	South America	Less Developed
Vila Velha	Brazil	-23.08	South America	Less Developed
Mombasa	Kenya	-22.12	Africa, M. East	Less Developed
Lille	France	-21.40	W. Europe, Japan	Developed

(a) Bottom 20 Cities

City	Country	Ratio	Continent	Development status
Fresno	United States	39.43	USA	Developed
Indianapolis	United States	32.82	USA	Developed
Oklahoma City	United States	32.27	USA	Developed
Columbus	United States	31.86	USA	Developed
Omaha	United States	31.78	USA	Developed
Providence	United States	30.67	USA	Developed
Buffalo	United States	29.99	USA	Developed
Tucson	United States	29.33	USA	Developed
San Antonio	United States	28.57	USA	Developed
Cleveland	United States	27.95	USA	Developed
Detroit	United States	27.85	USA	Developed
Dà Nang	Viet Nam	27.70	Asia, E. Europe	Less Developed
Baltimore	United States	27.63	USA	Developed
Milwaukee	United States	27.51	USA	Developed
Las Vegas	United States	27.28	USA	Developed
Bakersfield	United States	24.76	USA	Developed
St. Louis	United States	24.71	USA	Developed
Sacramento	United States	24.50	USA	Developed
Kansas City	United States	22.64	USA	Developed
Houston	United States	22.40	USA	Developed

(b) Top 20 Cities

Note: A list of the top and bottom 20 cities, ranked by the gap ratio of income between suburban vs urban areas. Suburban neighborhoods are those containing the furthest 25 percent of the population.

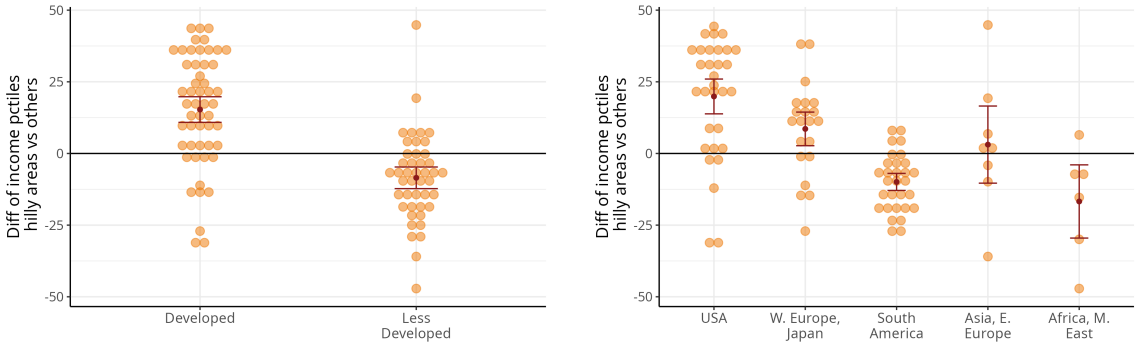
Table B.2: Suburban-Urban Income Gap: By Country

Country	ratio	Cities	continent	dev_status
Syrian Arab Republic	-42.63	1	Africa, M. East	Less Developed
Cambodia	-34.43	2	Asia, E. Europe	Less Developed
Peru	-32.61	1	South America	Less Developed
Japan	-29.47	1	W. Europe, Japan	Developed
D.R. of the Congo	-27.31	1	Africa, M. East	Less Developed
Sri Lanka	-20.28	1	Asia, E. Europe	Less Developed
Côte d'Ivoire	-17.11	1	Africa, M. East	Less Developed
Myanmar	-16.46	1	Asia, E. Europe	Less Developed
Pakistan	-15.89	2	Asia, E. Europe	Less Developed
Viet Nam	-15.17	5	Asia, E. Europe	Less Developed
Bangladesh	-14.32	2	Asia, E. Europe	Less Developed
Brazil	-14.00	31	South America	Less Developed
Lao People's DR	-13.67	1	Asia, E. Europe	Less Developed
Nicaragua	-13.32	1	South America	Less Developed
Philippines	-12.46	2	Asia, E. Europe	Less Developed
Kenya	-12.10	3	Africa, M. East	Less Developed
Indonesia	-10.83	1	Asia, E. Europe	Less Developed
U.R. of Tanzania: Mainland	-10.17	1	Africa, M. East	Less Developed
Malaysia	-7.01	1	Asia, E. Europe	Less Developed
Egypt	-4.31	1	Africa, M. East	Less Developed
France	-3.73	7	W. Europe, Japan	Developed
Romania	-3.65	1	Asia, E. Europe	Less Developed
China	1.45	1	Asia, E. Europe	Less Developed
Spain	2.66	7	W. Europe, Japan	Developed
United Kingdom	6.64	9	W. Europe, Japan	Developed
United States	15.79	48	USA	Developed

Note: A list of all countries in our neighborhood-level income dataset ranked by the gap ratio of income between suburban vs urban areas. Suburban neighborhoods are those containing the furthest 25 percent of the population.

B.2. Residential Income and Hills/Rivers

Figure B.5: Residential Income and Hills: By City

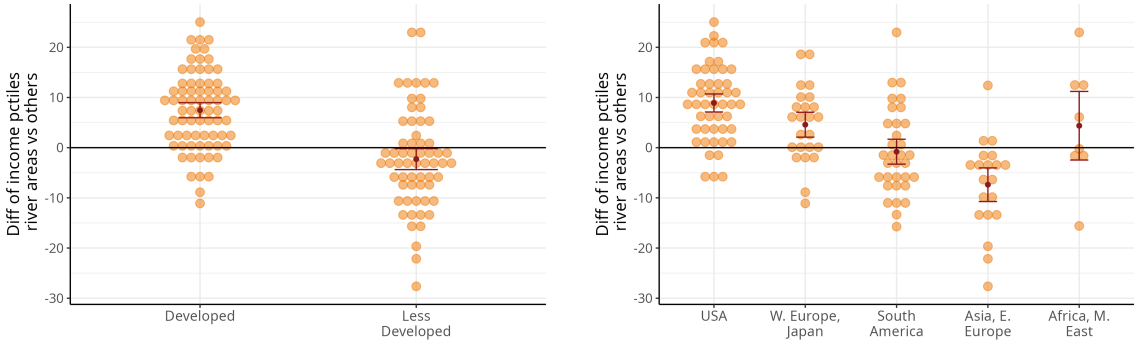


(a) By Development Status

(b) By Continents

Note: Differences in average income percentile between hilly neighborhoods and non-hilly neighborhoods, as defined in Section 2. Emulates Figure 4, but focuses only on hills. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

Figure B.6: Residential Income and Rivers: By City



(a) By Development Status

(b) By Continents

Note: Differences in average income percentile between neighborhoods that are near a river, meaning within 100 meters of a natural waterway. Emulates Figure 4, but focuses only on rivers. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

Table B.3: Residential Income and Hills/Rivers: Top and Bottom 20 Cities

City	Country	Ratio	Continent	Development status
Lima	Peru	-30.17	South America	Less Developed
Phnom Penh	Cambodia	-27.63	Asia, E. Europe	Less Developed
Dhaka	Bangladesh	-22.14	Asia, E. Europe	Less Developed
Phnom Penh	Cambodia	-19.65	Asia, E. Europe	Less Developed
Vila Velha	Brazil	-16.64	South America	Less Developed
Cairo	Egypt	-15.73	Africa, M. East	Less Developed
Ho Chi Minh City	Viet Nam	-13.71	Asia, E. Europe	Less Developed
Ho Chi Minh City	Viet Nam	-13.36	Asia, E. Europe	Less Developed
Lahore	Pakistan	-13.08	Asia, E. Europe	Less Developed
Managua	Nicaragua	-12.53	South America	Less Developed
Florianópolis	Brazil	-12.42	South America	Less Developed
Bordeaux	France	-11.94	W. Europe, Japan	Developed
João Pessoa	Brazil	-11.89	South America	Less Developed
Maceió	Brazil	-11.79	South America	Less Developed
Sao Jose dos Campos	Brazil	-11.35	South America	Less Developed
Recife	Brazil	-10.50	South America	Less Developed
Quezon City	Philippines	-9.94	Asia, E. Europe	Less Developed
São Paulo	Brazil	-9.25	South America	Less Developed
Birmingham	United Kingdom	-8.97	W. Europe, Japan	Developed
Curitiba	Brazil	-8.79	South America	Less Developed

(a) Bottom 20 Cities

City	Country	Ratio	Continent	Development status
Damascus	Syrian Arab Republic	25.38	Africa, M. East	Less Developed
Bridgeport	United States	25.03	USA	Developed
Albuquerque	United States	22.99	USA	Developed
Portland	United States	22.72	USA	Developed
Concord	United States	21.79	USA	Developed
Cleveland	United States	21.40	USA	Developed
Minneapolis	United States	20.71	USA	Developed
Detroit	United States	20.45	USA	Developed
Leeds	United Kingdom	18.85	W. Europe, Japan	Developed
Seattle	United States	18.03	USA	Developed
Los Angeles	United States	17.20	USA	Developed
Columbus	United States	17.05	USA	Developed
New York	United States	16.69	USA	Developed
Dà Nang	Viet Nam	16.55	Asia, E. Europe	Less Developed
Milwaukee	United States	16.47	USA	Developed
Virginia Beach	United States	16.35	USA	Developed
Sacramento	United States	16.29	USA	Developed
Málaga	Spain	16.26	W. Europe, Japan	Developed
Miami	United States	16.17	USA	Developed
Austin	United States	15.89	USA	Developed

(b) Top 20 Cities

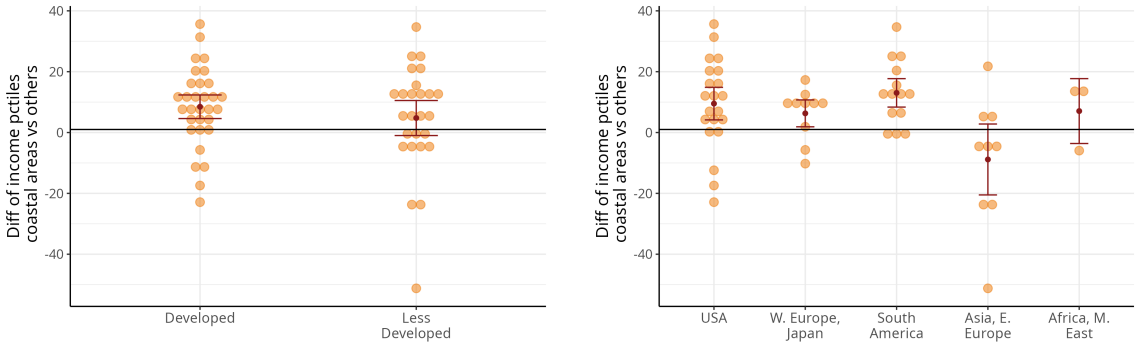
Note: A list of the top and bottom 20 cities, ranked by the gap in income percentile between neighborhoods that are hilly or near a river and thost that are not, as defined in Section 2

Table B.4: Residential Income and Hills/Rivers: By Country

Country	ratio	Cities	continent	dev_status
Peru	-30.17	1	South America	Less Developed
Cambodia	-23.64	2	Asia, E. Europe	Less Developed
Egypt	-15.73	1	Africa, M. East	Less Developed
Bangladesh	-12.83	2	Asia, E. Europe	Less Developed
Nicaragua	-12.53	1	South America	Less Developed
Philippines	-9.03	2	Asia, E. Europe	Less Developed
Pakistan	-8.32	2	Asia, E. Europe	Less Developed
Romania	-6.04	1	Asia, E. Europe	Less Developed
Lao People's DR	-3.91	1	Asia, E. Europe	Less Developed
Sri Lanka	-3.78	1	Asia, E. Europe	Less Developed
Brazil	-3.78	31	South America	Less Developed
Myanmar	-2.99	1	Asia, E. Europe	Less Developed
Japan	-2.75	1	W. Europe, Japan	Developed
Côte d'Ivoire	-2.41	1	Africa, M. East	Less Developed
Viet Nam	-2.25	5	Asia, E. Europe	Less Developed
Indonesia	-1.03	1	Asia, E. Europe	Less Developed
China	1.63	1	Asia, E. Europe	Less Developed
Malaysia	2.74	1	Asia, E. Europe	Less Developed
Kenya	3.44	3	Africa, M. East	Less Developed
Spain	3.95	7	W. Europe, Japan	Developed
D.R. of the Congo	4.20	1	Africa, M. East	Less Developed
United Kingdom	4.78	9	W. Europe, Japan	Developed
U.R. of Tanzania: Mainland	6.10	1	Africa, M. East	Less Developed
France	7.15	7	W. Europe, Japan	Developed
United States	10.76	48	USA	Developed
Syrian Arab Republic	25.38	1	Africa, M. East	Less Developed

Note: A list of countries, ranked by the gap in income percentile between neighborhoods that are hilly or near a river and those that are not, as defined in Section 2

Figure B.7: Residential Income and Coasts: By City



(a) By Development Status

(b) By Continents

Note: Differences in average income percentile between neighborhoods that are within 100m of a coast and those that are not. Emulates Figure 4, but focuses on coasts. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

B.3. Robustness of Regression Analysis

Table B.5: Regression Results of Neighborhood Residential Income: log income instead of income percentiles

Dependent Variable:	Log nbhd average income			
Model:	(1)	(2)	(3)	(4)
Variables				
Developed × Top 25% distance from center	0.153***			0.135***
	(0.025)			(0.025)
Less Developed × Top 25% distance from center	-0.310***			-0.302***
	(0.037)			(0.037)
Developed × Hilly		0.206***		0.192***
		(0.043)		(0.044)
Less Developed × Hilly		-0.198***		-0.181***
		(0.039)		(0.039)
Developed × < 100m from river			0.116***	0.097***
			(0.015)	(0.014)
Less Developed × < 100m from river			-0.070***	-0.052**
			(0.021)	(0.021)
Difference in slopes: Developed vs Less Developed				
Top 25% distance from center	-0.462***			-0.438***
	(0.0446)			(0.0442)
Hilly		-0.404***		-0.373***
		(0.0583)		(0.0591)
< 100m from river			-0.186***	-0.149***
			(0.0258)	(0.0249)
Weight	City	City	City	City
Subset	Full	Full	Full	Full
Fixed-effects				
City	Yes	Yes	Yes	Yes
Fit statistics				
Observations	145,500	145,500	145,500	145,500

*Note: Robustness results to Table 2 using Log neighborhood average income in place of income percentiles. Panel (a) reports the results of the regression (1), and the bottom panel reports the differences in the regression coefficients between developed and less-developed cities calculated through at Wald test. Unit of observation is a neighborhood and weights are the inverse number of neighborhoods in each city c. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.*

Table B.6: Regression Results of Neighborhood Residential Income: Neighborhood Controls and Restrictions

Dependent Variable:	Income percentile (high is rich)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Developed × Top 25% distance from center	7.55***	11.1***	7.12**	3.84**	9.73***
	(1.72)	(2.09)	(3.12)	(1.89)	(1.74)
Less Developed × Top 25% distance from center	-14.8***	-15.4***	-12.9***	-14.6***	-14.8***
	(1.41)	(1.88)	(2.41)	(1.71)	(1.63)
Developed × Hilly	13.3***	12.6***	11.9***	8.48**	14.3***
	(3.32)	(3.42)	(3.82)	(3.80)	(3.19)
Less Developed × Hilly	-8.21***	-7.27***	-7.19***	-8.64***	-7.25***
	(1.34)	(1.61)	(1.72)	(1.30)	(1.73)
Developed × < 100m from river	4.72***	5.95***	6.14***	5.50***	6.24***
	(0.861)	(1.01)	(1.10)	(0.978)	(0.886)
Less Developed × < 100m from river	-3.13***	-3.60***	-3.17***	-3.31***	-2.15
	(1.05)	(1.14)	(1.16)	(1.10)	(1.32)
Difference in slopes: Developed vs Less Developed					
Top 25% distance from center	-22.3***	-26.5***	-20.0***	-18.5***	-24.5***
	(2.22)	(2.81)	(3.94)	(2.55)	(2.39)
Hilly	-21.5***	-19.9***	-19.1***	-17.1***	-21.6***
	(3.59)	(3.78)	(4.18)	(4.02)	(3.63)
< 100m from river	-7.85***	-9.55***	-9.31***	-8.81***	-8.38***
	(1.35)	(1.52)	(1.60)	(1.47)	(1.59)
Weight	City	City	City	City	Nbhd pop
Subset	Full	<25km CBD	<15km CBD	Fully urban	Full
Fixed-effects					
City	Yes	Yes	Yes	Yes	Yes
Varying Slopes					
Polygon Area (City)	Yes				
NE (City)	Yes				
SW (City)	Yes				
NW (City)	Yes				
Fit statistics					
Observations	145,520	127,596	97,104	134,552	145,520

*Note: Robustness to Table 2 exploring three dimensions; Including controls, more restrictive definitions of the city (to ensure we omit rural areas), and weighting by neighborhood population. Panel (a) reports the results of the regression (1), and the bottom panel reports the differences in the regression coefficients between developed and less-developed cities calculated through at Wald test. Unit of observation is a neighborhood and weights are the inverse number of neighborhoods in each city c. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.*

Table B.7: Regression Results of Neighborhood Residential Income: Continents Leave-One-Out

Dependent Variable:	Income percentile (high is rich)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Developed × Top 25% distance from center	9.16***	9.16***	9.16***	-0.061	14.3***
	(1.78)	(1.78)	(1.78)	(2.66)	(1.96)
Less Developed × Top 25% distance from center	-17.8***	-15.1***	-15.6***	-15.9***	-15.9***
	(2.77)	(1.72)	(1.88)	(1.71)	(1.71)
Developed × Hilly	14.0***	14.0***	14.0***	7.36	20.0***
	(3.19)	(3.19)	(3.19)	(4.55)	(3.34)
Less Developed × Hilly	3.30	-8.93***	-7.71***	-7.17***	-7.17***
	(3.44)	(1.36)	(1.62)	(1.58)	(1.58)
Developed × < 100m from river	6.25***	6.25***	6.25***	4.64***	6.87***
	(0.907)	(0.907)	(0.906)	(1.53)	(1.05)
Less Developed × < 100m from river	-3.65**	-2.32	-4.93***	-3.77***	-3.77***
	(1.70)	(1.41)	(1.03)	(1.13)	(1.13)
Difference in slopes: Developed vs Less Developed					
Top 25% distance from center	-26.9***	-24.3***	-24.8***	-15.8***	-30.1***
	(3.30)	(2.48)	(2.59)	(3.17)	(2.60)
Hilly	-10.7**	-23.0***	-21.8***	-14.5***	-27.2***
	(4.69)	(3.46)	(3.58)	(4.81)	(3.69)
< 100m from river	-9.90***	-8.57***	-11.2***	-8.40***	-10.6***
	(1.93)	(1.67)	(1.37)	(1.90)	(1.54)
Weight	City	City	City	City	City
Subset	No South America	No Asia, E. Europe	No Africa, M. East	No USA	No W. Europe, Japan
Fixed-effects					
City	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	51,073	141,441	144,186	117,865	127,515

*Note: Robustness to Table 2 exploring omitting continents, one by one, from analysis. Panel (a) reports the results of the regression (1), and the bottom panel reports the differences in the regression coefficients between developed and less-developed cities calculated through at Wald test. Unit of observation is a neighborhood and weights are the inverse number of neighborhoods in each city c. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.*

Table B.8: Neighborhood-level regressions: Alternative distance measures

Dependent Variable:	Income percentile (high is rich)		
Model:	(1)	(2)	(3)
Variables			
Developed × Top 50% distance from center	9.65***		
	(1.88)		
Less Developed × Top 50% distance from center	-15.7***		
	(1.75)		
Developed × Log dist. from center		5.47***	
		(1.20)	
Less Developed × Log dist. from center		-10.3***	
		(1.25)	
Developed × Dist. to center, neighborhood percentile rank			0.186***
			(0.035)
Less Developed × Dist. to center, neighborhood percentile rank			-0.293***
			(0.032)
Difference in slopes: Developed vs Less Developed			
Top 50% distance from center	-25.3***		
	(2.57)		
Log dist. from center		-15.8***	
		(1.73)	
Dist. to center, neighborhood percentile rank			-0.479***
			(0.0479)
Weight	City	City	City
Subset	Full	Full	Full
Fixed-effects			
City	Yes	Yes	Yes
Fit statistics			
Observations	145,520	145,520	145,520

*Note: Robustness to Table 2 exploring alternative measures of distance from the city center. Panel (a) reports the results of the regression (1), and the bottom panel reports the differences in the regression coefficients between developed and less-developed cities calculated through at Wald test. Unit of observation is a neighborhood and weights are the inverse number of neighborhoods in each city c. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.*

Table B.9: Regression Results of Neighborhood Residential Income: Including Coast

Dependent Variable:	Income percentile (high is rich)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Developed × Top 25% distance from center	10.3***				8.95***
	(1.79)				(1.77)
Less Developed × Top 25% distance from center	-16.2***				-15.9***
	(1.75)				(1.70)
Developed × Hilly		15.0***			14.0***
		(3.09)			(3.17)
Less Developed × Hilly		-8.02***			-7.06***
		(1.63)			(1.60)
Developed × < 100m from river			7.58***		5.89***
			(0.946)		(0.893)
Less Developed × < 100m from river			-4.68***		-3.76***
			(1.25)		(1.13)
Developed × < 100m from coast				11.6***	9.25***
				(1.98)	(1.93)
Less Developed × < 100m from coast				4.37*	5.19**
				(2.58)	(2.36)
Difference in slopes: Developed vs Less Developed					
Top 25% distance from center	-26.5***				-24.9***
	(2.50)				(2.46)
Hilly		-23.0***			-21.1***
		(3.49)			(3.55)
< 100m from river			-12.3***		-9.65***
			(1.57)		(1.44)
< 100m from coast				-7.28**	-4.05
				(3.25)	(3.05)
Weight	City	City	City	City	City
Subset	Full	Full	Full	Full	Full
Fixed-effects					
City	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	145,520	145,520	145,520	145,520	145,520

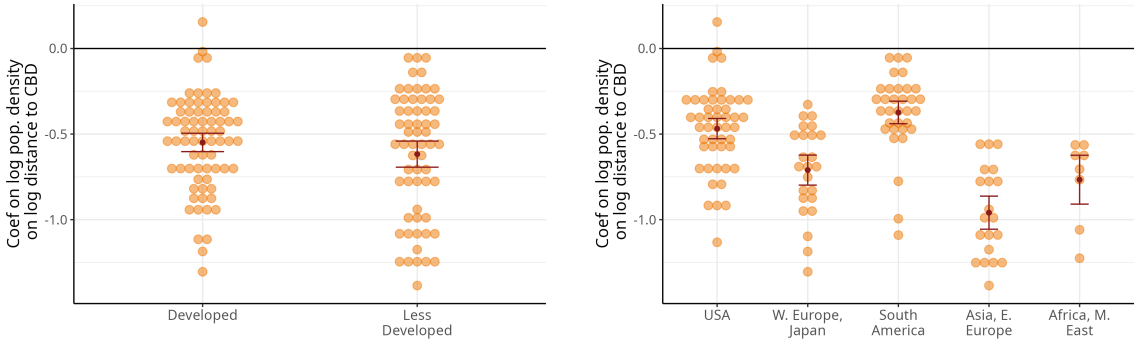
*Note: Analysis similar to Table 2 where we analyze income sorting patterns by distance to a coast. Coastal neighborhoods are those within 100m from a coastline, as defined in Section 2. Panel (a) reports the results of the regression (1), and the bottom panel reports the differences in the regression coefficients between developed and less-developed cities calculated through at Wald test. Unit of observation is a neighborhood and weights are the inverse number of neighborhoods in each city c. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels.*

Table B.10: Regression Results of Population Density

Dependent Variable:	log_pop_density			
Model:	(1)	(2)	(3)	(4)
Variables				
Developed × Top 25% distance from center	-0.785***			-0.686***
	(0.057)			(0.055)
Less Developed × Top 25% distance from center	-1.06***			-1.01***
	(0.093)			(0.083)
Developed × Hilly		-0.849***		-0.772***
		(0.113)		(0.116)
Less Developed × Hilly		-0.461***		-0.415***
		(0.109)		(0.083)
Developed × < 100m from river			-0.689***	-0.593***
			(0.035)	(0.032)
Less Developed × < 100m from river			-0.721***	-0.662***
			(0.063)	(0.052)
Difference in slopes: Developed vs Less Developed				
Top 25% distance from center	-0.271**			-0.323***
	(0.109)			(0.0995)
Hilly		0.388**		0.357**
		(0.157)		(0.142)
< 100m from river			-0.0313	-0.0687
			(0.0722)	(0.0612)
Weight	City	City	City	City
Subset	Full	Full	Full	Full
Fixed-effects				
City	Yes	Yes	Yes	Yes
Fit statistics				
Observations	145,520	145,520	145,520	145,520

*Note: Analysis similar to 2 using population density, as opposed to income as the outcome variable. Panel (a) reports the results of the regression (1), and the bottom panel reports the differences in the regression coefficients between developed and less-developed cities calculated through at Wald test. Unit of observation is a neighborhood and weights are the inverse number of neighborhoods in each city c. ***, ** and * indicate statistical significance at the 1-percent, 5-percent, and 10-percent levels.*

Figure B.8: Population Density and Distance to City Center

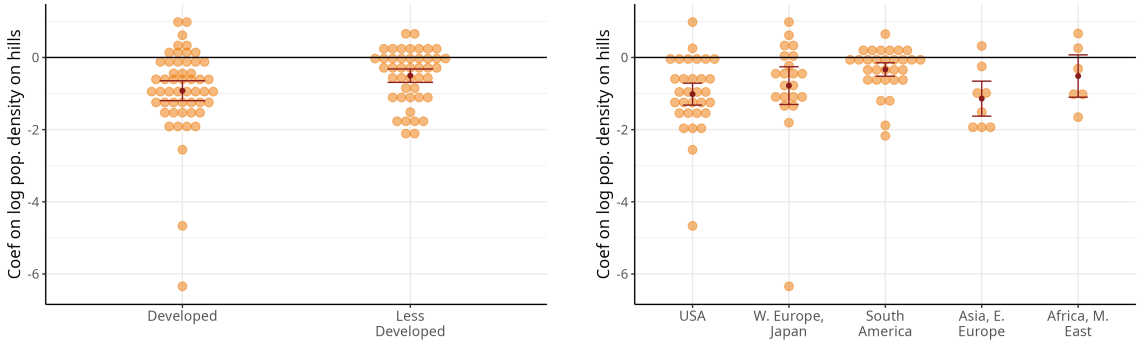


(a) By Development Status

(b) By Continents

Note: Population density gradient across cities. Emulates Figure 3, however instead of income ratios as the outcome, we analyze the analyze the population density gradient, defined as the coefficient of log distance to the city center regressed on log population density. Dots represent cities. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

Figure B.9: Population Density and Hills

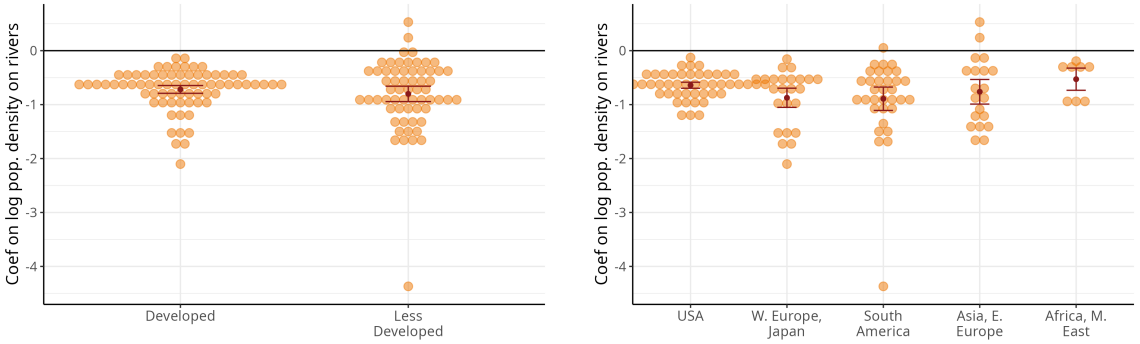


(a) By Development Status

(b) By Continents

Note: Population density and hilliness across cities. Emulates Figure B.5, however instead of income ratios as the outcome, our outcome is the coefficient of hilliness when regressed on log population density. Dots represent cities. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

Figure B.10: Population Density and Rivers



(a) By Development Status

(b) By Continents

Note: Population density and being near a river across cities. Emulates Figure B.6, however instead of income ratios as the outcome, our outcome is the coefficient of being near a river when regressed on log population density. Dots represent cities. Panel (a) groups cities by development status, Panel (b) by continent. We also plot the average value and its 95 percent confidence interval.

C. Additional Figures and Tables for Quantitative Analysis

Figure C.1: Estimated Elasticity of Commuting to Road Distance

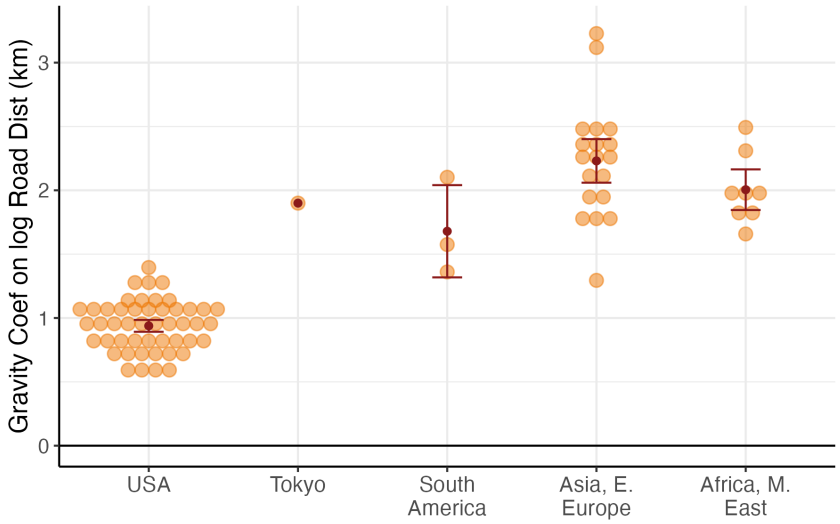


Table C.1: Regression Results of Estimated A_j and $\overline{w}_j$: Elasticity Specification for Gravity

Dependent Variables:	$\log A_j (= \tilde{\psi}_j/\theta)$	$\log \overline{w}_j = (-\eta_j/\theta)$
Model:	(1)	(2)
Variables		
Developed × Top 25% distance from center	-0.130***	-0.105***
	(0.015)	(0.009)
Less Developed × Top 25% distance from center	-0.352***	-0.368***
	(0.033)	(0.036)
Developed × Hilly	-0.261***	-0.024***
	(0.034)	(0.007)
Less Developed × Hilly	-0.233***	-0.173***
	(0.035)	(0.041)
Developed × < 100m from river	-0.024***	-0.015***
	(0.007)	(0.002)
Less Developed × < 100m from river	-0.171***	-0.100***
	(0.021)	(0.020)
Difference in slopes: Developed vs Less Developed		
Top 25% distance from center	-0.222***	-0.263***
	(0.0360)	(0.0375)
Hilly	0.0281	-0.149***
	(0.0490)	(0.0412)
< 100m from river	-0.147***	-0.0843***
	(0.0228)	(0.0198)
Weight	City	City
Subset	USA, Tokyo, JICA Cities	USA, Tokyo, JICA Cities
Fixed-effects		
City	Yes	Yes
Fit statistics		
Observations	33,453	33,560

Note: A version of Table 3 by alternatively specifying the travel cost as an isoelastic function of road distance (instead of power function). Estimates based on $\theta = 5$. $\tilde{\psi}_{nc} \equiv \psi_{nc} - \log Area_{nc}$.

Table C.2: Regression Coefficients on Income: Model vs Data

	Dependent variable:	
	log income (Model)	log income (Data)
	(1)	(2)
Suburban	0.213^{***}	0.213^{***}
	(0.002)	(0.007)
Hilly	0.295^{***}	0.295^{***}
	(0.004)	(0.014)
River	0.116^{***}	0.116^{***}
	(0.002)	(0.006)
Observations	27,129	27,129
R^2	0.672	0.165
Adjusted R^2	0.672	0.164

Table C.3: Counterfactual Simulation: Sorting of High- vs Low-Earning Potential Households

	Dependent variable:			
	log Fraction of High Earning Potential			
	(1)	(2)	(3)	(4)
Suburban	1.815^{***}	0.282^{***}	3.330^{***}	-0.680^{***}
	(0.011)	(0.010)	(0.020)	(0.007)
Hilly	2.304^{***}	-0.222^{***}	3.473^{***}	-1.022^{***}
	(0.024)	(0.022)	(0.042)	(0.014)
River	0.780^{***}	0.088^{***}	1.448^{***}	-0.508^{***}
	(0.010)	(0.009)	(0.018)	(0.006)
Cities	US	US	US	US
Spec	Data	Lower Income	Increase Comm Costs	Lower Income & Increase Comm Costs
Observations	27,129	27,129	27,129	27,129
R^2	0.662	0.085	0.635	0.511
Adjusted R^2	0.661	0.083	0.634	0.510

Note: Results of the regression (1) using log mean residential income as an outcome variable. For outcome variables, Column (1) uses the prediction in our calibrated model to the USA, where the regression coefficients coincide with those using actual data due to our calibration strategy (Section 6.1); Column (2) uses the prediction from the counterfactual to lower $\{A_{jc}\}_j$ by 190 log points; Column (3) uses the prediction from the counterfactual to increase $\tilde{\kappa}_c$ by 0.30; Column (4) uses the prediction from changing $\{A_{jc}\}_j$ and $\tilde{\kappa}_c$ simultaneously.