The Spatial Distribution of Income in Cities: New Global Evidence and Theory

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Abstract

We study how the spatial distribution of income and commuting patterns within cities vary across the development spectrum, drawing on new granular data from 50,000 neighborhoods in 121 cities across developed and developing countries. We document that in developing countries, poorer urban households are significantly more likely to live far from city centers, in hilly terrain, and near rivers. These patterns are absent or reversed in developed cities. Commuting shares decline more sharply with distance in less developed countries, indicating higher commuting costs that exacerbate spatial inequality in job access. Job-access measures are considerably worse for the urban poor than for the urban rich in developing countries, while the opposite is true in developed countries. We interpret these findings in a quantitative urban model and show that a parsimonious set of factors—nonhomothetic preferences over amenities, commuting costs, and the spatial concentration of jobs—helps explain most of the cross-country patterns we document.

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1. Introduction

More than half of the world's population now live in cities. Most of these urbanites—an estimated 3.7 billion people—reside in less developed nations, in crowded metropolises such as Dhaka or Dar es Salaam (United Nations, 2022). For some people, cities serve as the pathway out of poverty, providing reliable access to earning opportunities (Busso, Carrillo, and Chauvin, 2023). Yet many others are stuck in slums, where jobs are few and far away (Marx, Stoker, and Suri, 2013).

A growing literature on the urban economics of low- and middle-income countries has sought to better understand how cities can foster job opportunities for wide swaths of the urban population and not just a select few. However, this research has typically focused on individual cities in the developing world, studying the distributional implications of specific policy changes (see Bryan, Glaeser, and Tsivanidis, 2020; Bryan, Frye, and Morten, 2025, and the references therein). The literature still lacks a comprehensive picture of how cities vary across the development spectrum and how economic development shapes the lives of the urban poor relative to the urban rich.

This paper contributes by building and analyzing a new dataset with granular information on income and commuting from 50,000 neighborhoods in 121 cities of all levels of income per capita. Our primary data sources for developing countries are microdata from travel surveys conducted by the Japan International Cooperation Agency (JICA), which they collect as part of urban transportation projects in partner countries. These microdata provide detailed information about urban households, reporting each respondent's residential and workplace locations alongside demographic, employment, and income information. We manually harmonize these surveys across dozens of heterogeneous questionnaires, and we georeference the survey zones to merge with various neighborhoods' geographic features, such as the locations of city centers, hilly terrain, rivers, built-up areas, and bilateral travel distances. The resulting harmonized dataset covers roughly 1.6 million urban households across 25 cities in developing countries. We further integrate these data with fine-grained administrative census sources for selected developed and developing countries, yielding a globally harmonized dataset covering 121 cities, spanning major metropolitan areas in Asia and Africa, middle-income megacities such as Lima and São Paulo, and the world's largest developed cities, including Los Angeles, London, Paris, and Tokyo.

Using this database, we document prominent ways in which residential income distributions and commuting patterns within cities vary across the development spectrum. First, we show that in less developed cities, average household income declines steadily with distance from city centers. On average, incomes fall from around the 65th percentile of the city income distribution at the center to the 40th percentile in neighborhoods 20 kilometers from the center. This pattern is present among Latin American, African, and Asian cities. In developed cities, by contrast, income gradients are generally flat (in Western Europe) or increasing with distance from the city center (in the United States). Our focus on distance to the city center is motivated by the long tradition in urban economics positing that more central locations have a higher concentration of jobs (e.g. Alonso, 1964). In simple terms, our first fact states that, on average, poorer city dwellers in less developed economies are farther from employment centers than richer ones.

Second, we examine how neighborhood incomes vary with natural amenities. We focus on proximity to hilly terrain and waterways—features of the landscape that are desired by many urban residents in developed countries (Lee and Lin, 2018). We find that in less developed cities, average incomes are significantly *lower* in hilly neighborhoods and near rivers. In developed cities, household incomes are either unrelated to these geographic features on average (in Western Europe) or even higher in hilly areas and near riverfronts (in the United States). This contrast underscores how natural amenities play different roles in less developed and developed cities. Incomplete urban transportation and residential infrastructure in less developed countries likely contributes to this pattern, an issue we return to below.

We next examine patterns of commuting and job access, and how they relate to the spatial distribution of residential income noted earlier. We estimate commuting-gravity equations for each city, measuring the decay of commuting shares across neighborhoods over bilateral distance, while controlling for residential and workplace fixed effects. We find that, in less developed cities, the share of commuters declines more rapidly with distance. In the United States, the semielasticity of commuting with respect to road distance is approximately 0.1, implying that an additional kilometer reduces commuting by 10%, holding workplace attractiveness constant. In Western Europe and Japan, the semielasticities are around 0.2, roughly twice those in the United States, potentially reflecting differences in reliance on public transit versus private cars. In developing countries, the average semielasticity rises to 0.35, with a large variation across cities.

We also find that the estimated commuting semielasticities are strongly correlated with road traffic speeds measured using the Google Maps API (Akbar, Couture, Duranton, and Storeygard, 2023a,b). Therefore, slower traffic speeds in less developed cities—partly reflecting weaker transportation infrastructure—are indeed associated with shorter effective commuting distances. However, the estimated regression slope of log semielasticities on the log speed index significantly exceeds one in absolute value, indicating that differences in traffic speed alone cannot account for the observed variation. This suggests that additional factors, such as differences in available transportation modes, likely contribute to higher commuting costs in slower, less developed cities.

The higher commuting semielasticity in less developed cities suggests that neighborhoods differ markedly in terms of job access within those cities. To explore this point further, we construct a proxy for job access as the distance-discounted sum of workplace fixed effects (Tsivanidis, 2025) and examine its relationship with residential income. In less developed cities, job access is monotonically increasing in neighborhood income. In other words, poorer residents tend to live in neighborhoods with worse job access. This mirrors our earlier finding that in less developed cities, neighborhoods located away from the city center or near hills and rivers—often remote from employment hubs—tend to be poorer. The incomes increase from around the 35th percentile of the city income in the neighborhoods with the lowest job access to the 60th percentile in those with the highest job access. By contrast, in developed cities, in both the United States and Western Europe, the relationship is opposite: It falls from the 65th percentile to around the 40th percentile.

What drives these differences in the spatial distribution of job access? Two mechanisms play central roles. First, in less developed cities, where commuting costs are higher, distance from employment centers more sharply reduces job access. Second, the spatial distribution of job opportunities—captured by the workplace fixed effects—differs systematically across development levels. We find that in less developed cities, these fixed effects are disproportionately higher in urban cores, reflecting stronger centralization of employment opportunities relative to developed cities.

Taken together, our facts point to markedly different spatial patterns of income distribution and commuting among poor and rich residents across cities throughout the development spectrum. Why do these differences arise? To answer this question, we turn to a quantitative urban model in which ex ante heterogeneous households with varying earning potentials choose residential locations by trading off job access, housing costs, and neighborhood amenities. We incorporate nonhomothetic preferences for housing and amenities, which imply that the relative importance of these factors evolves with income. In particular, nonhomotheticity in amenities makes equilibrium income sorting patterns depend on a city's overall income level. In cities with low average incomes, the primary consideration of households is access to jobs, even for relatively richer households. As income rises, they start to place a higher value on neighborhood amenities (if an amenity is a "luxury good"). Beyond this mechanism, commuting costs and spatial distribution in productivity, amenities, and housing supply further shape equilibrium residential and commuting patterns.

Our model highlights four potential explanations for the contrasting spatial income distribution between developed and less developed cities. The first is nonhomothetic preference for amenities, with richer households placing greater value on features such as open space in the suburbs, scenic hills, or waterfront views. Second, commuting costs tend to be higher in less developed countries, due in particular to weaker transportation infrastructure and lower rates of private car ownership

(Akbar et al., 2023a,b; Tsivanidis, 2025). Third, jobs may be more centralized in developing cities, which we model as a steeper decline in workplace productivity with distance from the city center (Baum-Snow, 2020; Davis and Dingel, 2020). Finally, residential amenity value may fall faster away from the city center and in hills and near rivers in less developed cities. This could capture a decline in the supply of residential infrastructure, such as sewage and embankments, or a lack of security and property rights (Harari, 2024; Gertler, Gonzalez-Navarro, Undurraga, and Urrego, 2025; McCulloch, Schaelling, Turner, and Kitagawa, 2025).[1]

How important is each channel quantitatively? We answer this question in three steps. First, we calibrate the model to match commuting and residential income patterns in U.S. cities. Here, we also estimate preferences for amenities and the degree of nonhomotheticity to target observed income sorting across neighborhoods with different housing costs, amenities, and job access. Second, we identify differences in overall productivity, commuting costs, and the spatial distribution of productivity between the United States and less developed cities, using the commuting-gravity equations estimated earlier. Third, starting from the U.S.-calibrated model, we counterfactually offset these three differences, with each counterfactual corresponding to one of the first three hypotheses laid out above. Since we lack direct data on neighborhood-level amenities and their valuations, we treat the final hypothesis—differences in amenity gradients across development levels—as a residual explanation.

We find that when lowering overall city productivity, the residential income premiums in suburban areas and areas with natural amenities decline substantially and approach zero. Increasing the commuting costs and changing the productivity concentration further reduce the income premiums and turn them negative, though these effects are smaller in magnitude than those of lowering income alone. Together, these three forces account for 80% of the observed income premium gaps in suburban, hilly, and river neighborhoods between U.S. cities and less developed cities.

While these three forces jointly explain much of the observed gap in spatial income distributions, some residual variation remains. These unexplained patterns likely reflect differences in amenity gradients within cities by development status. Central areas could have greater police protection than neighborhoods on the outskirts of town, or better provision of plumbing, electricity, and residential infrastructure (Harari, 2024). The same could be true of hilly areas, where infrastructure is more expensive to provide, and rivers in less developed cities are almost surely dirtier than their counterparts in richer countries (McCulloch et al., 2025). We leave the task of

[1] In the United States, Glaeser, Kahn, and Rappaport (2008) and Su (2022) argue that higher commuting costs faced by lower-income households without car ownership lead them to sort into central urban areas. We argue that this mechanism cannot account for the disparity between developed and less developed cities, as lower-income workers in less developed cities face even *higher* commuting cost penalties (Section 6.3).

unpacking these residual variations to future work.

Understanding spatial patterns of income distribution and commuting is crucial for designing effective urban policies. The contrasting spatial income distributions between developed and less developed cities imply that place-based interventions—such as transportation investments or residential infrastructure improvements—can have markedly different, and even opposite, distributional effects across income groups in these two contexts. Furthermore, our analysis suggests that even citywide productivity-enhancing policies may yield unequal welfare effects. As citywide income levels rise, richer households tend to relocate from dense urban cores to suburban neighborhoods with higher amenities. This relocation alleviates rent pressures in central areas, benefiting poorer residents in the urban core.

Our paper contributes to a growing body of work studying how cities differ across the development spectrum. Most cross-country comparisons of urban economic activity either rely on city-level aggregate indicators (Chauvin, Glaeser, Ma, and Tobio, 2017; Jedwab, Loungani, and Yezer, 2021; Lebrand and Kleineberg, 2024) or examine aggregate spatial statistics, such as population density gradients (Henderson and Turner, 2020), building density gradients (Ahlfeldt, Baum-Snow, and Jedwab, 2023; Rosenthal-Kay, 2024), or average road speeds (Akbar et al., 2023a,b). Much has been learned as well from detailed analyses of individual cities in developing countries.[2] Our study is closely related to those focused on cross-city comparisons of internal city structure in developing countries, such as Harari (2024) and Adukia, Asher, Jha, Novosad, and Tan (2025), who study income segregation and public access and public goods provision within Brazil and India, respectively, and Dingel, Miscio, and Davis (2021) who use data from Brazil and China to show that residents living closer to city centers are more skilled on average. We contribute to this literature by building and analyzing granular information on income and commuting from 50,000 neighborhoods in 121 cities across 26 countries, covering a wide range of income levels.

We also contribute to the empirical and theoretical literature on the spatial distribution of income within cities. Traditionally, this literature has predominantly focused on U.S. cities and has sought to explain U.S. patterns using nonhomotheticities in demand for housing or land (Alonso, 1964; Becker, 1965; Margo, 1992; Hoelzlein, 2023; Couture, Gaubert, Handbury, and Hurst, 2024; Finlay and Williams, 2025), transportation infrastructure (Glaeser et al., 2008; Su, 2022), and natural amenities (Lee and Lin, 2018). A smaller strand of research has highlighted differences between

[2] See, for example, Khanna, Nyshadham, Ramos-Menchelli, Tamayo, and Tiew (2023); Zárate (2024); Tsivanidis (2025); Bordeu (2025), and Balboni, Bryan, Morten, O'Connor, and Siddiqi (2025) for transportation infrastructure in Medellin, Mexico City, Bogota, Santiago, and Dar es Salaam, respectively; Michaels, Nigmatulina, Rauch, Regan, Baruah, and Dahlstrand (2021) and Franklin, Imbert, Abebe, and Mejia-Mantilla (2024) for residential infrastructure and urban public works programs in Dar es Salaam; and Gechter and Tsivanidis (2023) and Harari and Wong (2025) for slum-upgrading interventions in Mumbai and Jakarta, respectively.

U.S. cities and specific cities in other developed countries, attributing them to other amenities such as restaurants and bars concentrated in central areas (Brueckner, Thisse, and Zenou, 1999 for Paris; Tabuchi, 2019 for Tokyo; Almagro and Domínguez-Iino, 2025 for Amsterdam). By contrast, little has been documented or explained about the patterns in less developed cities. Our main contribution here is to adopt a cross-country perspective: we document how these patterns manifest in less developed economies and explain why they differ.

While our central focus is the comparison between developed and less developed cities, we also present systematic evidence on developed cities outside the United States, rather than relying on a few specific megacities, such as Paris or Tokyo. On average, Western European cities exhibit flat, rather than negative, income gradients with distance to the city center, as well as with hills and rivers. We show that the differences between U.S. cities and other developed cities in Western Europe and Japan stem from differences in amenity dimensions beyond the suburban and natural amenities emphasized in the U.S. context, and to a lesser extent, differences in commuting costs and spatial productivity distribution.

Although we analyze cross-sectional comparisons across cities, our findings also speak to the literature on how the spatial organization of economic activity evolves with development. Empirically, our result that residential income declines monotonically with greater distance to the city center in less developed cities parallels the evidence in Lee and Lin (2018), who show that U.S. cities exhibited this pattern in 1880, but that it reversed after 1930. Theoretically, our paper relates to work on the interaction between structural transformation of industries—from agriculture to manufacturing to services—and spatial population reallocation across cities (e.g., Bohr, Mestieri, and Robert-Nicoud, 2024; Chatterjee, Giannone, Tatjana, Kuno, and Luca, 2025; Eckert and Peters, 2025) or within them (Coeurdacier, Oswald, and Teignier, 2025). While we also emphasize the role of nonhomothetic preferences, our focus is on those for housing and amenities and how they shape spatial income distribution within cities.

2. Data

This section outlines how we integrate diverse data sources to build a comprehensive database on household income and commuting flows from 50,000 neighborhoods in 121 cities across 26 countries.

2.1. Travel Surveys From Developing Countries

Our primary data source for developing countries is microdata of travel surveys from 25 cities in 21 developing countries conducted by the Japan International Cooperation Agency (JICA), the official development cooperation agency of Japan. JICA collects these data as part of urban transportation projects in partner countries.[3] These surveys gather detailed information on residential and workplace locations, demographic characteristics (e.g., age, household size), income, employment status, and daily travel activities, including trip timing, geolocation, purpose, and transportation mode. In developed countries, such surveys are usually carried out at regular intervals in major metropolitan areas. In developing countries, they are often conducted ad hoc, typically in preparation for major infrastructure projects or city master plans, and often with support from international aid agencies such as JICA. The surveys typically follow a two-stage random sampling design based on the latest available population census, first dividing the city into survey zones and then randomly selecting clusters of households within each zone, with the targeted sampling rates of 1 to 10% depending on the city.

Panel (a) of Table 1 lists the cities included in this dataset, which spans multiple continents: three cities in Latin America, four in South Asia, 11 in East Asia, one in Eastern Europe, two in the Middle East, and five in Africa. The surveys, conducted between 1996 and 2018, vary in terms of questionnaire design and local implementation. Sample sizes range from 5,000 to 300,000 respondents, with an average of 60,000 per city.

Our travel surveys are particularly well-suited to our analysis due to their fine spatial resolution. Each survey divides the city into a large number of neighborhoods, or "survey zones," and records respondents' residential and workplace locations, as well as the origins and destinations of daily trips, at this neighborhood level.

Compiling these data required substantial manual effort. The surveys differ widely in format, structure, and documentation across cities, with many available only as scanned, non-georeferenced maps. To recover the spatial boundaries, we manually geocoded these maps to merge with other various geographic datasets (Appendix Figure A.3). On average, each city contains about 200 survey zones, with a typical zone covering roughly 5 square kilometers.

We also harmonized questionnaires to obtain household-level income information at the neighborhood level. In most cities, respondents report their household's total income, either as a continuous value or within finely disaggregated bins. In three cities (Bucharest, Dhaka, and Managua), the surveys do not directly ask for household income, but instead they collect individual income for each household member, which we aggregate to construct household-level income.

[3]JICA collaborates with governments in developing countries on urban development planning, specifically focusing on the long-term structuring of urban transportation infrastructure and developing city master plans. The initiation of these projects is demand-driven, responding to requests from JICA partner countries. Naturally, the cities covered by the surveys tend to be the capital or prime cities of each country, while they sometimes cover multiple cities from each country (i.e., Vietnam and the Philippines).

Table 1: List of Cities Covered in Our Analysis

	Latin America	Asia and Eastern Europe	Africa and Middle East
Number of Cities	3	15	7
Number of Countries	3	12	6
Avg Number of Respondents	70,469	79,214	46,113
Avg Number of Neighborhoods	190	257	178
List of Cities	Belem (00), Lima (03), Managua (98)	Bucharest (98), Cebu (14), Chengdu (00), Colombo (13), Da Nang (08), Dhaka (14), Hanoi (05), Ho Chi Minh (14), Jakarta (10), Kuala Lumpur (99), Lahore (10), Manila (96), Phnom Penh (12), Viang Chan (07), Yangon (13)	Abidjan (13), Cairo (01), Damascus (98), Dar es Salaam (07), Kinshasa (18), Mombasa (15), Nairobi (13)

(a) Less Developed Cities Surveyed by JICA, by Region

	United States	Western Europe and Japan	Latin America	Asia and Eastern Europe	Africa and Middle East
Number of Cities	48	24	27	15	7
... with Commuting Flows	48	17	3	15	7
Number of Countries	1	4	3	12	6
... with Commuting Flows	1	3	3	12	6
Total Number of Neighborhoods	27,579	13,170	4,146	3,864	1,246
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 the Neighborhood-Level Income Dataset, by Region

Notes: The two digits in the parentheses for each city in Panel (a) indicate the year in which the survey was conducted. See Appendix Tables A.1, A.2, and A.3 for the characteristics of each city in our JICA survey data; see Table A.4 for the list of cities covered in surveys other than the JICA surveys; and see Figure A.1 for a map of all the cities.

Spatially disaggregated income data are rarely available for cities in developing countries. As such, our dataset represents the first comprehensive effort to measure neighborhood-level income across a broad set of cities in developing countries. Nevertheless, concerns may arise regarding data accuracy, particularly since the travel surveys are based on a random sample of households rather than censuses. To assess the validity of our income measures, we examine the case of Belém, Brazil, the only city in our sample for which neighborhood-level income from a national census is publicly available (see Section 2.2). In Appendix A.2, we show that the travel survey data closely align with the census data in both the overall spatial income distribution and the gradient of income with respect to distance from the city center.

We also extract households' commuting information from these travel surveys. For each respondent, the survey typically records whether the individual is employed (either as a wage worker or self-employed) and, if so, their workplace location, coded at the survey-zone level.[4] In seven cities, the surveys do not directly ask about work locations. In those cases, we rely on the travel activity module, which documents the time, location, and purpose of each trip. We infer workplace locations by identifying trips made for the purpose of going to work. Using these data, we construct origin-destination commuting flows between survey zones within each city.

2.2. Additional Data on Income and Commuting Flows

We further supplement these data with fine-grained administrative census sources for selected developed and less developed countries. We collect average residential neighborhood income from census and tax data for four developed countries (United States, United Kingdom, Spain, and France) and a less developed country (Brazil). Information from the United States stems from the 2015–2019 aggregated American Community Survey (ACS) at the census-tract level. For the United Kingdom, we obtain average income at the *small-area* level from the Office of Tax Statistics in 2018. For France, we derive income from tax returns in 2016 at the *communes*, with further disaggregation into *arrondissements* within some metropolitan areas (e.g., Paris).[5] In Spain, average neighborhood income derived from tax information is available at the *sección* level for 2019. In Brazil, average neighborhood income from the 2010 census is available at the *bairros* level.[6]

For Tokyo, we have access to the microdata of the 2018 Tokyo Person Trip Survey (Tokyo Metropolitan Area Transportation Planning Council, 2018). The data share a similar structure

[4]For self-employed workers (e.g., street vendors), survey instruments typically ask respondents to report the usual location where their work activities are carried out.

[5]We use median neighborhood income, instead of mean income, for France, as the latter is not publicly available. While income information is available at the more finely disaggregated *IRIS* level, we use *communes/arrondissements* because of the availability of commuting flow data.

[6]In some parts of the country where *bairros* are not defined, we use *subdistritos*, a coarser disaggregation. While income information is available at the more finely disaggregated *setores* level (about one-tenth of the area of a U.S. census tract), we use *bairros/subdistritos* because of the comparability of neighborhood sizes with other countries.

to 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.

We obtain bilateral commuting flows in the United States, the United Kingdom, and France from various administrative datasets. We obtain commuting flow information in the United States from the Census Transportation Planning Packages (CTPP) for the years 2012 through 2016, which are constructed using the ACS data on usual residence and workplaces. The CTPP data report the aggregate number of workers living and working in any given pair of census tracks.[7] We use bilateral commuting flows from the United Kingdom derived from censuses at the *small-area* level, and from France at the *communes/arrondissements* level, with the same level of disaggregation as the income data. There are no publicly available commuting flow data from Spain or Brazil (except for Belém, where the JICA travel survey is available).

2.3. City Boundaries and Additional Geographic Data

Defining cities consistently across countries with vastly different geographies and levels of development is not a straightforward task. Rather than relying on administrative boundaries or survey coverage—which vary widely across contexts—we delineate city boundaries using the World Settlement Footprint's "Built Up Areas" dataset (Florczyk et al., 2019). This dataset classifies land use globally at a fine spatial resolution using satellite imagery, identifying contiguous "built-up" areas—regions densely covered by buildings, roads, and pavement, as opposed to agricultural or forested land. We define each city as a geographically contiguous built-up area, thereby capturing entire metropolitan areas rather than individual municipalities.[8] We show that our results are robust to alternative definitions of city boundaries. We restrict our analysis to cities with more than 400,000 residents, to align with the coverage of JICA travel surveys, which tend to cover relatively large cities.

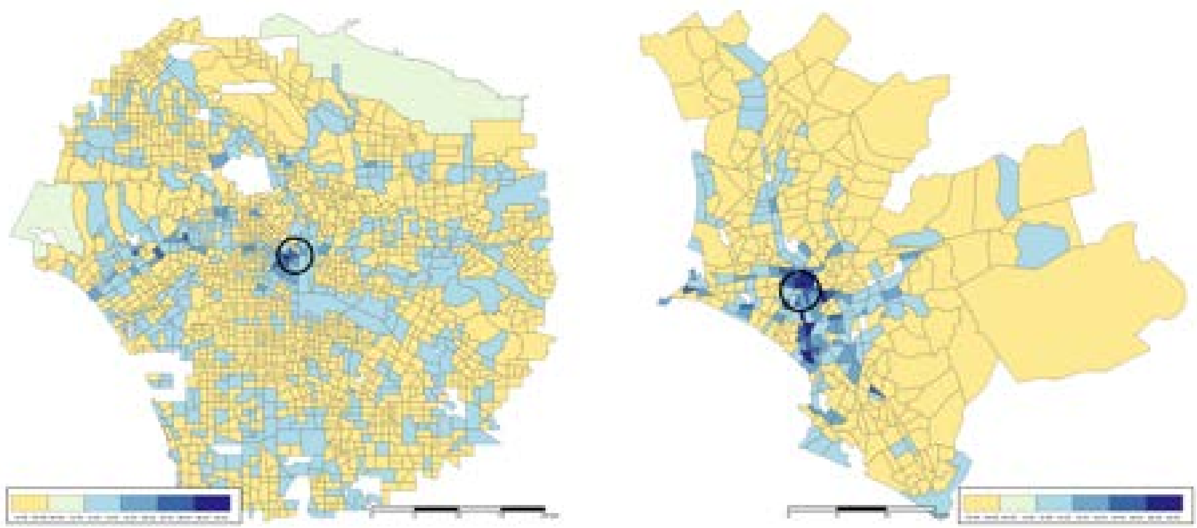
We further merge this data with various neighborhoods' geographic features. We obtain *city centers* using coordinates from OpenStreetMap (OSM), an open-source collaborative mapping platform of the world. Contributors typically assign city-center locations based on prominent

[7]An alternative commuting dataset in the United States is the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES). This dataset is constructed from the Quarterly Census of Employment and Wages, which covers all firms with paid employees and that are subject to unemployment insurance laws. While LODES provides a near-census coverage of paid workers with their precise residential locations, it excludes the self-employed and imputes worksite locations for multiestablishment firms. Due to these differences, LODES yields commuting semielasticities that are roughly two-thirds the magnitude of those estimated from the CTPP and from travel surveys in Chicago and San Francisco (Appendix A.3; see also Spear, 2011).

[8]For instance, our definition of New York City encompasses the urbanized corridor extending from New Brunswick in the south to White Plains in the north, while London includes the built-up area reaching west to Heathrow Airport. Our results are robust to changing the definitions of these boundaries (Table 3).

landmarks such as city halls or central plazas. Although this approach is heuristic, it aligns well with intuitive notions of a city center.[9] As shown in Figure 1, these locations coincide with the highest net commuter densities (in-commuters minus out-commuters per unit area) in cities such as Los Angeles and Lima. To address potential measurement error of the exact city-center locations or the presence of polycentric structures, we also analyze broader patterns between suburban areas and others, defining *suburban areas* as the neighborhoods comprising 50% of the population living farthest from the city center.

Figure 1: Net Commuting and City Centers in Los Angeles and Lima



(a) Net Commuter Density (Los Angeles) (b) Net Commuter Density (Lima)

Notes: The panels show the density of net commuters (total in-commuters minus out-commuters) for each neighborhood in Los Angeles and Lima. Darker blue indicates a higher net commuter density. Yellow indicates negative values for net-commute. The circle depicts a 2-kilometer radius from the city center.

We compute the *bilateral road distance* between all pairs of neighborhoods using the Open Source Routing Machine (OSRM), an open-source algorithm for finding the shortest path between two locations along OSM's road network (Luxen and Vetter, 2011).

We classify a neighborhood as *hilly* if its average slope (average change in elevation across four adjacent grid cells) exceeds 5 degrees, based on 30m×30m elevation data from Amazon Web Services Terrain Tiles (Larrick, Tian, Rogers, Acosta, and Shen, 2020).[10]

River proximity is defined using the HydroSHEDS dataset (Lehner and Grill, 2013), which maps

[9]For example, Cebu City's center is at the city hall, while London's is at Trafalgar Square. As an additional validation, for the 54 cities with data on "prime locations" (Ahlfeldt, Albers, and Behrens, 2020), we find that in 88% of cases our city center definitions fall within two kilometers of the centroids of the prime locations.

[10]While Lee and Lin (2018) use a 15-degree threshold, we adopt a lower cutoff to capture a broader set of moderately sloped areas, reflecting the generally less steep terrain in many cities worldwide.

global water flows based on topography and rainfall. A neighborhood is classified as *near a river* if any part lies within 100 meters of a riverbank, considering only rivers with an average flow above 1.3 cubic meters per second.

We obtain neighborhood population using the 2015 LandScan global population dataset (Bright, Rose, and Urban, 2016) for all cities covered by our travel surveys. For the United States, the United Kingdom, France, Spain, and Brazil, we rely instead on population size from the original administrative sources.

2.4. Final Datasets

We define *developed* cities as those in the United States, the United Kingdom, France, Spain, and Japan. We define *less developed* cities as those surveyed by JICA and Brazil. The poorest country covered in our data is the Democratic Republic of the Congo (the city of Kinshasa), whose GDP per capita is US$1,020. To gauge further heterogeneity within the developed and less developed cities, we often separately report estimates by *regions*, constituting the "United States" and "Western Europe and Japan" for developed cities, with "Latin America," "Asia and Eastern Europe," and "Africa and Middle East" for less developed cities.

Our final neighborhood-level income dataset contains 50,005 neighborhoods in 121 cities across 26 countries. Of these cities, 72 are classified as developed (48 from "United States" and 24 from "Western Europe and Japan") and 49 are classified as less developed (27 from "Latin America," 15 from "Asia and Eastern Europe," and 7 from "Africa and Middle East"). For bilateral commuting flows, we have data at the same level of disaggregation, except for all cities in Spain and all cities in Brazil, other than Belém. Panel (b) of Table 1 lists all the cities in our analysis.

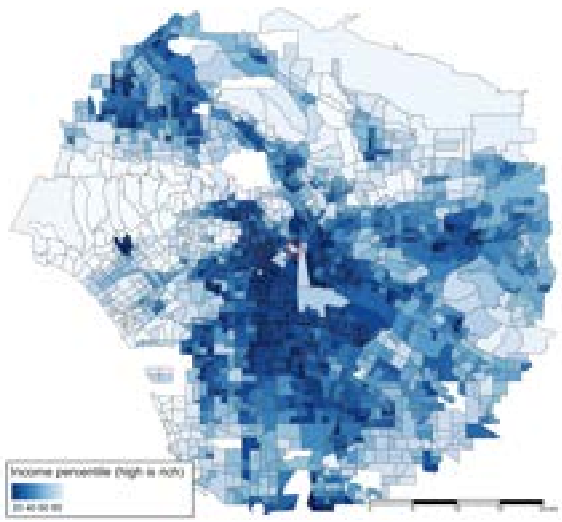
3. Spatial Distribution of Income

This section documents several prominent ways in which the spatial distribution of income within cities varies across regions and between developed and less developed cities.

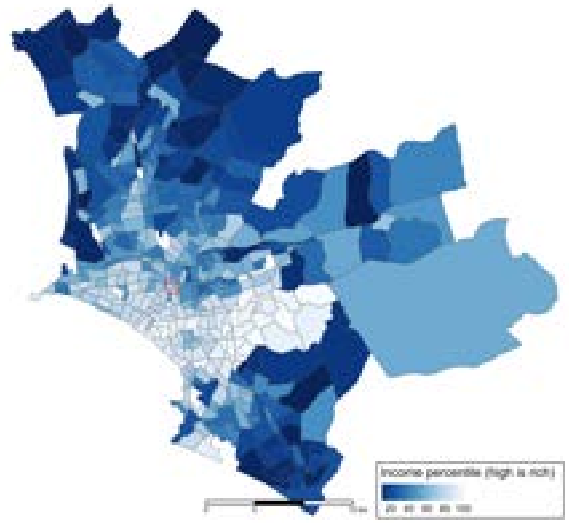
3.1. A First Look From Two Examples: Los Angeles and Lima

Before proceeding to the full statistical analysis, we begin by comparing two cities: Los Angeles and Lima. Figure 2 illustrates the income distribution and geographic features of the two cities. Panels (a) and (b) show the average residential income by neighborhood, measured as each neighborhood's percentile rank within the city, with lighter colors corresponding to higher income levels. The red circle in each panel marks the city center. Panels (c) and (d) highlight neighborhoods that are hilly or located near major waterways.

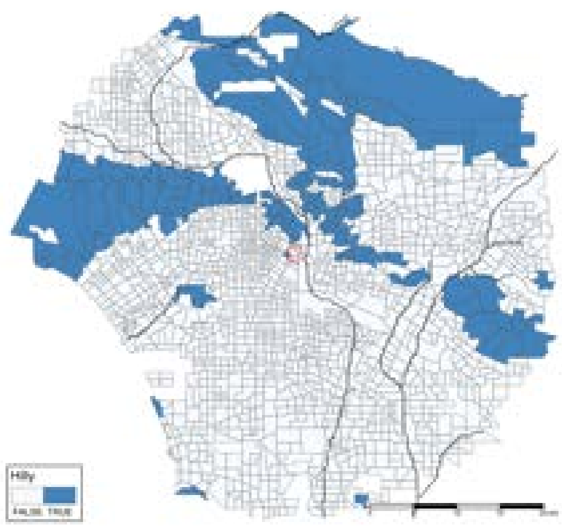
Figure 2: Residential Income and Hilly Areas in Los Angeles and Lima



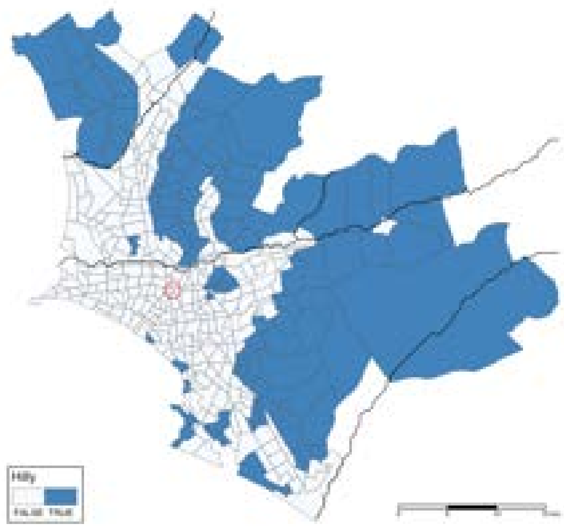
(a) Residential Income (Los Angeles)



(b) Residential Income (Lima)



(c) Hills and Rivers (Los Angeles)



(d) Hills and Rivers (Lima)

Notes: Panels (a) and (b) show the average residential income by neighborhood, measured as each neighborhood's percentile rank within the city; lighter colors correspond to higher income levels. Figures (c) and (d) show a binary measure for hilliness (blue is hilly) along with the path of waterways in black. The red circle in each panel marks the city center. Neighborhoods further than 30 kilometers from the city center are omitted.

Focusing first on Panels (a) and (b), the two cities display starkly contrasting relationships between average income and distance to the city center. In Los Angeles, lower-income neighborhoods surround the city center, with the exception of a small cluster of higher-income blocks at the core. Moving outward, particularly toward the north (Pasadena) and west (Santa Monica), average income tends to rise. In contrast, Lima exhibits the opposite pattern: neighborhoods near the city center are generally wealthier, and income declines with distance from the city center.

Panels (c) and (d) reveal similarly contrasting patterns between income and hilly areas. In Los Angeles, hilly areas such as Laurel Canyon and Beverly Hills—situated northwest of the city center—are associated with high incomes. In Lima, by contrast, Los Olivos, a middle-income area nestled in a valley northwest of the center, is surrounded by poorer hillside neighborhoods on both sides.

In what follows, we show that these patterns reflect broader, systematic differences in spatial income distribution between developed and less developed cities, extending beyond the specific cases of Los Angeles and Lima.

3.2. Residential Income and Distance to the City Center

Figure 3 shows the relationship between distance from the city center and average neighborhood residential income percentiles for each region up to 25 kilometers from the city center. Each light line represents a single city, while averages are highlighted in bold.

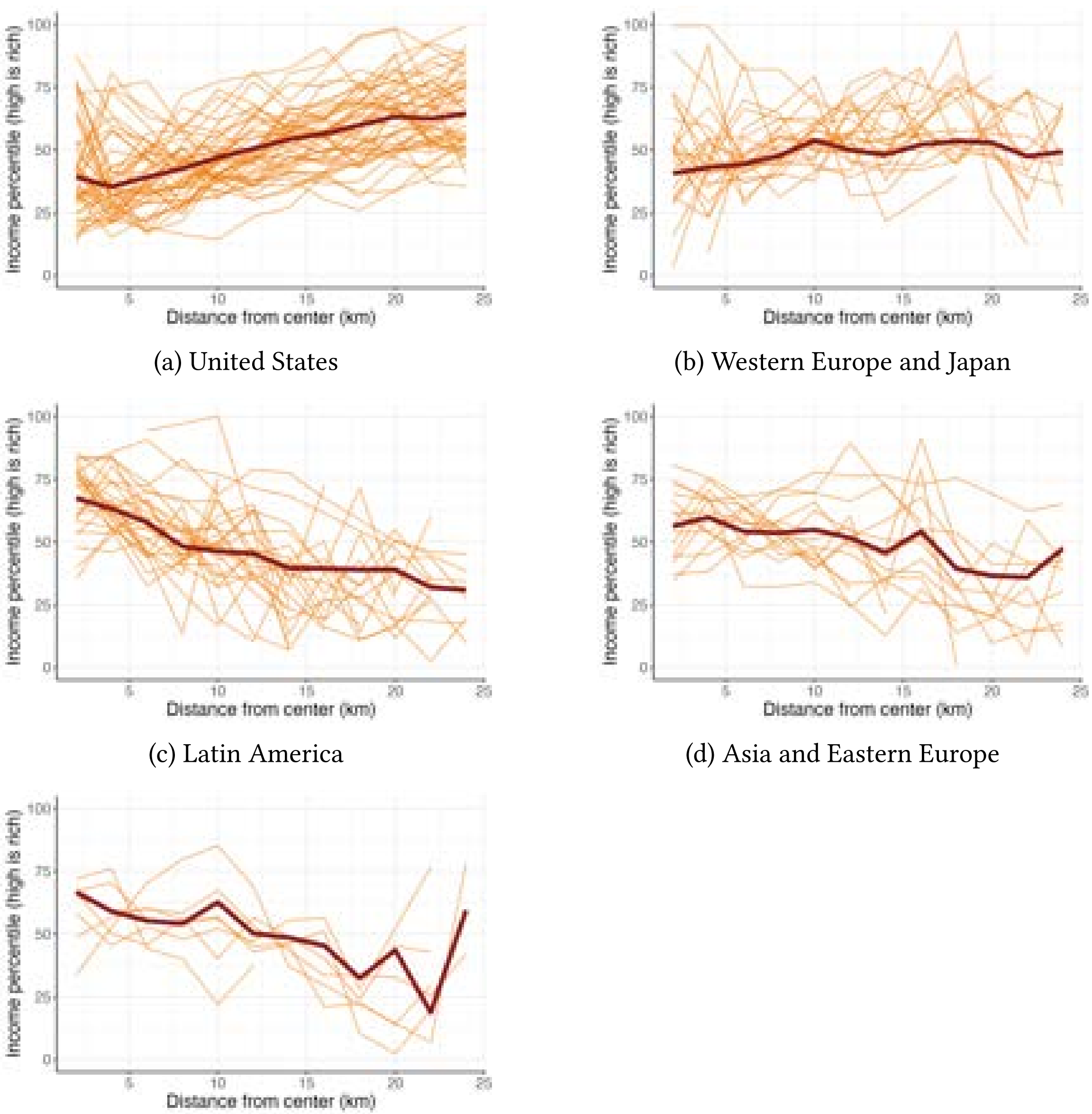
In Panel (a), we show that in the U.S. cities, income exhibits a modest U-shaped pattern with respect to distance from the city center. On average, neighborhoods exactly at the city center are slightly below the 50th percentile. Income declines up to 4 kilometers from the center, reaching a low point at around the 40th percentile. Beyond this distance, income gradually increases toward the urban periphery. Overall, this pattern reflects a positive income gradient from the inner suburbs to the outer edges of the city.

In Panel (b), we show the patterns of other developed cities from Western Europe and Japan. We find that, on average, the income profiles are mostly flat. Some specific megacities, such as Tokyo and Paris, exhibit downward-sloping patterns (see Appendix Figure B.3), but these cases are not representative of the broader set of European cities.

In contrast, in Panels (c)–(e), we find a strong, monotonic decline in income with distance from the city center in less developed cities across all regions. On average, incomes fall from around the 65th percentile of the city income distribution at the center to the 40th percentile in neighborhoods 20 kilometers from the center.

Figure 4 further examines cross-city variation in the relationship between income and

Figure 3: Residential Income and Distance to City Center, by Regions



(a) United States

(b) Western Europe and Japan

(c) Latin America

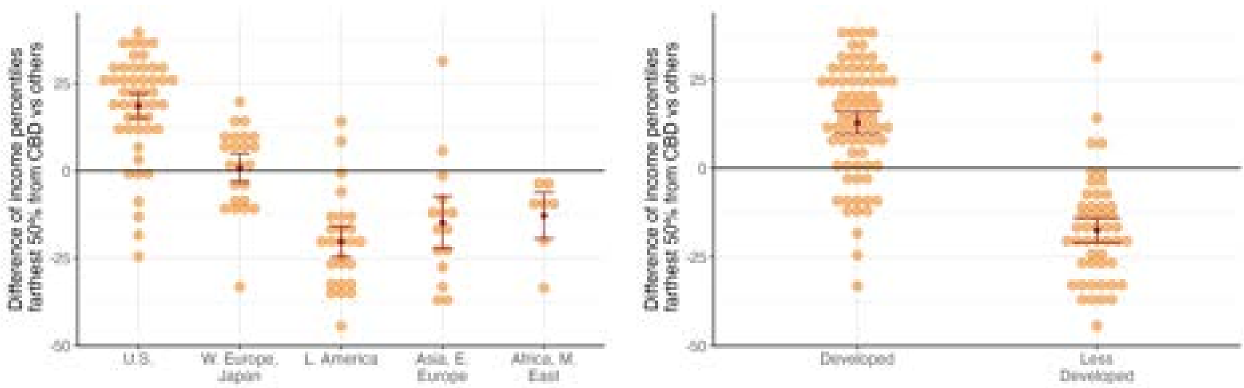
(d) Asia and Eastern Europe

(e) Africa and Middle East

Notes: The figures show the relationships between distance from the city center and the average neighborhood residential income percentile for each region. Panels (a) and (b) correspond to developed cities and Panels (c)–(e) correspond to less developed cities. Appendix Figure B.1 shows the same figures by aggregating developed and less developed cities.

distance to the city center. For each city, we compute the "suburban-urban income gap," defined as the difference in average income percentiles between suburban neighborhoods (neighborhoods housing the 50% of the population farthest from the city center) and the remaining neighborhoods. Panel (a) groups them by region, while Panel (b) groups cities by development status. In both panels, each dot represents a city; we plot group means and 95% confidence intervals.

Figure 4: Suburban-Urban Income Gap



(a) Regions

(b) Development Status

Notes: The panels display the difference in average income percentiles between suburban and urban core neighborhoods for each city, where suburban areas are defined as the neighborhoods containing the 50% of the population located farthest from the city center, and urban core areas are defined as the rest. Each dot represents a city. Panel (a) groups cities by region, while Panel (b) groups cities by development status. In both panels, we also report the group averages and their 95% confidence intervals. Appendix Figure B.4 shows the same set of figures using log income instead of income percentiles. Appendix Tables B.1 and B.2 report the values for each city and country, respectively.

Panel (a) confirms the patterns we reported in Figure 3. The suburban-urban income gap is on average positive in the United States (around 15 percentile points), while it is on average zero in Western Europe and Japan.[11] Among less developed regions, the gap is consistently negative across all regions. Panel (b) aggregates these patterns for developed and less developed regions. In developed cities, the suburban-urban income gap is positive, averaging around 10 percentile points, while in less developed cities, it is negative, at approximately minus 15 percentile points. Therefore, the differences between developed and less developed cities are large and significant.

Appendix Tables B.1 and B.2 provide city- and country-level rankings of the suburban-urban income gap. Of the 20 cities with the most negative gaps, 18 are in less developed countries; only Tokyo and Seattle are from developed countries. Conversely, 19 of the 20 cities with the largest positive gaps are in developed countries—all in the United States—with only one in a less developed country, Da Nang (Vietnam).

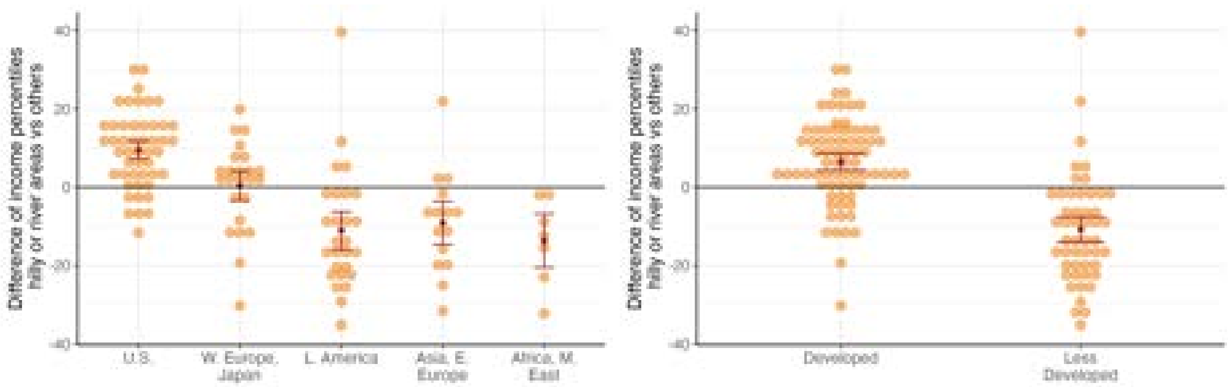
[11] In Appendix Figure B.7, we find that the U.S. pattern is similar between cities with above and below median shares of racial minorities (Black or Hispanic), suggesting that racial segregation is unlikely to be the main driver of this pattern.

3.3. Residential Income and Hills/Rivers

We now turn to the relationship between residential income and natural geologic features, specifically hills and rivers. Lee and Lin (2018) show that in the United States such features are important predictors of neighborhood affluence: areas near hills and rivers tend to be wealthier than average. They interpret this pattern as reflecting the value households place on natural amenities, such as scenic views from elevated terrain or proximity to water. However, little is known about whether these patterns generalize to cities outside the United States.[12]

Figure 5 presents the difference in average income percentiles between neighborhoods located in hilly or river-adjacent areas and those that are not, city by city. For simplicity, we combine the hilly and river neighborhoods in this figure, while the patterns are qualitatively similar when looking at them separately (Appendix Figures B.5 and B.6). In the regression analysis that follows, we show that the patterns remain qualitatively similar when hills and rivers are analyzed separately.

Figure 5: Residential Income and Hills/Rivers: by City



(a) Regions (b) Development Status

Notes: The panels show the difference in average income percentiles between neighborhoods that are hilly or located near a river and those that are not. River neighborhoods are defined as areas within 100 meters of a natural waterway, while hilly neighborhoods are those with an average slope greater than 5 degrees. Each dot represents a city. Panel (a) groups cities by region; Panel (b) groups cities by development status. In both panels, we report the group means and 95% confidence intervals. Appendix Figures B.5 and B.6 show the same set of figures, separately for hills or rivers, respectively. Appendix Tables B.3 and B.4 report the values for each city and country, respectively.

Panel (a) shows that, on average, neighborhoods located in hilly or river-adjacent areas are

[12] In Appendix Figures B.8, we examine proximity to a coast as an alternative proxy for natural amenities. Income premiums are positive but statistically insignificant in both developed and less developed cities. This pattern is consistent with the findings of Lee and Lin (2018) for U.S. cities.

approximately 10 percentile points richer than other neighborhoods in the United States, consistent with the findings of Lee and Lin (2018). In Western Europe and Japan, these differences are zero on average, while there are large variations across cities. The differences between the United States and other developed cities may be driven by various factors, such as different types of amenities other than natural amenities emphasized in the U.S. context, or differences in commuting costs. While our main focus is on comparing developed and less developed cities, in Section 6.4, we use our quantitative framework to examine the differences among developed cities.

By contrast, in less developed cities incomes in hilly or river neighborhoods are systematically lower than those in other neighborhoods, consistently across all three regions. By aggregating less developed cities altogether in Panel (b), we find that their hilly and river areas exhibit lower income by 10 percentile points and that they are statistically significantly different from developed cities.

Appendix Tables B.3 and B.4 report these gaps at the city and country levels, respectively. Of the 20 cities with the most negative income differences in hilly or river neighborhoods, 18 are in less developed countries; only two are in a developed country (Newcastle, U.K., and Toulouse, France). Conversely, among the 20 cities with the largest positive gaps, 18 are in developed countries; only two are in a less developed country (Campinas, Brazil, and Da Nang, Vietnam).

3.4. Regression Results: Developed vs. Less Developed Cities

So far, we have examined the correlation between income and each geographic feature in isolation. However, these features are often interrelated—for instance, hilly areas may lie farther from city centers. Moreover, the geographic attributes highlighted above may themselves be correlated with other neighborhood characteristics, such as the direction from the city center, while developed and less developed cities may differ systematically in their age or spatial extent. To account and control for these interdependencies, we employ a multiple regression framework. Specifically, we begin by estimating the following specification:

$$\text{Income}_{j,c} = \beta' X_{j,c} \times \text{Developed}_c + \gamma' X_{j,c} \times \text{Less Developed}_c + \nu_c + \epsilon_{j,c} \tag{1}$$

where c indexes a city, j indexes neighborhoods, $\text{Income}_{j,c}$ denotes the proxy for residential neighborhood income (income percentiles and log residential income), and $X_{j,c}$ includes indicators for suburban, hilly, and river-adjacent areas, as defined in Section 2. The specification includes city fixed effects ν_c, and the error term $\epsilon_{j,c}$ captures idiosyncratic neighborhood-level variation. We weight observations by the fraction of residents in each neighborhood within each city, such that the regression assigns equal weight to each city. We cluster standard errors at the city level.

Table 2 presents the results. Column (1) uses income percentile rank as the outcome, while column (2) uses log average residential income. For each specification, the top panel reports the estimated coefficients from Equation (1) and the bottom panel reports the differences in coefficients between developed and less developed cities.

Column (1) shows that the associations between income and suburban, hilly, and river locations remain robust when these geographic features are jointly included in the regression. Income levels in suburban neighborhoods are 12.6 percentile points higher in developed cities and 16.3 percentile points lower in less developed cities, both statistically significant, consistent with Figure 4. As for natural amenities, when disaggregated between hilly and river areas, the coefficients for developed cities are larger for hilly areas (13.7 percentile points) than for river areas (3.3 percentile points), with both estimates statistically significant. In contrast, for less developed cities, the coefficients are similar and negative (-6.8 and -6.1 percentile points, respectively). In both cases, the differences between developed and less developed cities are statistically significant and sizable, as reported in the bottom panel.

Column (2) shows that these patterns are robust when using log average income instead of income percentiles as the dependent variable. They also indicate economically meaningful magnitudes: for example, column (2) shows that suburban areas are associated with incomes that are 0.17 log points higher in developed cities, and 0.28 log points lower in less developed cities. Overall, the results indicate robust and statistically significant differences in income premiums associated with suburban, hilly, and river neighborhoods between developed and less developed cities.

Robustness In Table 3, we show that the differences between developed and less developed cities remain robust across a variety of alternative specifications and samples. Row (1) replicates the baseline estimates from the bottom panel of column (2) in Table 1. Our results are robust to restricting neighborhoods within 15 kilometers and 20 kilometers from the city center (rows 2 and 3), indicating that the definition of city boundaries or differences in city size across development levels do not drive our results. In rows (4) and (5), we exclude the United States and Brazil, respectively, as they contain a relatively large share of the cities in our sample (48 and 25, respectively). Excluding these countries attenuates the differences between developed and less developed cities, but the estimates remain statistically significant, except for the river coefficients when the United States is excluded.

Rows (6) and (7) restrict the sample to “New World” cities (North and Latin America) and “Old

Table 2: Regression Results of Residential Income on Suburban, Hilly, and River Dummies

Dependent Variables:	Income percentile (high is rich)	Log average income
Model:	(1)	(2)
Variables		
$\text{Developed}_c \times \text{Suburban}_{j,c}$	12.6***	0.17***
	(1.9)	(0.03)
$\text{Less Developed}_c \times \text{Suburban}_{j,c}$	-16.3***	-0.28***
	(2.1)	(0.04)
$\text{Developed}_c \times \text{Hilly}_{j,c}$	13.7***	0.17***
	(3.3)	(0.04)
$\text{Less Developed}_c \times \text{Hilly}_{j,c}$	-6.8**	-0.11**
	(2.8)	(0.05)
$\text{Developed}_c \times \text{River}_{j,c}$	3.3***	0.06***
	(1.2)	(0.01)
$\text{Less Developed}_c \times \text{River}_{j,c}$	-6.1***	-0.09***
	(1.9)	(0.03)
Difference: Less Developed$_c$ vs Developed$_c$		
$\text{Suburban}_{j,c}$	-28.9***	-0.45***
	(2.8)	(0.05)
$\text{Hilly}_{j,c}$	-20.5***	-0.28***
	(4.3)	(0.07)
$\text{River}_{j,c}$	-9.5***	-0.16***
	(2.3)	(0.04)
Observations	50,004	50,004
Unique Cities	121	121
City FE	✓	✓
Weight by neighborhood pop within city	✓	✓

*Notes: The top panel reports the results of Regression (1). The bottom panel reports the differences in the coefficients between developed and less developed cities. The unit of observation is a neighborhood with a positive average income. We weight observations by the fraction of residents in each neighborhood for each city, such that the regression assigns equal weight to each city. Standard errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels. The slightly smaller sample size in the regression, relative to the total number of neighborhoods reported in Section 2, reflects the omission of neighborhoods with zero income.*

World" cities (all others), respectively. This historical distinction has been highlighted as a key driver of subnational economic geography (Henderson, Squires, Storeygard, and Weil, 2018).

Table 3: Robustness: Differences in Income Premiums in Suburban, Hilly, and River Neighborhoods, Less Developed vs. Developed Cities

		Difference: Less Developed vs. Developed		
	Specification	Suburban	Hilly	River
1	Baseline	-28.9 (2.8)***	-20.5 (4.3)***	-9.5 (2.3)***
2	Exclude neighborhoods ≥ 15km from center	-21.2 (2.8)***	-19.9 (5.4)***	-8.4 (2.6)***
3	Exclude neighborhoods ≥ 20km from center	-25.8 (2.8)***	-20.0 (4.9)***	-8.5 (2.5)***
4	Exclude United States	-17.0 (3.2)***	-13.8 (5.8)**	-5.1 (3.2)
5	Exclude Brazil	-25.9 (3.5)***	-16.4 (5.9)***	-11.4 (2.7)***
6	New World cities	-37.5 (3.4)***	-29.7 (4.5)***	-10.2 (3.1)***
7	Old World cities	-13.5 (3.9)***	-5.2 (6.5)	-6.9 (3.5)**
8	Control: neighborhood area x city FE	-25.9 (2.8)***	-21.2 (4.3)***	-6.8 (2.0)***
9	Control: neighborhood quadrant to center x city FE	-28.9 (2.8)***	-22.3 (4.4)***	-9.1 (2.1)***
10	Control: city population x neighborhood attributes	-27.4 (3.0)***	-20.2 (4.4)***	-9.3 (2.4)***
11	Control: city area x neighborhood attributes	-28.4 (2.9)***	-19.4 (4.5)***	-8.8 (2.4)***

*Notes: This table presents robustness checks for the bottom panel of column (1) in Table 2, which reports differences in the coefficients on suburban, hilly, and river dummies between less developed and developed cities, estimated using Regression (1). Row (1) reproduces the baseline results from the bottom panel of column (2) in Table 1. Rows (2) and (3) exclude neighborhoods located more than 15 kilometers and 20 kilometers from the city center, respectively. Rows (4) and (5) exclude cities in the United States and Brazil, respectively. Rows (6) and (7) restrict the sample to "New World" cities (North and Latin America) and "Old World" cities (all others), respectively. Rows (8) and (9) augment Regression (1) by adding controls for neighborhood log area and for the quadrant relative to the city center (north, south, east, or west) interacted with city fixed effects, respectively. Rows (10) and (11) augment Regression (1) by adding controls for log city population and geographic area, interacted with suburban, hilly, and river dummies, respectively. All regressions cluster standard errors at the city level. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% levels.*

While the patterns are stronger among New World cities, they remain statistically significant in Old World cities as well, with the exception of hilly coefficients. Row (8) adds controls for neighborhood log area, interacted with city fixed effects, to address concerns that differences in neighborhood definitions or geographic boundaries might bias the results. Row (9) includes controls for quadrant location within the city (north, south, east, or west), interacted with city fixed effects, given prior evidence that neighborhood orientation influences income patterns (Heblich, Trew, and Zylberberg, 2021). In both cases, the main results are unaffected. Finally, rows (10) and (11) augment Regression (1) by including interactions between the suburban, hilly, and river dummies and log city population or geographic area. The results remain robust, suggesting that differences in city size, either in population or land area, do not explain the observed income patterns across development levels.

Additional Statistics Appendix B.4 investigates additional statistics related to income. Among less developed cities with available household-level data, we find no significant association between suburban, hilly, or riverside locations and average household size or employment status (Appendix Tables B.5 and B.6). In contrast, these areas tend to have residents who are younger and less educated on average (Appendix Tables B.7 and B.8), suggesting that the observed income patterns may in part reflect sorting by age and skill. Population density in suburban, hilly, and riverside areas is lower in both developed and less developed cities, though the rate of population decay differs: suburban areas exhibit faster declines, while hilly areas show slower declines in less developed cities (Appendix Table B.9).

4. Commuting Costs and Job Access

We next examine detailed bilateral commuting patterns across neighborhoods. We start by estimating the following "commuting gravity" equations for each city c separately:

$$\log \mathbb{E}\left[\lambda_{jn,c}\right] = \psi_{n,c} - \kappa_c \text{RoadDistance}_{jn,c} + \eta_{j,c} \tag{2}$$

Here, $\lambda_{jn,c}$ is the fraction of commuters who live in neighborhood j and work in neighborhood n in city c; $\text{RoadDistance}_{jn,c}$ is the road distance between j and n measured using OSRM as described in Section 2; $\psi_{n,c}$ and $\eta_{j,c}$ are destination and origin fixed effects, respectively; and $\mathbb{E}$ is the conditional mean of commuting flows given the road distance and fixed effects. The coefficients on the road distance κ_c capture the semielasticity of commuting with road distance, i.e., the average percentage decline in the probability of commuting associated with an additional 1-kilometer increase in distance.[13] In our theoretical model in Section 5, Equation (2) is microfounded by households' optimal discrete commuting-choice decisions, where $\psi_{n,c}$ is proportional to the log wage rates at workplace n, and $\eta_{j,c}$ is proportional to the negative of the expected log wage rate conditional on residing in j. We leverage these structural interpretations for our quantitative analysis in Section 6.

We estimate this equation using a Pseudo-Poisson Maximum Likelihood (PPML) estimator to

[13] Appendix Table C.1 reports the results of Regression (2) when road travel time is used instead of distance. Because OSRM-calculated travel times are not directly comparable across countries, we construct bilateral road travel time by multiplying OSRM road distance by each city's average traffic speed, measured by the Google Maps API (Akbar et al., 2023b). The estimated differences in commuting semielasticities, expressed in minutes, between developed and less developed cities are smaller than those in kilometers (Figure 6) but remain large and statistically significant. This attenuation suggests that factors beyond traffic speed—such as differences in transportation modes—also contribute to cross-city variation. See Figure 7 for further discussion.

handle the presence of neighborhood pairs with zero commuters (Dingel and Tintelnot, 2025).[14] For this analysis, we exclude cities from Spain and Brazil due to a lack of bilateral commuting flow data, except for the city of Belém in Brazil, where the JICA travel survey is available.

4.1. Commuting Costs

Figure 6 presents the estimated commuting semielasticities. As before, each dot represents an estimate from each city; Panel (a) groups them by region, while Panel (b) groups them by development status. In Panel (a), we find stark differences in commuting semielasticities across regions. In the United States, the semielasticity of commuting with respect to road distance is approximately 0.1, implying that an additional kilometer reduces commuting by 10%, holding workplace attractiveness constant. In Western Europe and Japan, the semielasticities are around 0.2, which is somewhat higher than in the United States, potentially reflecting differences in reliance on private cars versus public transit. In developing countries, the average semielasticity rises to 0.35, with a large variation across cities. Despite this heterogeneity, the semielasticities in less developed cities are significantly larger than those in developed cities, as shown in Panel (b).[15]

In Figure 7, we assess how the estimated commuting semielasticities relate to the traffic speed and commuting modes. In Panel (a), we plot the estimated commuting semielasticities against the "speed index" from Akbar et al. (2023b), which measures log-point differences in average road speed across cities using Google Maps API. We observe a tight negative relationship: in cities with faster average road speeds, commuting semielasticities tend to be lower. Therefore, slower traffic speeds in less developed cities—partly reflecting weaker transportation infrastructure—are indeed associated with shorter effective commuting distances.

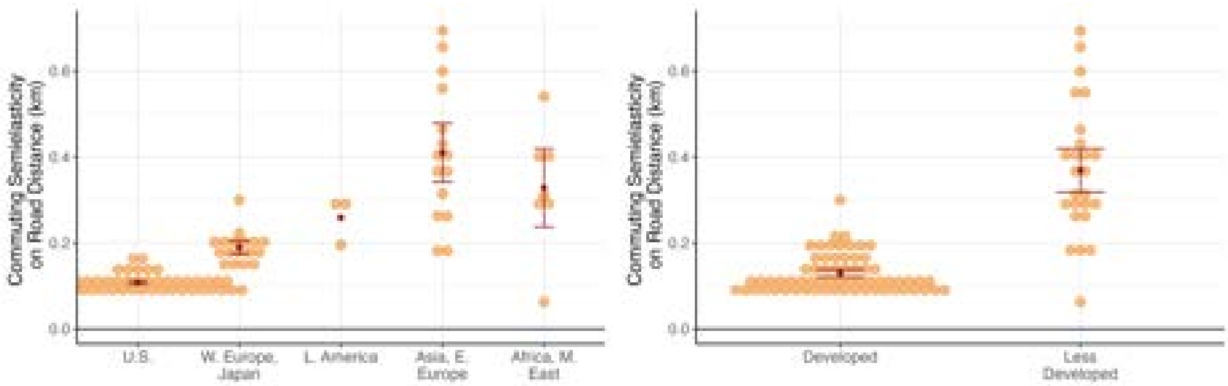
The estimated regression slope of log semielasticities on the log speed index is -1.83. If differences in semielasticities were driven solely by variation in road speed—implying that the semielasticities with respect to *road travel time* are constant across cities—all points would lie along the minus-45-degree line. Instead, the slope exceeds unity in absolute value, indicating that commuting frictions rise more than proportionally as road speeds decline.

One potential explanation for this pattern is that, in faster cities, residents are more likely to rely

[14] In Appendix C.2, we assess how the sampling rates of travel surveys may affect the estimates of κ_c through a Monte Carlo simulation. We find that the statistical uncertainty associated with sample size is negligible. In Lima, the confidence interval of the estimates based on simulated data centers around the assumed true value (0.28 from our point estimate using actual data), with a confidence interval that covers less than 0.01 given the sample size.

[15] The cross-region patterns are robust to using log distance instead of the level (Appendix Figure C.3), and estimating the coefficients on bins of distances nonparametrically instead of a single index (Appendix Figure C.4). Consistent with these findings, commuting distances are significantly longer for the developed cities than for less developed cities (Appendix C.5), although those of Western Europe and Japan are more similar to those of less developed cities, likely because of more dispersed employment in the former cities.

Figure 6: Estimated Semielasticity of Commuting to Road Distance (κ_c)



(a) Regions

(b) Development Status

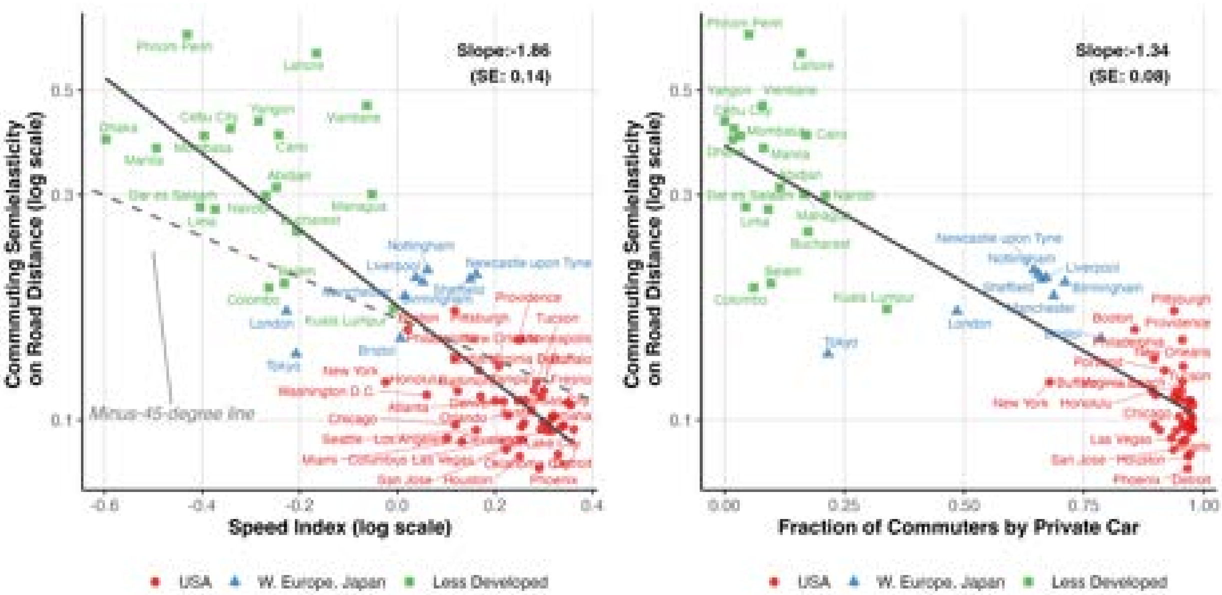
Notes: The panels show the estimated semielasticity of commuting to road distance using the PPML estimator of Specification (2)*. Each dot represents an estimate for each city. Panel (a) groups them by region, while Panel (b) groups them by development status. Sample cities exclude Spain and Brazil (except for the city of Belém) due to a lack of bilateral commuting flow data. In both panels, we report the group means along with 95% confidence intervals, except for "Latin America" in Panel (b), where we only show the mean due to the small sample size. Appendix Table C.1 reports the estimated semielasticity of road travel time.*

on efficient transportation modes such as private vehicles, whereas in slower cities, individuals may be constrained to slower options like informal transit or walking. To further assess the role of transportation mode, in Panel (b), we plot the estimated commuting semielasticities against the fraction of commuters by private car. We measure this value using our travel surveys whenever they are available, and for other cities, we use the data constructed by Prieto-Curiel and Ospina (2024) based on various surveys and administrative data. We find a strong, significant negative relationship. Therefore, the choice and availability of cars appear to be another key determinant of the commuting semielasticity.

4.2. Job Access

The higher commuting semielasticity in less developed cities suggests that neighborhoods differ markedly in job access within those cities. We now analyze how job access relates to residential income, continuing the analysis begun in Section 3. Intuitively, a neighborhood offers better job access when its residents can reach many job opportunities with relatively short or inexpensive commutes. To capture this idea, we construct a measure of job access that aggregates potential workplace opportunities, weighting each by the commuting distance and the attractiveness of the workplace. Formally, we define the job access of neighborhood j in city c as the distance-

Figure 7: Commuting Semielasticity, Speed, and Modes



(a) Speed

(b) Commuting by Car

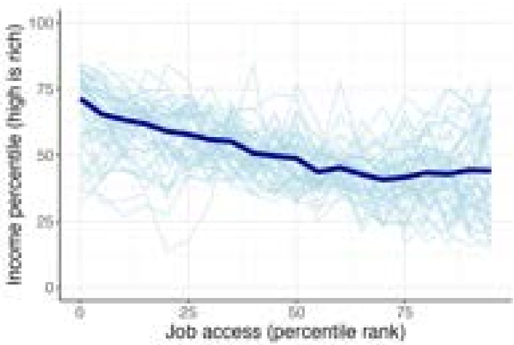
Notes: The panels show the patterns of the estimated commuting semielasticities with road distance from Specification (2). In Panel (a), we plot them against the "speed index" from Akbar et al. (2023b), which measures log-point differences in average road speed across cities using Google Maps API. In Panel (b), we plot them against the fraction of commuters by private car. We measure this value using our travel surveys whenever they are available, and for other cities, we use the data constructed by Prieto-Curiel and Ospina (2024) based on various surveys and administrative data. In both panels, we restrict our analysis to cities where both of these data are available. "Slope" and "SE" indicate the regression slopes of the log of semielasticity against each variable, as well as the standard errors for those estimates. Appendix Table C.4 reports the results based on joint regressions.

discounted sum of workplace fixed effects (Tsivanidis, 2025), given by

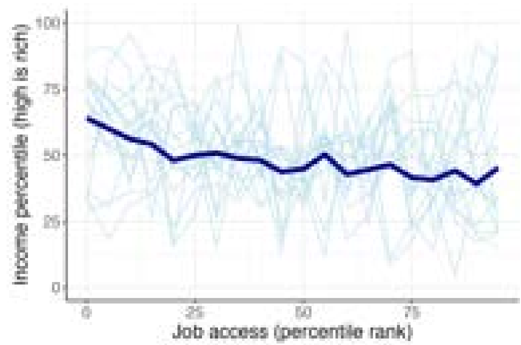
$$\text{JobAccess}_{j,c} = \log\left(\sum_n \exp(-\hat{\kappa}_c \text{RoadDistance}_{jn,c} + \hat{\psi}_{n,c})\right) \tag{3}$$

where $\hat{\kappa}_c$ and $\hat{\psi}_{j,c}$ are estimates of κ_c and $\psi_{n,c}$ from Equation (2). Under the PPML specification, the negative of the estimated origin fixed effects $\hat{\eta}_{j,c}$ is numerically equivalent (up to scale) to the geometric sum of the workplace fixed effects and the distance-related commuting costs: $\text{JobAccess}_{j,c} = -\hat{\eta}_{j,c}$ (Fally, 2015). Since the level of the fixed effects $(\hat{\eta}_{\ell,c}, \hat{\psi}_{j,c})$ is not identified from Equation (2), we normalize these objects for each city to mean zero. Again, in our structural model in Section 5, this measure of job access is proportional to the log expected wage per efficiency unit of labor for residents in j.

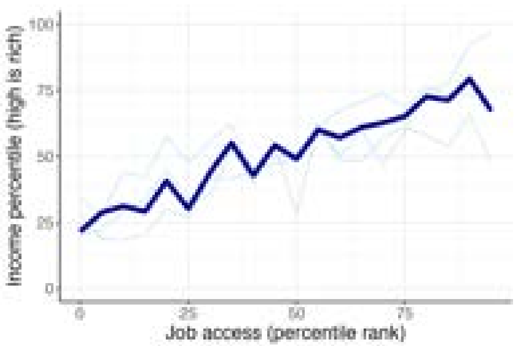
Figure 8: Residential Income and Job Access, by Region



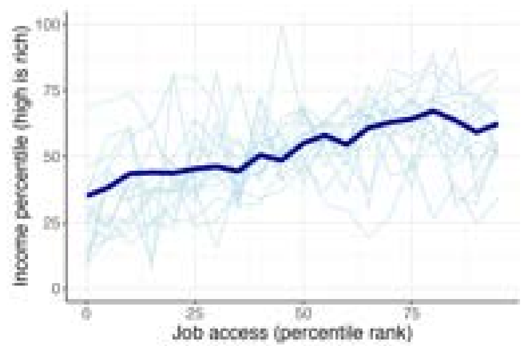
(a) United States



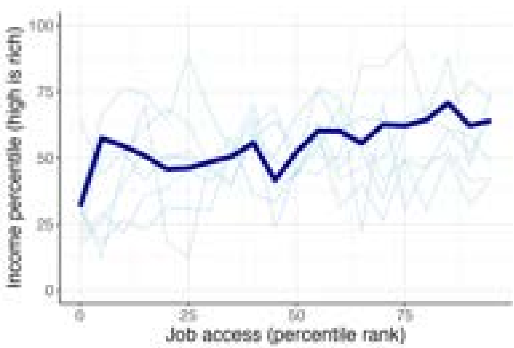
(b) Western Europe and Japan



(c) Latin America



(d) Asia and Eastern Europe



(e) Africa and Middle East

Notes: The panels show the relationships between the percentiles of estimated job access (Equation 3) within each city and average neighborhood residential income percentile for each region. Panels (a) and (b) correspond to developed cities, and Panels (c)-(e) correspond to less developed cities. Each light line represents a single city; averages are highlighted in bold. Appendix Figure C.7 presents the figures for developed and less developed cities. Appendix Figure C.8 shows the income premiums in neighborhoods with above-median job access.

Figure 8 presents the relationship between residential income and the percentile point of job access within each city, separately for each region. We find that income is monotonically decreasing in job access in developed cities, both in the United States (Panel a) and Western

Europe and Japan (Panel b): On average, the incomes fall from around the 65th percentile of the city income in the neighborhoods with the least job access to the 40th percentile in those with the highest job access. In contrast, the opposite is true in less developed cities, consistently across regions (Panels c-e): On average, incomes increase from the 35th percentile to around the 60th percentile. This mirrors our earlier finding that in less developed cities, neighborhoods located away from the city center or near hills and rivers—often distant from employment hubs—tend to be poorer.[16]

Interestingly, in contrast to the flat relationships of income with distance to the city center, hills, and rivers for Western Europe and Japan, we find a downward-sloping relationship for job access, similar to the ones in the United States. These patterns indicate that, in those cities, there are rich neighborhoods that tend to be farther from employment but not necessarily far from the city center or in hills or near rivers—this potentially reflects other dimensions of amenities.

What explains cross-city differences in the spatial distribution of job access? Equation (3) highlights two main drivers. The first is variation in the semielasticity of commuting, $\hat{\kappa}_c$, discussed in Section 4.1. In less developed cities, where $\hat{\kappa}_c$ is higher, neighborhoods located farther from employment centers experience disproportionately lower job access. The second driver is the spatial distribution of job opportunities, summarized by the workplace fixed effects $\hat{\psi}_{n,c}$.

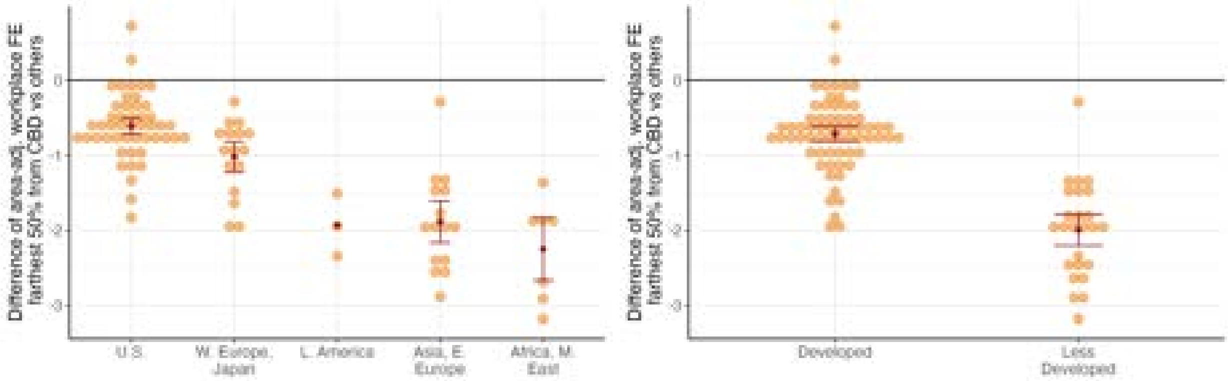
To illustrate the second force, Figure 9 compares the average estimated workplace fixed effects between suburban and urban-core neighborhoods in each city. Following Kreindler and Miyauchi (2023), we adjust $\hat{\psi}_{n,c}$ by subtracting log neighborhood area size to remove the mechanical scaling of fixed effects with area. We find that, across all regions, the area-adjusted workplace fixed effects are systematically lower in suburban neighborhoods, consistent with job opportunities being concentrated in urban cores. However, this suburban penalty is substantially larger in less developed cities, indicating more concentrated job opportunities within urban core areas. In the following sections, we examine how these differences in the spatial concentration of jobs and commuting costs—along with other factors such as amenities—shape the equilibrium spatial distribution of income.

5. Model

In this section, we develop a quantitative theoretical framework to analyze the drivers of spatial income distribution and commuting within a city. The goal is to assess the extent to which a

[16]In Appendix Table C.5, we show that job access tends to be indeed lower in hills and near rivers in both developed and less developed cities, while the penalty is larger in less developed cities.

Figure 9: Suburban-Urban Gap in Area-Adjusted Workplace Fixed Effects



(a) Regions

(b) Development Status

Notes: The panels show the differences in the average estimated workplace fixed effects $\hat{\psi}_{n,c}$ *from Equation (2), net of log area (Kreindler and Miyauchi, 2023), between suburban and urban core neighborhoods for each city. Suburban and urban core areas are defined as in Figure 4. Each dot represents an estimate for each city. Panel (a) groups them by region, while Panel (b) groups them by development status. Sample cities exclude Spain and Brazil (except for the city of Belém) due to a lack of bilateral commuting flow data. In both panels, we report the group means along with 95% confidence intervals, except for "Latin America" in Panel (b), where we only show the mean due to the small sample size.*

parsimonious set of factors can explain the empirical differences of spatial income distributions between developed and less developed cities that we document above. Our analysis focuses on three factors highlighted by the quantitative urban literature (e.g., Ahlfeldt, Redding, Sturm, and Wolf, 2015; Tsivanidis, 2025), plus one new factor that we argue the data support. Specifically, we focus on developed and less developed differences in (i) average commuting costs, (ii) concentration of jobs in more central areas, and (iii) spatial distribution of residential amenities, plus (iv) nonhomothetic preferences for residential amenities.

5.1. Environment and Households' Preferences

Consider a city c that consists of $j \in \mathcal{J}_c$ neighborhoods. Each neighborhood j is endowed with exogenous amenity $B_{j,c}$, the productivity of final goods $A_{j,c}$, and the supply shifter of housing $S_{j,c}$. Furthermore, each pair of locations $j, n \in \mathcal{J}_c$ is endowed with commuting costs $\tau_{jn,c}$. For notational brevity, we omit subscripts c in this section and reintroduce them in the next section for the quantitative analysis.[17]

There is a unit measure of households ω. 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).

We specify households' preferences over final goods and housing using nonhomothetic constant elasticity of demand (NH-CES) preferences (Albouy, Ehrlich, and Liu, 2016; Comin, Lashkari, and Mestieri, 2021; Hoelzlein, 2023; Finlay and Williams, 2025). Nonhomotheticity in housing is a robust empirical regularity, and it has been noted as a force for gentrification and income sorting in the United States (Couture et al., 2024). Specifically, given the consumption amount of final goods y and housing h, the subutility of households U_j derived from the consumption of final goods and housing is implicitly determined by the following equation:

$$1 = \left(\frac{y}{U_j}\right)^{\frac{\sigma-1}{\sigma}} + \chi^{\frac{1}{\sigma}} \left(\frac{h}{U_j^{\varepsilon}}\right)^{\frac{\sigma-1}{\sigma}} \tag{4}$$

Here, σ determines the elasticity of substitution between housing and final goods. χ regulates the relative demand for housing. $\varepsilon(>0)$ is the parameter that governs the degree of nonhomotheticity in housing. When $\varepsilon = 1$, Equation (4) reduces to standard CES preferences. In the parameter range $0 < \sigma < 1$, where housing and final goods are net complements (as documented by Finlay and Williams, 2025 for the United States), housing is a subsistence good if and only if $0 < \varepsilon < 1$ (i.e., its expenditure share declines with income, holding prices fixed). The NH-CES preference class provides well-defined demand functions over any positive value of income and prices, and hence suitable for our applications that involve large dispersion of income and prices within and across cities.[18]

Given this subutility from consumption U_j, household ω's overall utility by residing in j is given

[17] In practice, these fundamentals $\{B_{j,c}, A_{j,c}, S_{j,c}, \tau_{jn,c}\}$ are in part shaped by endogenous forces, such as the endogenous supply of amenities (e.g., schools, restaurants), productivity spillovers (e.g., knowledge diffusion), and policy choices (e.g., infrastructure investment). The primary purpose of our model is not to model these processes explicitly, but rather to account for how each of these objects, inferred from our data, maps to the differences in observed spatial income distribution across cities (Section 6). For this purpose, it is not crucial to endogenize these objects. Endogenizing them becomes more important when addressing explicit policy counterfactuals.

[18] Alternative classes of nonhomothetic preferences commonly used in studies of individual cities or countries, such as Stone-Geary preferences (Tsivanidis, 2025) or unit-demand preferences (Couture et al., 2024), are not well suited for our application. Utilities under these formulations are not well-defined over certain ranges of income and prices, and cannot accommodate large income differences across cities, as we consider here.

by

$$\log\left(U_j^{\rho}+B_j^{\rho}\right)^{\frac{1}{\rho}}+\epsilon_j(\omega) \tag{5}$$

where B_j is an exogenous amenity in location j, capturing factors such as the natural amenities available in hills or near rivers or the open space available in suburban areas. ρ regulates the nonhomotheticity of residential location choice with respect to B_j. To see why, if $\rho < 0$, $\frac{\partial}{\partial B_j}\frac{\partial}{\partial \log U_j}\log\left(U_j^{\rho}+B_j^{\rho}\right)^{\frac{1}{\rho}} > 0$, i.e., the elasticity of overall utility with respect to consumption subutility U_j increases in amenity B_j. Therefore, individuals with a higher earning potential, and hence U_j, tend to value an increase in amenity B_j more. If $\rho < 0$, the opposite is true. In the limit as $\rho \to 0$, the utility function converges to an additive form: $\log\left(U_j^{\rho}+B_j^{\rho}\right)^{\frac{1}{\rho}} \to (\log U_j + \log B_j)/2$, as in Couture et al. (2024), Finlay and Williams (2025), or Tsivanidis (2025). In the next subsection, we revisit how this property shapes the patterns of residential location choices.

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

$$\begin{aligned} U_j(s(\omega)) \equiv \arg\max_{\{h,y\}} \quad & U_j \\ \text{s.t.} \quad & P_j h + y \leq \overline{w}_j s(\omega) \quad \text{and Equation (4)} \end{aligned} \tag{6}$$

where P_j is the housing rent, $s(\omega)$ 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 5.3.

Anticipating this decision, household ω chooses the residential location that maximizes Utility (5):

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

Following the quantitative urban literature (e.g., Ahlfeldt et al., 2015; Tsivanidis, 2025), we assume that $\epsilon_j(\omega)$ is independently drawn from the Gumbel distribution with scale parameter ν. Then, the probability that households with earning potential s reside in location j is given by

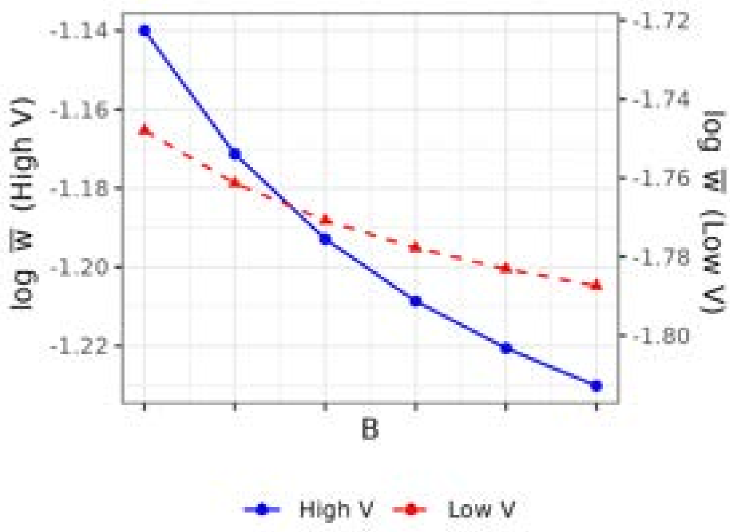
$$\pi_j(s) = \frac{\exp\left(\nu V_j(s)\right)}{\sum_{\ell}\exp\left(\nu V_{\ell}(s)\right)} \tag{8}$$

5.2. Nonhomotheticity in Residential Location Choice

The residential location choice probability $\pi_j(s)$ depends on the individual's earning potential s because of the nonhomothetic preferences with housing and amenities. To illustrate this point, in

Figure 10, we plot the indifference curves between the wage rate $\overline{w}_j$ and amenity B_j. Specifically, assuming $\rho < 0$, the figure shows the combinations of $\{\overline{w}_j, B_j\}$ that deliver the same level of overall utility $V_j \in \{V^{High}, V^{Low}\}$, holding housing rents P_j fixed. Although the indifference curve for V^{High} lies above that for $V^{Low} (< V^{High})$, we normalize the vertical axis for each curve for ease of exposition.

Figure 10: Indifference Curves Between $\overline{w}_j$ and B_j With $\rho < 0$



Notes: This figure shows the combinations of $\{\overline{w}_j, B_j\}$ *that deliver the same level of utility (excluding idiosyncratic taste shocks) corresponding to* $V_j \in V^{High}, V^{Low}$*, where* $V^{High} > V^{Low}$*, holding housing rents* P_j *fixed, for the case with* $\rho < 0$*.*

Figure 10 demonstrates that the trade-off between wages $\overline{w}_j$ and amenities B_j varies with the overall utility level. When overall utility is low, the indifference curve is relatively flat, indicating that agents are more responsive to wages than to amenities in their residential choice. Conversely, when overall utility is high, the indifference curve becomes steeper, suggesting a greater sensitivity to amenities. This pattern reflects the nonhomothetic nature of preferences: with $\rho < 0$, B_j behaves like a "luxury" good in location choice, valued more by higher-utility (or higher-income) individuals. When $\rho > 0$, the reverse holds.[19]

The "luxury" feature of amenity ($\rho < 0$) potentially explains why the spatial income distribution within cities varies depending on overall income levels. If the city's overall income level is

[19]At first glance, it may seem puzzling that the constant-elasticity-of-substitution specification with B_j (Equation 5) gives rise to nonhomotheticity. This arises because B_j is fixed at the location level and does not require spending out of the household's budget, allowing individuals of any income level to access it conditional on residing there.

sufficiently high, households with greater earning potential place higher value on amenity-rich locations, while those with lower earning potential sort into areas with amenity-scarce, higher-wage locations. In contrast, if the city's overall income level is sufficiently low, households place limited value on amenities and base their residential choices primarily on wages, regardless of their earning potential.

Furthermore, in the equilibrium, housing rents P_j are endogenously determined by supply and demand in the housing market (as we define in Section 5.4), and hence neighborhoods with higher residential demand tend to exhibit higher housing rents. When housing is a subsistence good ($1 > \epsilon > 0; 1 > \sigma > 0$), as robustly documented in prior work, this creates an additional force toward gentrification. Households with lower earning potential s are more sensitive to housing costs due to their higher expenditure share on housing (Couture et al., 2024; Finlay and Williams, 2025).

5.3. Commuting (Labor Supply) Decisions

Each household ω consists of a continuum of members of unit measure, each endowed with $s(\omega)$ efficiency units of labor.[20] Members independently choose their work location. If member v decides to commute to work in location $n = n(v)$, she earns income at wage rate $w_n \tilde{\epsilon}_n(v)$ per efficiency unit of labor, where $\tilde{\epsilon}_n(v)$ captures idiosyncratic productivity at that workplace. She also incurs commuting costs in the form of iceberg earnings losses, $\tau_{jn} \geq 1$, where j denotes the household's residential location. These costs reflect both distance and variation in transportation infrastructure—such as road quality in suburban, hilly, or river-adjacent areas. Together, the labor supply decision of a member v is given by

$$n(v) = \arg\max_{n} \tau_{jn}^{-1} w_n \tilde{\epsilon}_n(v) \tag{9}$$

We assume that $\tilde{\epsilon}_n(v)$ 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

$$\lambda_{jn} = \frac{\left(\tau_{jn}^{-1} w_n\right)^{\theta}}{\sum_{\ell} \left(\tau_{j\ell}^{-1} w_{\ell}\right)^{\theta}} \tag{10}$$

Notice that this equation provides a microfoundation for our empirical gravity equations in Section 4. Specifically, by parametrizing that $\tau_{jn,c}$ is a power function of road distance such

[20] We assume a continuum of household members, instead of a discrete number, to eliminate ex-post heterogeneity in wage rates conditional on residential location. Although this assumption can be relaxed without difficulty, it serves to simplify the exposition of residential location decisions in Section 5.1.

that $\tau_{jn,c} = \exp(\tilde{\kappa}_c \text{RoadDistance}_{jn,c})$,

$$\log \lambda_{jn,c} = \theta \log w_{n,c} - \tilde{\kappa}_c \theta \text{RoadDistance}_{jn,c} - \log \sum_{\ell} \left(\tau_{j\ell,c}^{-1} w_{\ell,c} \right)^{\theta} \tag{11}$$

which corresponds to Equation (2), where $\psi_{n,c} \equiv \theta \log w_{n,c}$ is the workplace fixed effects, $\eta_{j,c} \equiv -\log \sum_{\ell} \left(\tau_{j\ell,c}^{-1} w_{\ell,c} \right)^{\theta}$ is the origin fixed effects, and $\kappa_c \equiv \tilde{\kappa}_c \theta$.

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

$$\log \overline{w}_j = \varrho + \frac{1}{\theta} \log \sum_{\ell} \left(\tau_{j\ell}^{-1} w_{\ell} \right)^{\theta} \tag{12}$$

where $\varrho \equiv \log \Gamma \left(\frac{\theta - 1}{\theta} \right)$, where $\Gamma(\cdot)$ is the Gamma function. Therefore, the empirical job access measure defined in Equation (3) coincides with the log of expected wage rate, up to scale.

5.4. Production, Market Clearing, and Equilibrium

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

$$w_j = A_j \tag{13}$$

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 may vary across neighborhoods, reflecting differences in development costs driven by local geographic features, such as hills or proximity to rivers. We assume that the inverse supply function of housing is given by

$$P_j = \frac{1}{S_j} H_j^{\mu} \tag{14}$$

where H_j is the aggregate supply of housing.

The market clearing of housing in location j is given by

$$H_j = \int_s h_j(s) \pi_j(s) dG(s) \tag{15}$$

where $G(\cdot)$ is the cumulative distribution function of earning potential $s(\omega)$ across households, and $h_j(s)$ is housing consumption by residents in j with earning potential s.

The equilibrium is defined by households' consumption $\{h_j(s), y_j(s)\}$, residential choice probabilities $\{\pi_j(s)\}$, labor supply probabilities $\{\lambda_{jn}\}$, wages $\{w_j\}$, and house prices $\{P_j\}$, which satisfy households' optimal consumption decision (6), residential location decision (7) and (8), labor supply decision (9) and (10), final goods producers' optimality condition (13), and housing supply and market-clearing conditions (14) and (15).

5.5. Spatial Income Distributions

The average residential income in neighborhood j is given by

$$\text{Income}_j = \overline{w}_j \frac{\int_s s\pi_j(s)dG(s)}{\int_s \pi_j(s)dG(s)} \tag{16}$$

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 (12). 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, residential income is affected by the average earning potential of households residing in the neighborhood j, $\int_s s\pi_j(s)dG(s)/\int_s \pi_j(s)dG(s)$. This component is shaped by the nonhomotheticity in residential location choice, together with the distribution of wages, housing costs, and amenities, as discussed in Section 5.2.

Our model offers a structural interpretation of the spatial distribution of residential income that we analyzed in Section 3. In particular, it offers four potential explanations for the contrasting spatial income distribution between developed and less developed cities. The first is nonhomothetic preference for amenities, where households with high earning potential sort into high-amenity locations. Second, commuting costs tend to be higher in less developed countries, which disproportionately penalize expected wages $\overline{w}_j$ in peripheral areas, including hilly and river areas. Third, jobs may be more centralized in developing cities, with disproportionately lower A_j in peripheral areas. Finally, residential amenity value falls faster away from the city center and in hills and near rivers in less developed cities, with relatively lower B_j in peripheral areas. In the following section, we assess the quantitative relevance of each channel.

6. Quantitative Analysis

In this section, we take our model to data to assess the driving forces behind the contrasting spatial income distribution between developed and less developed cities. First, we calibrate the model to match commuting and residential-income patterns in U.S. cities. Second, we identify differences in (1) overall productivity, (2) commuting costs, and (3) the spatial distribution of productivity between the United States and less developed cities; the latter two are disciplined by the commuting gravity equations estimated in Section 4. Third, starting from the U.S.-calibrated model, we counterfactually offset these three differences. We also use the calibrated model to analyze the differences between the United States and developed cities elsewhere in the world.

6.1. Calibrating the Model to U.S. Cities

We calibrate the structural parameters and fundamental variables for U.S. cities using both existing estimates from the literature and our own estimates based on the data, as summarized in Table 4.

Table 4: Calibrated Parameters Targeting U.S. cities

Symbol	Value	Description	Source
σ	0.52	Elasticity of substitution for housing	Finlay and Williams (2025)
ε	0.36	Elasticity of nonhomotheticity in housing	Finlay and Williams (2025)
$G(\cdot)$	{3,1} wp 0.5	Earning potential distribution	Variance of income
θ	5	Dispersion of idiosyncratic productivity shock	Literature
$\{\kappa_c\}$	–	Semielasticity of commuting cost to road distance	Gravity equation
$\{A_{j,c}\}$	–	Productivity	Gravity equation
χ	0.09	Preference shifter for housing	GMM
ν	12.0	Residential location choice elasticity	GMM
ρ	-0.30	Elasticity of nonhomotheticity in amenity	GMM
β_0	9.00	Amenity level	GMM
β_1	0.90	Amenity for suburban areas	GMM
β_2	1.03	Amenity for hilly areas	GMM
β_3	0.26	Amenity for river areas	GMM
μ	0.30	Inverse housing supply elasticity	Literature
$\{S_{j,c}\}$	–	Housing supply shifter	Rents

We calibrate the elasticity of substitution between housing and final goods to $\sigma = 0.52$, and the elasticity of nonhomotheticity in housing demand to $\varepsilon = 0.36$, based on Finlay and Williams (2025), who estimate these parameters from the Panel Study of Income Dynamics (PSID) for U.S. cities. A value of $0 < \sigma < 1$ implies that housing and final goods are complements, while $0 < \varepsilon < 1$ indicates that housing behaves as a subsistence good, consistent with robust empirical patterns observed in the United States and many other countries.

We assume that the distribution of earning potential $G(\cdot)$ follows a bimodal structure, with two mass points at 1 and 3 (normalized), each occurring with probability 0.5. This specification generates a degree of income variance comparable to that observed in the U.S. economy, as reported by Heathcote, Perri, and Violante (2010).

We set the shape parameter of the idiosyncratic productivity shock at $\theta = 5$, consistent with median estimates reported in the literature for both developed and less developed cities.[21] Given θ, we can back out the productivity at workplaces using the workplace fixed effects from the gravity equations $A_{n,c} \propto \exp\left(\psi_{n,c}/\theta\right)$, city by city.[22] We also parametrize the commuting cost as a power function of road distance (Equation 11), and we recover city-specific commuting cost semielasticity by $\tilde{\kappa}_c = \hat{\kappa}_c/\theta$, where $\hat{\kappa}_c$ is as estimated in Section 4 by Equation (2). Notice that we can also back out wage rates at residential location $\overline{w}_{j,c} \propto -\exp\left(\eta_{n,c}/\theta\right)$.

We calibrate the inverse housing supply elasticity to $\mu = 0.3$. This value lies within the range estimated in the literature (e.g., Saiz, 2010), though toward the lower end, reflecting the long-run nature of our counterfactual analysis. We also set the housing supply shifter $S_{j,c}$ for each location to be consistent with the observed rents $P_{j,c}$.

We estimate the remaining preference parameters and amenities using our U.S. income, commuting, and rents data. We begin by introducing additional parametric assumptions for the amenity term $B_{j,c}$, modeling it as a function of observable geographic features highlighted in Section 3:[23]

$$\log B_{j,c} = \beta_0 + \beta_1 \text{Suburban}_{j,c} + \beta_2 \text{Hills}_{j,c} + \beta_3 \text{Rivers}_{j,c} \tag{17}$$

where $\text{Suburban}_{j,c}$, $\text{Hills}_{j,c}$, and $\text{Rivers}_{j,c}$ indicate the dummies for the suburban, hilly, and river areas, as defined for our income regression Equation (1), and $\{\beta_0, \beta_1, \beta_2, \beta_3\}$ are common parameters across all U.S. cities.[24]

We estimate the nonhomotheticity in amenity preferences ρ, the amenity parameters $\{\beta_0, \beta_1, \beta_2, \beta_3\}$, the elasticity of residential location choice ν, and the housing-preference shifter

[21]The estimates from prior research range from 2.2 to 8.3 (e.g., Ahlfeldt et al., 2015; Kreindler and Miyauchi, 2023; Severen, 2023; Tsivanidis, 2025), without clear systematic differences between developed and less developed cities.

[22]This procedure only reveals the relative $\{A_{j,c}\}_j$ within the city, but not the levels. We set the common level shifter across U.S. cities to replicate the observed mean income of U.S. cities. We also subtract the log neighborhood area size from the estimated fixed effects $\psi_{n,c}$ to offset the mechanical effect that the destination fixed effects proportionally increase in neighborhood area size (Kreindler and Miyauchi, 2023).

[23]We take the approach of parameterizing amenities $\{B_{j,c}\}$, rather than inferring them directly from residential location choices, as often implemented in the literature of quantitative spatial models (e.g., Redding, 2023). This choice in part reflects a data limitation: we do not observe residential location choice for each value of earning potential s, but only the average income at each location.

[24]$\{\beta_0, \beta_1, \beta_2, \beta_3\}$ can be interpreted either as direct preferences toward suburban open space and natural amenities, or preferences toward endogenous amenities that emerge in those places (e.g., schools). In our accounting analysis below, we first ask how much the observed differences in overall productivity, commuting costs, and spatial productivity distribution can explain the gap between U.S. cities and less developed cities, fixing these parameters. The residuals could reflect the differences in $\{\beta_0, \beta_1, \beta_2, \beta_3\}$ between developed and less developed cities, arising either from differences in innate preferences (e.g., culture) or endogenous amenities (e.g., schooling, pollution, or residential infrastructure).

χ using a generalized method of moments (GMM) procedure, to replicate the key properties of spatial income distribution observed in the U.S. cities. Specifically, using observed rents $\{P_{j,c}\}$ and the estimated wage rates at residential locations $\{\overline{w}_{j,c}\}$ from the gravity equations, we solve for the equilibrium residential location choice $\{\pi_{j,c}(s)\}$ for each earning potential s given a candidate parameter vector $\Theta \equiv \{\beta_0, \beta_1, \beta_2, \beta_3, \rho, \nu, \chi\}$.[25] We then construct a set of moments $g_{j,c}(\Theta)$, defined as the difference between model-implied and empirically observed values for key location-specific statistics: (1) log average residential income in location j, as well as its interaction with suburban, hilly, and river dummies; (2) the interaction of log average residential income and estimated job access; (3) the interaction with (2) and hilly and river dummies[26]; (4) average housing expenditure share of residents in location j; and (5) residential-location-choice elasticity with respect to job access.[27] Finally, we choose the value that minimizes the GMM objective function with a two-step optimal weighting matrix.

While the GMM procedure jointly determines all parameters using all moments, specific moments are particularly informative about certain parameters. The first set of moments is particularly informative about the value for $\{\beta_1, \beta_2, \beta_3\}$, which determines the differential sorting across s toward suburban areas, hills, and river-adjacent neighborhoods. The second moments are informative about the value for ρ, since a more negative ρ implies that households with lower earning potential are disproportionately more responsive to job access. The third set of moments is informative about the value of β_0, as the level of amenities determines differential responses across different s to job access. The fourth moment is informative about the preference shifter for housing χ. The fifth moment is informative about the residential location choice elasticity ν.

Table 4 provides the point estimates, which we use for our quantitative analysis. Consistent with the moment choices, Appendix D.1 demonstrates that our model accurately replicates the relationship between observed residential income and suburban, hilly, river areas, and job access, capturing the patterns documented in Sections 3 and 4.

6.2. Unpacking the Gap Between U.S. and Less Developed Cities

We now use our calibrated model for U.S. cities to conduct counterfactual simulations that eliminate differences in fundamentals between U.S. and less developed cities. Specifically, we

[25] We use median housing rents for U.S. cities from the 2015–2019 ACS at the census-tract level for $\{P_{j,c}\}$.

[26] To mitigate concerns that the placement of roads may be endogenously correlated with unobserved residential amenities, we use job access estimated using straight-line distance, instead of road distance, to construct these moments.

[27] In the model, it is defined by $\frac{\partial \ln \pi_j(s)}{\partial \ln \overline{w}_j} = \nu \frac{U_j^\rho}{U_j^\rho + B_j^\rho}(1-\pi_j(s))\frac{\partial \ln U_j}{\partial \ln \overline{w}_j}$. In the data, we target this elasticity to 2.2 (averaged across earning potential s), consistent with estimates from prior studies examining residential responses to transportation network expansions (Severen, 2023; Tsivanidis, 2025).

first recover $\{A_{j,c}\}$ and $\{\kappa_c\}$ for less developed cities by applying the same procedure described above using the estimated commuting gravity equations. Next, we implement three sets of counterfactuals (as well as their combinations): (1) lowering the overall city productivity ($\{A_{j,c}\}$) to match the average income levels observed in less developed cities; (2) increasing commuting costs (κ_c) to the levels estimated for less developed cities in Section 4; and (3) adjusting the relative productivity penalty of neighborhoods in suburban, hilly, and river areas ($\{A_{j,c}\}$) to reflect the patterns observed in less developed cities.

Figure 11 presents the results. In each column, we report the results of the estimated coefficients on suburban, hilly, and river dummies on residential income using the regression specification (1). Column (1) reports the patterns using our calibrated model to U.S. cities, which closely replicates the data pattern (Appendix Table D.1). Columns (2)–(4) report the regressions using U.S. cities under the counterfactual equilibrium under alternative scenarios, as we further describe below. Column (5) reports the regression coefficients for less developed cities using our data, as reported in Table 2. Consistent with the findings so far, column (1) exhibits positive income premiums in suburban, hilly, and river areas for the U.S. cities, and column (5) exhibits negative income premiums in those areas. We explore whether and what type of counterfactual closes this observed spatial income gap.

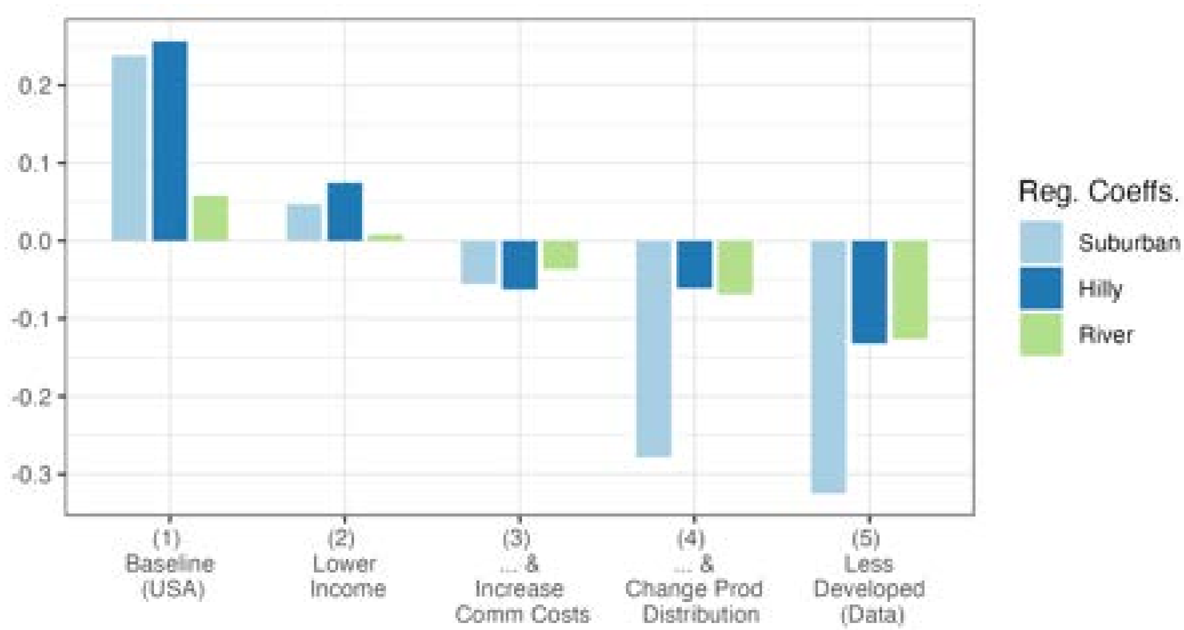
In column (2), we present results from a counterfactual in which average productivity levels $\{A_{j,c}\}_j$ are uniformly reduced by 2.5 log points across all neighborhoods and cities—reduced to roughly 9% of their baseline values. This magnitude corresponds to the mean income gap between U.S. and less developed cities in our sample. Under this scenario, the regression coefficients on the suburban, hilly, and river indicators decline substantially and approach zero. This result is consistent with the interpretation that when overall income levels are low, even households with higher earning potential place less value on amenities, leading to weaker sorting into amenity-rich areas.

In column (3), we run a counterfactual to additionally increase the commuting semielasticity κ_c by 0.24, which is the average difference in estimated κ_c between U.S. and less developed cities (Figure 6). Under this scenario, the regression coefficients for suburban, hilly, and river areas become negative, consistent with the observation that higher commuting frictions in less developed cities are contributing disproportionately worse job access in those areas.[28]

Column (4) reports results from a counterfactual in which we additionally adjust the relative

[28]Appendix Figure D.1 presents the results of a counterfactual exercise in which we implement the scenarios in columns (2)–(4) individually, rather than cumulatively. We find that all of these counterfactuals tend to reduce income premiums, while the counterfactual to lower income has a larger effect than increasing commuting costs and changing productivity distribution.

Figure 11: Unpacking the Spatial Income Distribution Gap: U.S. vs. Less Developed Cities



Notes: This figure displays the estimated coefficients on the suburban, hilly, and river indicators from the regression specification (1). Column (1) presents the baseline results from our model calibrated to U.S. cities. Column (2) shows the regression coefficients under a counterfactual in which average productivity levels $\{A_{j,c}\}_j$ are uniformly reduced by 2.5 log points across all neighborhoods and cities—reduced to roughly 9% of their baseline values. Column (3) reports coefficients from a counterfactual equilibrium in which we further increase the commuting semielasticity κ_c by 0.24, reflecting the average gap between U.S. and less developed cities (Figure 6). Column (4) presents results from a counterfactual in which we further adjust the relative productivity of suburban, hilly, and river neighborhoods to match the patterns observed in less developed cities (Table C.5, column 2). Column (5) displays the corresponding estimates for less developed cities based on observed data.

productivity of suburban, hilly, and river neighborhoods to match the patterns observed in less developed cities.[29] While the estimated area-adjusted productivity $\{A_{j,c}\}$ is lower in suburban, hilly, and river areas, in both developed and less developed cities, the latter cities feature disproportionately large penalties in suburban areas and, to some extent, river and hilly areas (column (2) of Table C.5). Consistent with these observations, we find that the negative income premiums in suburban areas become more pronounced with a more modest change in river and hilly areas. Together, these three forces account for 80% of the average differences in income

[29]Specifically, we first estimate regression (1), using the area-adjusted workplace fixed effects from Equation (2) as the dependent variable (Figure 9, Table C.5). We then adjust $\{A_{j,c}\}$ for suburban, hilly, and river neighborhoods by the differences in these estimated coefficients, divided by θ, between developed and less developed cities.

premiums in suburban, hilly, and river neighborhoods between U.S. cities and less developed cities.

While these three forces jointly explain much of the observed gap in spatial income distributions, some residual variation remains. These unexplained patterns likely reflect differences in amenity gradients within cities by development status. In contrast to developed cities, these areas may be perceived as less desirable due to environmental and infrastructural shortcomings, such as polluted rivers or the absence of sewage systems in suburban or hilly neighborhoods (Harari, 2024; McCulloch et al., 2025).[30]

To quantify the potential role of amenities, we ask: How much must the coefficients $\{\beta_1, \beta_2, \beta_3\}$ decline to account for the gap between columns (4) and (5)? Table 5 presents the results. While these coefficients lack natural units and should be interpreted cautiously, the findings suggest that differences in amenity valuations may indeed contribute to the residual spatial income gaps. Notably, we do not need to assume negative amenity valuations for suburbs, hills, or rivers; rather, much of the observed gap is already explained by differences in income levels and commuting costs.

Table 5: Estimated $\{\beta_1, \beta_2, \beta_3\}$ to Rationalize the Income Distribution in Less Developed Cities

Model	Suburban (β_1)	Hilly (β_2)	River (β_3)
Baseline Estimates (USA)	0.90	1.03	0.26
Estimates to Fully Rationalize Less Developed Cities	0.78	0.83	0.14

Notes: The first row reports the estimated $\{\beta_1, \beta_2, \beta_3\}$ using U.S. cities as reported in Table 4. The second row reports the estimated $\{\beta_1, \beta_2, \beta_3\}$ to fully rationalize the differences in the income premiums of suburban, hilly, and river neighborhoods, after accounting for the overall productivity differences, commuting cost differences, and differences in productivity premiums in those areas, as described further in Section 6.2.

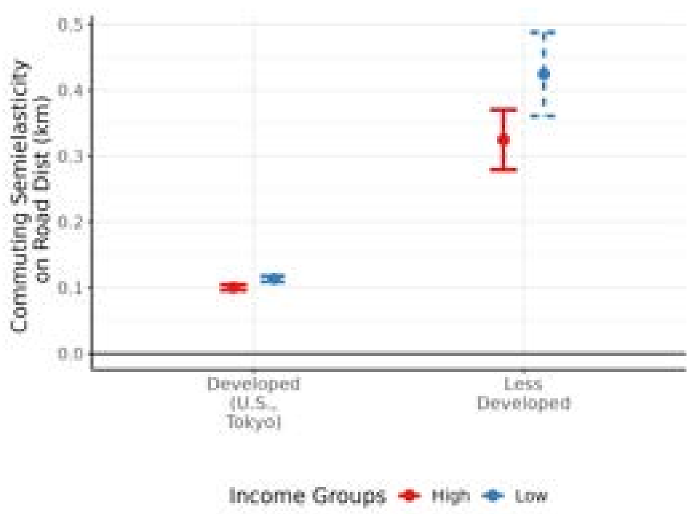
6.3. Heterogeneity of Commuting Costs and Wages by Income Groups

In our baseline analysis, we abstracted from income-related heterogeneity in commuting costs and wage distributions. However, in U.S. cities, disparities in transportation modes and commuting costs across income groups have been identified as one potential driver of residential sorting by income, where poorer residents without private cars sort into downtown areas (LeRoy and Sonstelie, 1983; Glaeser et al., 2008; Su, 2022). If this tendency is weaker in less developed cities, it could potentially explain the observed gap in spatial income distribution.

[30] Another part of the gap between columns (4) and (5) may arise from differences in the geographic structure of cities beyond the commuting cost disparities between U.S. and less developed cities; for example, the specific location of rivers and hills within the cities.

To assess this possibility, we estimate empirical commuting gravity, through Equation (2), separately for households with above- and below-median incomes within each city. Figure 12 reports the estimated commuting semielasticities for developed cities (U.S. cities and Tokyo; commuting data by income are not available for the United Kingdom and France) and for less developed cities. We find larger commuting semielasticities among low-income groups (0.11) than high-income groups (0.10) in developed cities (U.S. cities and Tokyo). However, this difference is *more* pronounced in less developed cities, with 0.42 for low-income groups and 0.32 for high-income groups. These findings suggest that, while these forces may contribute to the sorting of low-income households toward central areas in both developed and less developed cities, they are unlikely to account for the observed disparity between the two groups of cities.

Figure 12: Semielasticity of Commuting by Income Groups



Notes: This figure presents the estimated commuting semielasticities based on Equation (2) separately for households with above- and below-median income for each city. The left column shows the mean estimates and 95% confidence intervals separately for high- and low-income households—defined as above or below the city-specific median income—in developed cities (U.S. cities and Tokyo; we do not have commuting data for the United Kingdom and France separated by income), and the right column shows those estimates in less developed cities.

To further assess these points, in Appendix D.3, we extend our model from Section 5 to allow commuting costs and wages to depend on individuals' earning potential s. Specifically, we now let commuting costs $\tau_{jn,c}(s)$ and wages $w_{n,c}(s)$ vary with s. This model predicts a separate commuting gravity equation for each s. We then calibrate the extended model using the commuting gravity equations by above- and below-median income for high- and low-earning-potential groups.[31] Finally, we run the same counterfactual simulations as before, except that we change the commuting costs and spatial productivity distribution for each s. Using this extended model, we find that changing commuting costs and productivity distributions to the levels of less developed cities generates slightly *smaller* effects on the spatial income distribution compared to our baseline scenario (Figure D.2). Therefore, the heterogeneity across earning potentials s in commuting costs and spatial productivity distribution is unlikely to explain the differences in spatial income distribution. Other factors, such as nonhomotheticity in amenities and *overall* commuting cost and spatial productivity distribution, play a larger role.

6.4. Unpacking the Gap Between U.S. and Other Developed Cities

So far, we have focused on understanding the spatial income-distribution patterns in less developed cities, using U.S. cities as a benchmark for developed cities. At the same time, as we documented in Sections 3 and 4, there is some heterogeneity between U.S. and non-U.S. developed cities. While our main focus in this paper is comparing developed and less developed cities, our framework can also be used to analyze the differences among developed cities. We now conduct this exercise.

In Figure 13, we undertake the same set of counterfactual exercises as before, except that we feed in the differences in overall income, commuting cost, and productivity distribution using the estimates from Western Europe and Japan, instead of less developed cities. In the latter cities, the regression coefficients are around zero and insignificant (column 5).

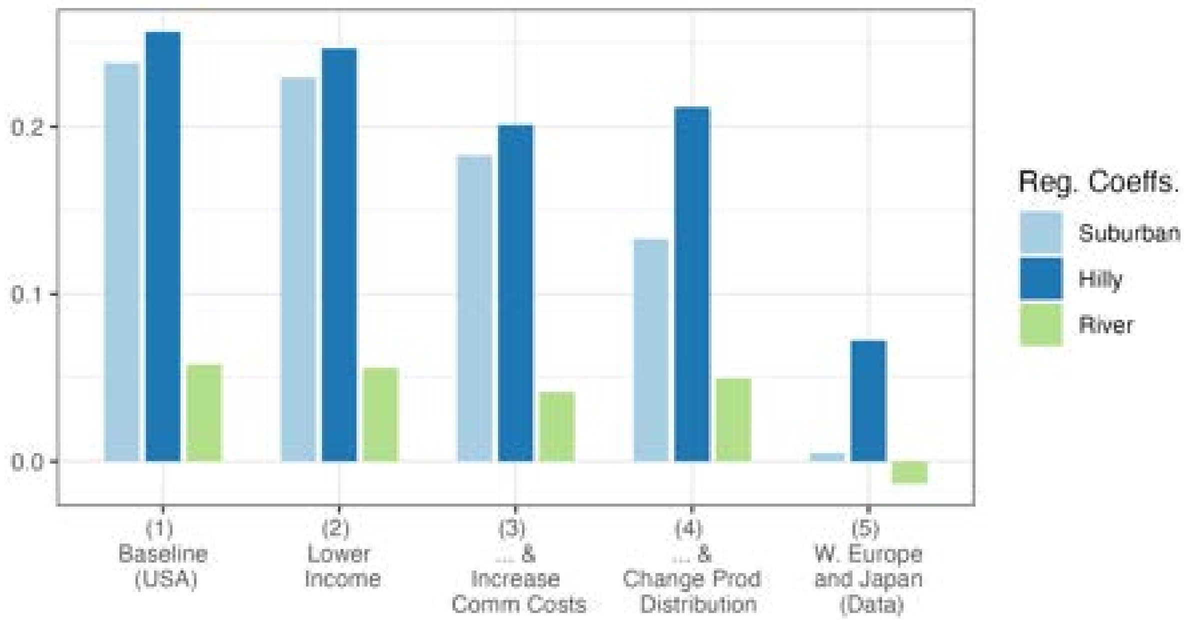
When we lower income to the level of other developed cities (a 0.17 log-point reduction) in column (2), all regression coefficients decrease, but only slightly. In column (3), when we raise the commuting-cost semielasticity to the level of non-U.S. developed cities (an increase of 0.08), the coefficients decline meaningfully, though they remain well above zero. Finally, in column (4), adjusting relative productivity in suburban, hilly, and river areas to match non-U.S. developed cities further reduces the suburban coefficient, consistent with more concentrated job opportunities in those cities (Figure 9), though the coefficients remain far from zero.

Our quantitative analysis indicates that differences in the spatial income distribution between these cities and the U.S. cities are largely driven by the spatial distribution of amenities.[32] This

[31] Realized income in our model is a product of earning potential s and the expected wage rates at the residential location $\overline{w}_{j,c}(s)$. Therefore, if the variance of earning potential s is much larger than the spatial variation of wage rates $\overline{w}_{j,c}(s)$, this strategy effectively splits the samples with high- and low-earning-potential households within each city.

[32] Appendix Table D.2 presents an analysis analogous to Table 5, where we estimate $\{\beta_1, \beta_2, \beta_3\}$ to rationalize the patterns observed in other developed cities. The estimated parameters are substantially smaller than the estimated values for U.S. cities, though still positive.

Figure 13: Unpacking the Spatial Income-Distribution Gap: U.S. vs. Other Developed Cities



Notes: This figure displays the results of the same counterfactual simulation as in Figure 11, except that the counterfactuals are targeted to non-U.S. developed cities (Western Europe and Japan).

suggests that, beyond the suburban open space and natural amenities emphasized in the United States, other forms of amenities may play a central role elsewhere. For instance, cities like Paris or Amsterdam have a wide variety of restaurants, cafes, and bars in their urban cores, attracting wealthier residents (Brueckner et al., 1999; Almagro and Domínguez-Iino, 2025). This naturally raises the question of why the distribution of amenities systematically diverges between U.S. and other developed cities. One possibility is that commuting frictions shape endogenous amenity supply. Using smartphone data from Tokyo, Miyauchi, Nakajima, and Redding (2025) show that commuters often combine workplace trips with visits to amenities, encouraging their agglomeration in central areas. Another explanation could be the decentralized nature of policymaking about local public goods: compared to the United States, provision in many other developed countries is more centralized at the metropolitan level (OECD, 2021). Pinpointing the precise mechanisms behind these differences remains an important task for future research.

6.5. Policy Implications

Understanding spatial patterns of income distribution and commuting is essential for designing effective urban policies. The contrasting spatial income structures between developed and less developed cities imply that place-based interventions—such as transportation investments or residential infrastructure improvements—can have opposite distributional consequences across income groups in these two settings. Our findings therefore suggest that policies successful in developed cities may not yield similar outcomes in less developed contexts, particularly with regard to their relative effects on poorer versus richer households.

Furthermore, our analysis suggests that even citywide productivity-enhancing policies may yield unequal welfare effects. In Appendix D.4, we use our calibrated model to examine a counterfactual where all residents experience a uniform productivity increase. As overall income levels rise, richer households tend to relocate from dense urban cores to suburban neighborhoods with higher amenities. This spatial re-sorting alleviates rent pressures in central areas, indirectly benefiting poorer residents who remain in the urban core.

7. Conclusion

How do internal city structures differ between developed and less developed cities? To answer this question, we construct new granular data from 50,000 neighborhoods in 121 cities across 26 countries, drawing on dozens of travel surveys from many developing-country cities and various administrative data.

We document that, in less developed cities, poorer residents are more likely to live farther from city centers and in hills and near rivers—areas with natural amenities but that are nonetheless distant from jobs. In developed cities, these patterns are absent or even reversed. In less developed cities, commuting shares also fall more steeply with distance, reflecting greater commuting frictions that exacerbate inequality in job access.

To interpret these findings, we develop a quantitative urban model that incorporates residential and commuting choices with nonhomothetic preferences for housing and amenities. We find that the differences in urban spatial income distribution between developed and less developed cities are largely driven by nonhomothetic preferences over amenities, higher commuting costs, and more spatially concentrated jobs in less developed cities. These mechanisms are particularly important for understanding the distributional consequences of place-based policies and even citywide productivity-enhancing policies.

Our paper is among the first to provide cross-country comparisons of city structure and income distribution, spanning countries with low to high incomes. We hope it is only the beginning. In particular, we see two key directions for future research. First, while we document systematic differences in productivity, amenities, and commuting costs as important drivers of city structure and income distribution, we do not specify *why* these fundamentals differ between developed and less developed cities. In practice, neighborhood-level fundamentals are partly shaped by the endogenous provision of amenities (e.g., schools, restaurants), productivity spillovers (e.g., knowledge diffusion), and policy choices (e.g., infrastructure investment). Understanding the sources of these differences more precisely is an important task for future work. Second, although our analysis is cross-sectional, our findings also inform the study of how the spatial organization of economic activity evolves with development. Historical evidence from developed countries (e.g., Lee and Lin, 2018) and theories of dynamic structural transformation of cities offer promising avenues for further exploration.

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Online Appendix for
"The Spatial Distribution of Income in Cities: New Global Evidence and Theory"

November 16, 2025

Peter Deffebach, David Lagakos, Yuhei Miyauchi, Eiji Yamada

Contents

A. Data Appendix

A.1. Additional Figures and Tables for Data

Table A.1: List of Cities From JICA Surveys (Latin 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	417.0	21.8
Lima	2003	Peru	144490	388	1998.5	40.6
Managua	1998	Nicaragua	37082	92	244.7	13.8

Table A.2: List of Cities From JICA Surveys (Africa and Middle 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	860.1	25.7
Cairo	2001	Egypt	137513	429	1576.3	36.5
Damascus	1998	Syrian Arab Republic	38280	74	1348.1	22.8
Dar es Salaam	2007	U.R. of Tanzania: Mainland	26687	159	1152.5	29.0
Kinshasa	2018	D.R. of the Congo	42031	321	538.8	21.4
Mombasa	2015	Kenya	10868	32	188.0	10.5
Nairobi	2013	Kenya	16794	102	590.7	20.1

Table A.3: List of Cities From JICA Surveys (Asia and Eastern 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	566.4	13.1
Cebu	2014	Philippines	28806	229	447.8	38.7
Chengdu	2000	China	31130	125	589.9	17.0
Colombo	2013	Sri Lanka	124673	376	1681.9	59.4
Da Nang	2008	Viet Nam	18171	50	368.3	14.3
Dhaka	2014	Bangladesh	118026	140	1536.6	29.7
Hanoi	2005	Viet Nam	63716	250	979.7	31.9
Ho Chi Minh	2014	Viet Nam	42908	210	1801.6	35.5
Jakarta	2010	Indonesia	154275	1041	3713.1	64.5
Kuala Lumpur	1999	Malaysia	80545	222	2537.7	46.9
Lahore	2010	Pakistan	89414	188	1873.4	43.1
Manila	1996	Philippines	231838	220	1553.7	37.4
Phnom Penh	2012	Cambodia	42074	85	511.3	17.5
Viang Chan	2007	Lao People's DR	27630	33	297.6	11.0
Yangon	2013	Myanmar	42224	620	712.4	29.7

Figure A.1: Locations of Cities in Our Dataset

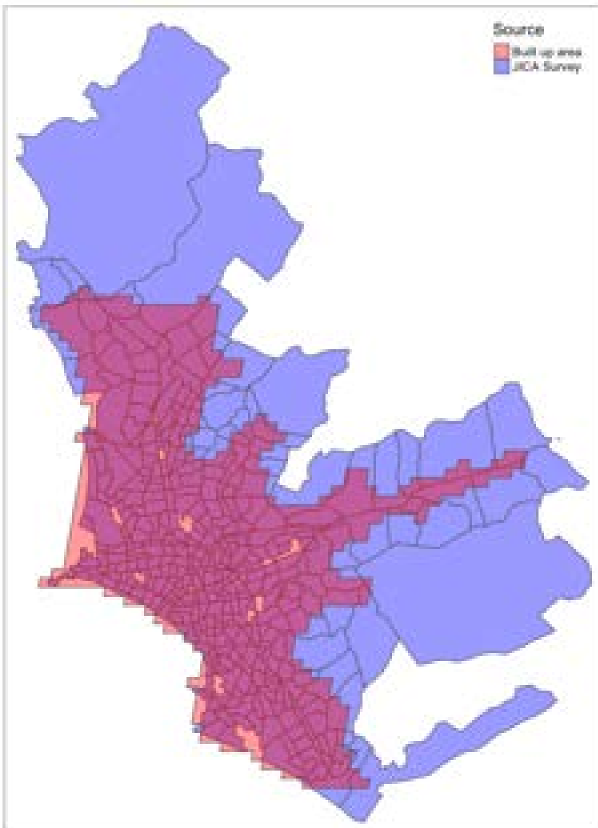
Notes: A map of all cities included in our dataset described in Section 2 .

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

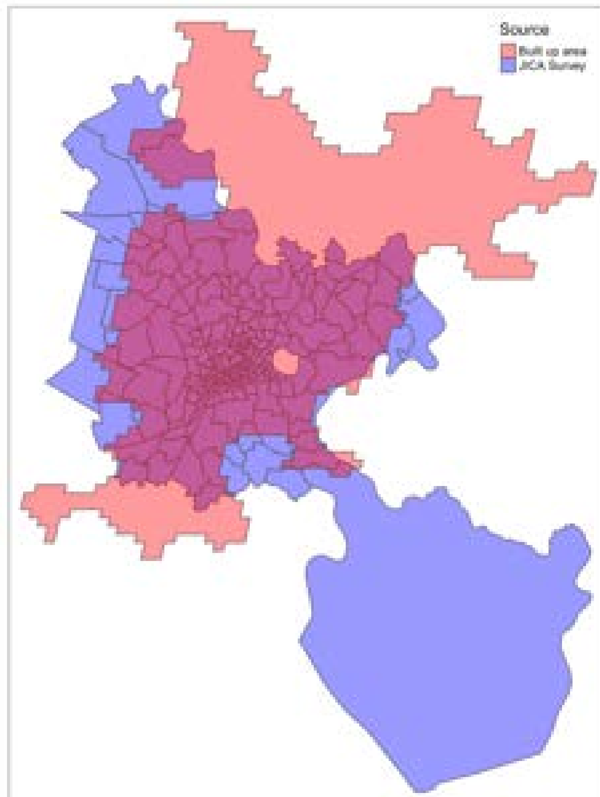
Country	Number of cities	Total number of survey zones	List of cities
Brazil	24	3575	Aracaju, Belo Horizonte, Campinas, Cuiabá, Curitiba, Florianópolis, Fortaleza, João Pessoa, Londrina, Maceió, Manaus, Natal, Novo Hamburgo, Porto Alegre, Recife, Ribeirao Preto, Rio de Janeiro, Santos, Sao Goncalo, Sao Jose dos Campos, São Paulo, Teresina, Uberlândia, Vila Velha
France	7	562	Bordeaux, Lille, Lyon, Marseille, Nice, Paris, Toulouse
Japan	1	190	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	27579	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.

Notes: List of all countries and cities in our dataset, excluding JICA surveys. See Section 2 for further description.

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



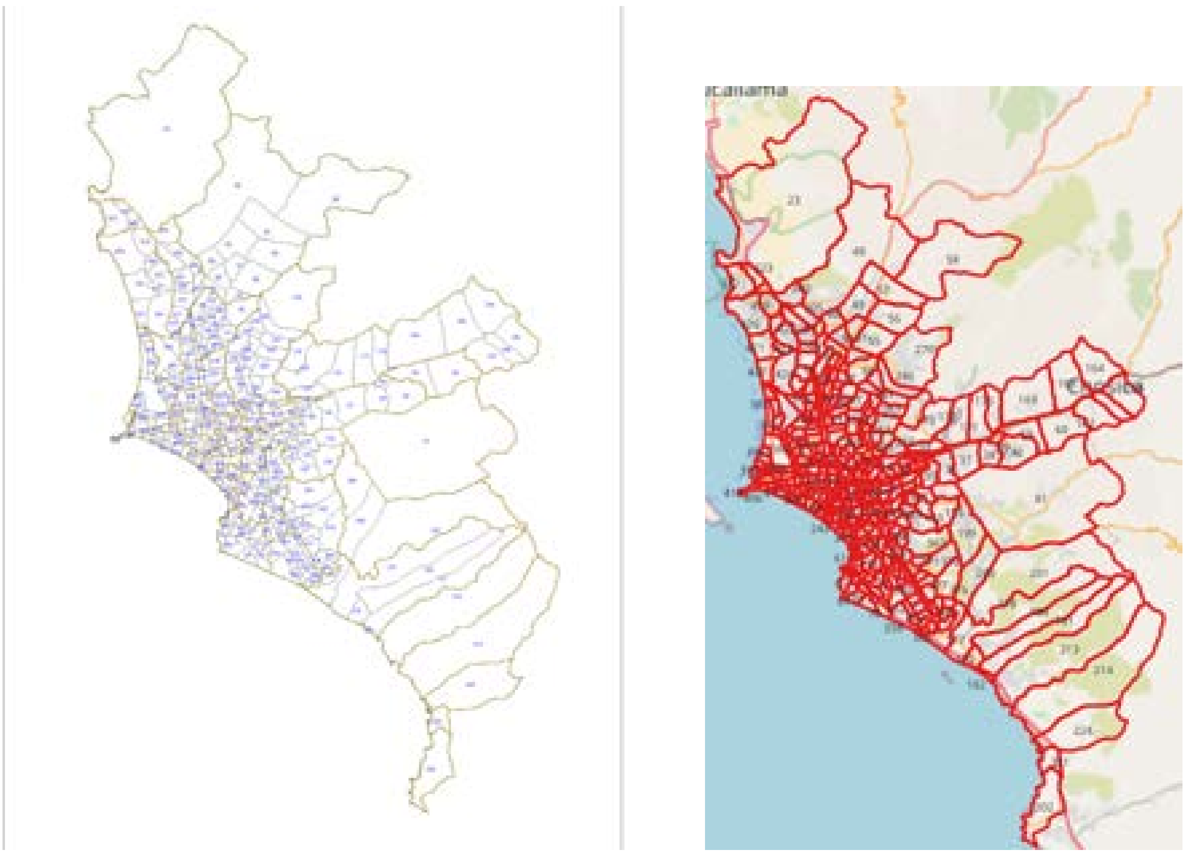
(a) Lima, Peru



(b) Ho Chi Minh City, Vietnam

Notes: "Built-up Area", in red, represents the shape of a city as defined by World Settlement Footprint's "Built Up Areas" dataset (Florczyk et al., 2019). "JICA Survey", blue, shows the neighborhoods surveyed by JICA in their surveys across the world.

Figure A.3: Geocoding Survey Zones (Lima)



(a) PDF

(b) Shapefiles

Notes: The left panel shows the screenshot of survey zones from a report for a travel survey. The right panel shows the screenshot of the manually geocoded shapefiles of survey zones.

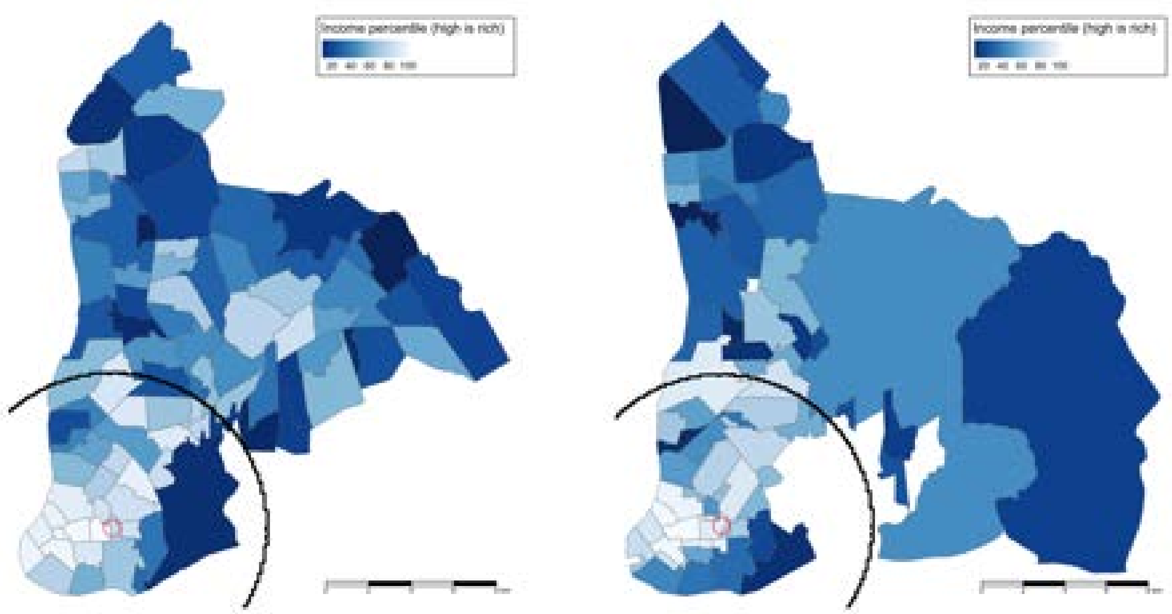
A.2. Comparison of Income between Travel Survey and Census in Belém, Brazil

In this section, we provide a cross-validation of our residential income data from travel survey data and census data in Belém, Brazil, the only city in our dataset where both types of data are available.

The two datasets show similar patterns of residential income. In Figure A.4, we show the neighborhood-level income percentiles for both data sources. The semicircle in each panel represents the border between suburban and nonsuburban neighborhoods as defined in Section 3, where suburban neighborhoods are defined as those containing 50% of the population farthest from the city center. Despite the differences in the spatial resolution, one can recognize a similarity in the broad pattern of the spatial income distribution between these two datasets. In particular, in both datasets, one can visually recognize the pattern that the average income is higher in urban center than in suburban areas.

To further reinforce this point, in Figure A.5, we show the relationship between income percentile and distance to the city center for the two data sources. The two thick lines represent the average income percentile within each 2 km bin from each dataset, with 95% confidence intervals. Both datasets exhibit a monotonically decreasing pattern in the distance from the city center, consistent with our findings in a typical less developed city (Section 3).

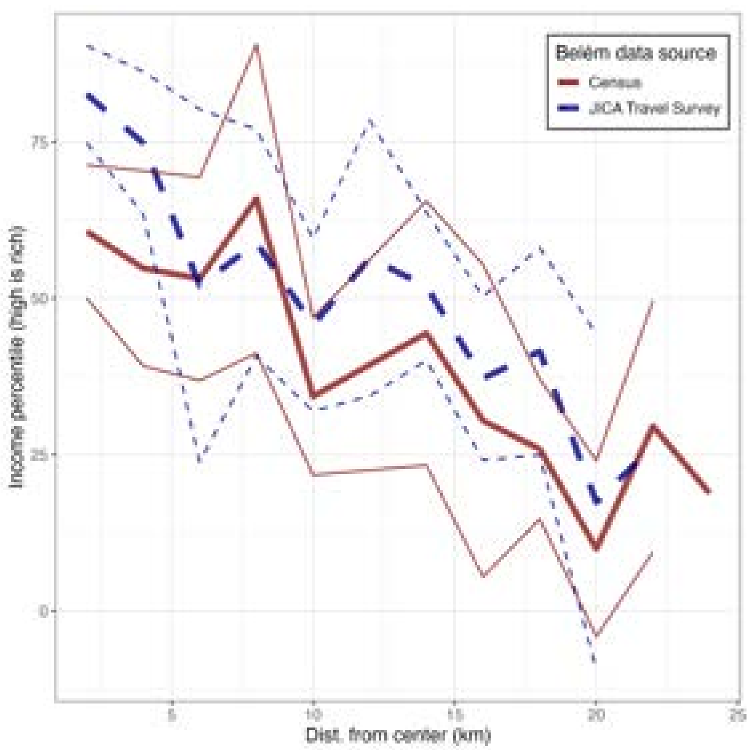
Figure A.4: Map of income percentiles in Belém, Brazil



(a) JICA Travel Survey

(b) 2010 Census

Figure A.5: Income percentile and distance from center in Belém



A.3. Commuting Flow Data in the United States: CTPP vs. LODES vs. Travel Surveys

For our analysis, we use commuting flow information in the United States from the Census Transportation Planning Packages (CTPP) for the years 2012-2016, which are constructed using the American Community Survey (ACS) data on usual residence and workplaces. The CTPP data reports the aggregate number of workers living and working in any given pair of census tracks.

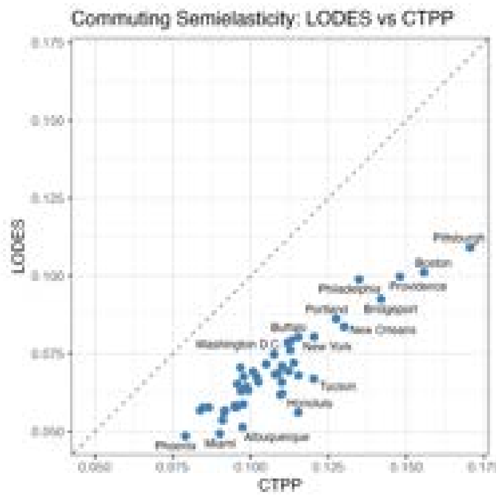
An alternative commuting dataset in the United States is the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics (LODES). This dataset is constructed from the Quarterly Census of Employment and Wages, which covers all firms with paid employees and are subject to unemployment insurance laws. While LODES provides a near-census coverage of paid workers with their precise residential locations, it excludes the self-employed and imputes worksite locations for multi-establishment firms. Spear (2011) reports that, reflecting these differences, LODES tend to report longer commuting distances than CTPP. Below, we further compare these two datasets, focusing on the commuting semielasticities, and compare them with alternative travel survey data from two cities: Chicago and San Francisco.

To assess these differences, in Figure A.6, we compare the commuting semielasticity estimates following the specification (2) using the two different datasets. We use 2015 data for LODES, similar in timing to our CTPP data (2012-2016). We find that the commuting semielasticities using LODES are roughly two-thirds the magnitude of those estimated from the CTPP.

In Figure A.7, we further compare the commuting semielasticities from these two datasets with the ones estimated from travel surveys for two cities, San Francisco (conducted in 2000) and Chicago (conducted in 2007), where that data is available.[33] Note that the timing of these surveys does not align with LODES and CTPP, and hence the estimates do not have to perfectly align with each other. Nonetheless, we find that the semielasticities from travel surveys align more closely with the CTPP data, with estimates from LODES are systematically lower than the other two datasets.

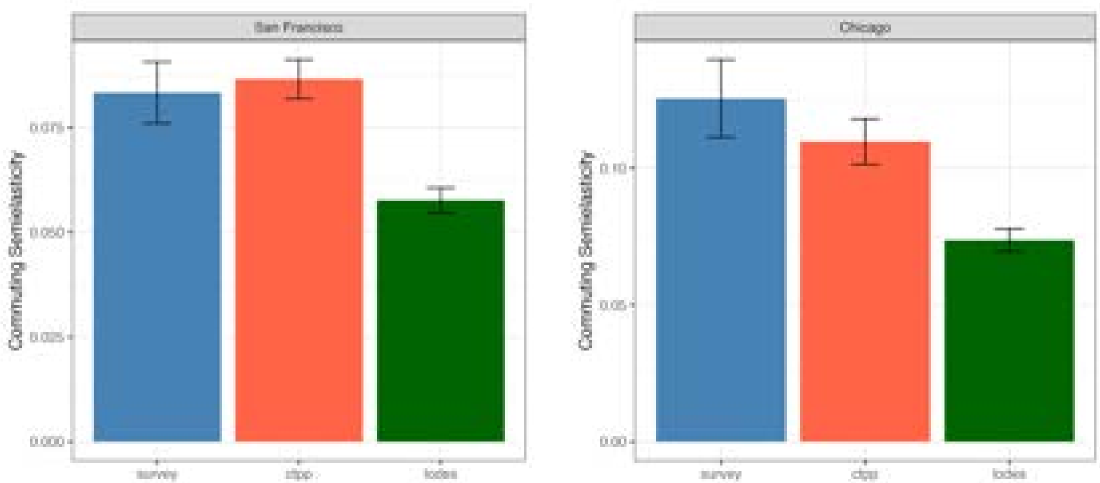
[33]The data is available from https://www.nrel.gov/transportation/secure-transportation-data/tsdc-chicago-household-travel-inventory and https://www.icpsr.umich.edu/web/ICPSR/studies/34805.

Figure A.6: Commuting Semielasticities from CTPP vs. LODES



Notes: The figures compare the estimates commuting gravity (2) *using PPML estimator for each city using CTPP and LODES.*

Figure A.7: Gravity Regression of Commuting Flows: Travel Survey vs. CTPP vs. LODES



(a) San Francisco

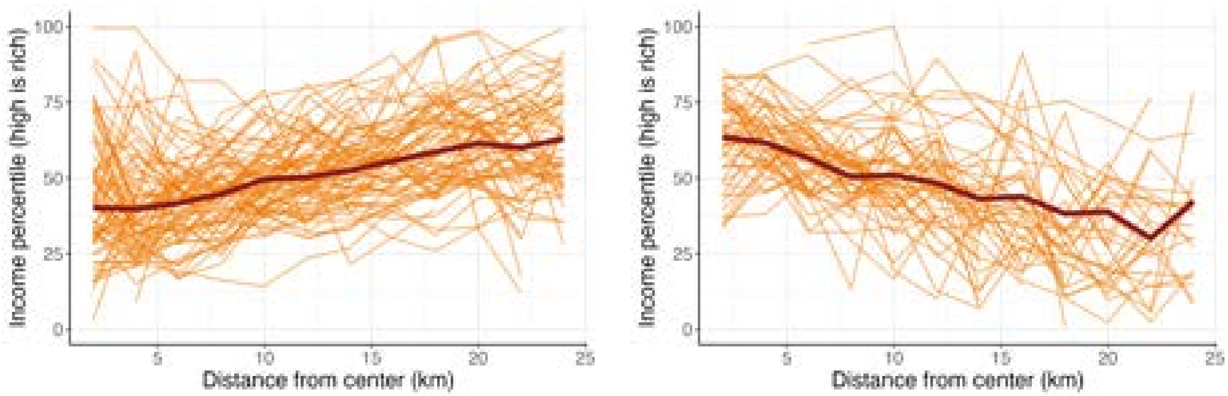
(b) Chicago

Notes: The figures compare the estimates commuting gravity (2) *using PPML estimator for Chicago and San Francisco, using CTPP (2012-2016), LODES (2015), and travel surveys (2007 for San Francisco and 2000 for Chicago). The error bars report 95% confidence intervals with two-way clustering at the origin and destination level.*

B. Appendix for Spatial Distribution of Income

B.1. Residential Income and Distance to City Center

Figure B.1: Residential Income and Distance from City Center

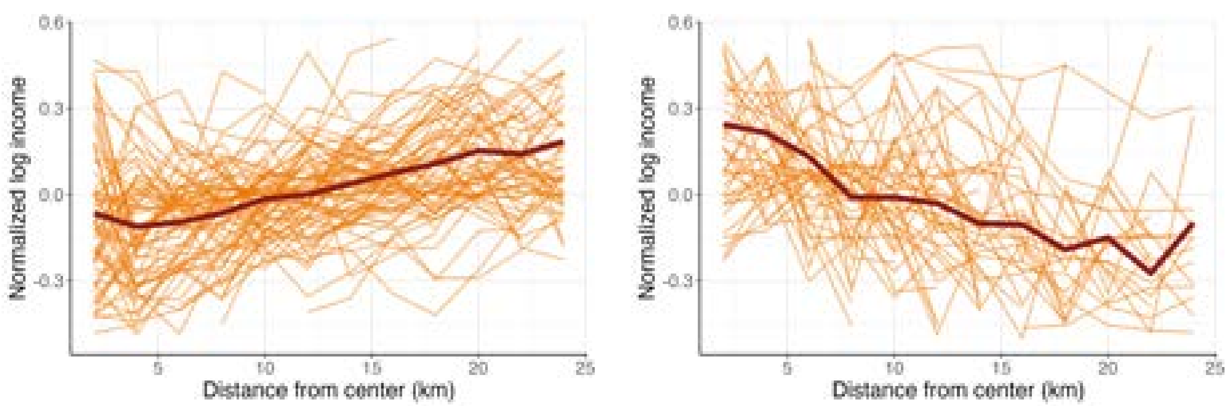


(a) Developed Cities

(b) Less Developed Cities

Notes: The figures show the relationships between 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.

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

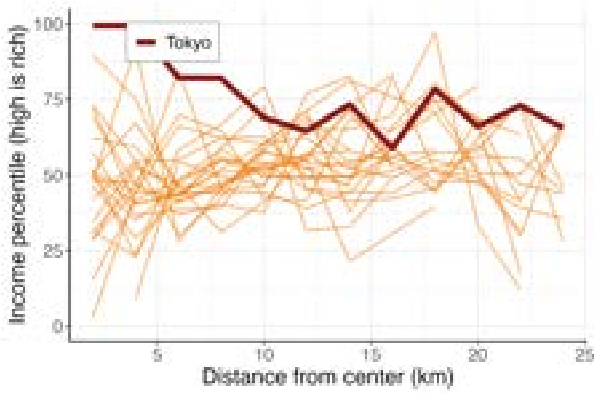


(a) Developed Cities

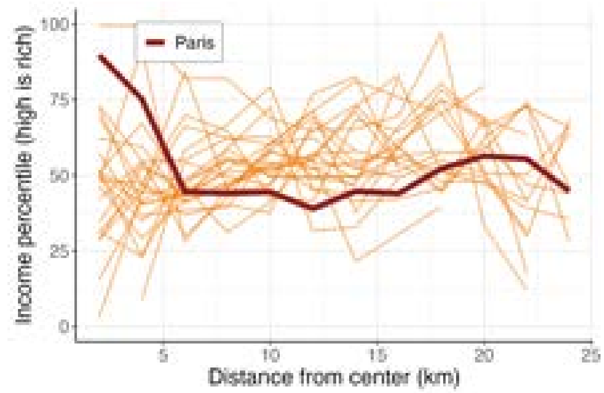
(b) Less Developed Cities

Notes: Distance from the city center and income. Emulates Appendix 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.

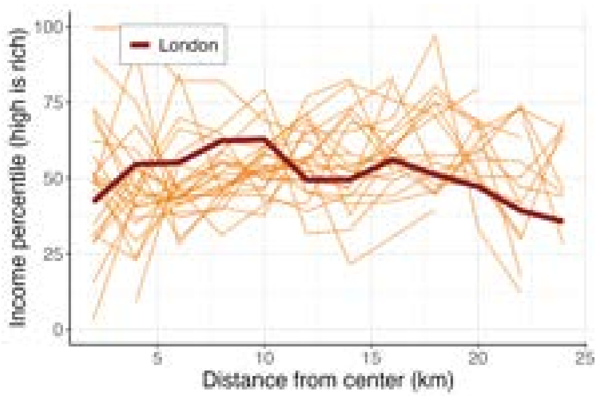
Figure B.3: Residential Income and Distance from City Center: Tokyo, Paris, London



(a) Tokyo



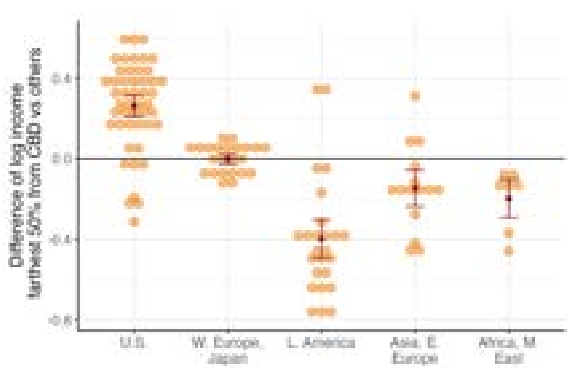
(b) Paris



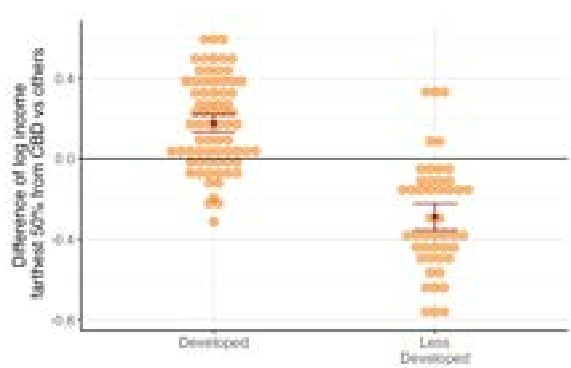
(c) London

Notes: The figures show a version of Panel (b) of Figure 3, which shows the income gradient of Western Europe and Japanese cities with respect to the city center, highlighting Tokyo, Paris, and London with bold lines.

Figure B.4: Suburban-Urban Income Gap: log Income



(a) By Regions



(b) By Development Status

Notes: Emulates Figure 4, except that we take log income, instead of income percentiles within each city.

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

City	Country	Difference	Region	Development Status
Florianópolis	Brazil	-44.4	L. America	Less Developed
Hanoi	Viet Nam	-37.9	Asia, E. Europe	Less Developed
Curitiba	Brazil	-36.0	L. America	Less Developed
Londrina	Brazil	-36.0	L. America	Less Developed
Dhaka	Bangladesh	-35.9	Asia, E. Europe	Less Developed
Porto Alegre	Brazil	-33.9	L. America	Less Developed
Mombasa	Kenya	-33.5	Africa, M. East	Less Developed
Phnom Penh	Cambodia	-33.2	Asia, E. Europe	Less Developed
Tokyo	Japan	-33.2	W. Europe, Japan	Developed
São Paulo	Brazil	-33.0	L. America	Less Developed
Vila Velha	Brazil	-32.4	L. America	Less Developed
Lima	Peru	-31.8	L. America	Less Developed
Belém	Brazil	-28.0	L. America	Less Developed
Jakarta	Indonesia	-27.5	Asia, E. Europe	Less Developed
Uberlândia	Brazil	-26.2	L. America	Less Developed
Fortaleza	Brazil	-25.3	L. America	Less Developed
Rio de Janeiro	Brazil	-24.6	L. America	Less Developed
Seattle	United States	-24.5	U.S.	Developed
Ho Chi Minh City	Viet Nam	-23.8	Asia, E. Europe	Less Developed
Colombo	Sri Lanka	-21.6	Asia, E. Europe	Less Developed

(a) Bottom 20 Cities

City	Country	Difference	Region	Development Status
Fresno	United States	39.5	U.S.	Developed
Bakersfield	United States	37.7	U.S.	Developed
Las Vegas	United States	37.3	U.S.	Developed
San Antonio	United States	36.8	U.S.	Developed
Omaha	United States	35.5	U.S.	Developed
Indianapolis	United States	33.9	U.S.	Developed
Buffalo	United States	32.3	U.S.	Developed
Dà Nang	Viet Nam	31.4	Asia, E. Europe	Less Developed
Oklahoma City	United States	30.8	U.S.	Developed
Detroit	United States	30.7	U.S.	Developed
Tucson	United States	30.4	U.S.	Developed
Columbus	United States	29.6	U.S.	Developed
Kansas City	United States	28.6	U.S.	Developed
Albuquerque	United States	28.3	U.S.	Developed
Providence	United States	27.3	U.S.	Developed
Cleveland	United States	27.3	U.S.	Developed
Houston	United States	26.9	U.S.	Developed
Louisville	United States	25.6	U.S.	Developed
Sacramento	United States	25.4	U.S.	Developed
Milwaukee	United States	25.3	U.S.	Developed

(b) Top 20 Cities

Notes: A list of the top and bottom 20 cities, ranked by the difference in average income percentiles between suburban and urban core neighborhoods for each city (as indicated by the column "Difference"), where suburban areas are defined as the neighborhoods containing the 50% of the population located farthest from the city center, and urban core areas are defined as the rest.

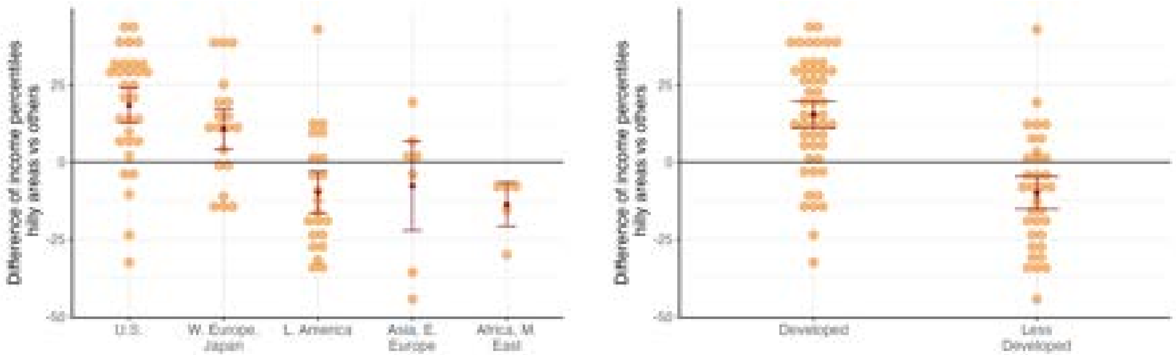
Table B.2: Suburban-Urban Income Gap: By Country

Country	Difference	Cities	Region	Development Status
Bangladesh	-35.9	1	Asia, E. Europe	Less Developed
Cambodia	-33.2	1	Asia, E. Europe	Less Developed
Japan	-33.2	1	W. Europe, Japan	Developed
Peru	-31.8	1	L. America	Less Developed
Indonesia	-27.5	1	Asia, E. Europe	Less Developed
Sri Lanka	-21.6	1	Asia, E. Europe	Less Developed
Brazil	-20.1	25	L. America	Less Developed
D.R. of the Congo	-20.0	1	Africa, M. East	Less Developed
Kenya	-17.9	2	Africa, M. East	Less Developed
Pakistan	-17.6	1	Asia, E. Europe	Less Developed
Myanmar	-15.8	1	Asia, E. Europe	Less Developed
Romania	-12.7	1	Asia, E. Europe	Less Developed
Nicaragua	-12.3	1	L. America	Less Developed
Malaysia	-11.7	1	Asia, E. Europe	Less Developed
Syrian Arab Republic	-10.2	1	Africa, M. East	Less Developed
Viet Nam	-10.1	3	Asia, E. Europe	Less Developed
Côte d'Ivoire	-9.9	1	Africa, M. East	Less Developed
Egypt	-8.6	1	Africa, M. East	Less Developed
Lao People's DR	-8.2	1	Asia, E. Europe	Less Developed
Philippines	-6.3	2	Asia, E. Europe	Less Developed
U.R. of Tanzania: Mainland	-4.9	1	Africa, M. East	Less Developed
Spain	0.4	7	W. Europe, Japan	Developed
France	2.5	7	W. Europe, Japan	Developed
United Kingdom	3.9	9	W. Europe, Japan	Developed
China	5.7	1	Asia, E. Europe	Less Developed
United States	18.6	48	U.S.	Developed

Notes: A list of all countries in our neighborhood-level income dataset ranked by the difference in average income percentiles between suburban and urban core neighborhoods for each country (as indicated by the column "Difference"), where suburban areas are defined as the neighborhoods containing the 50% of the population located farthest from the city center, and urban core areas are defined as the rest.

B.2. Residential Income and Hills/Rivers

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

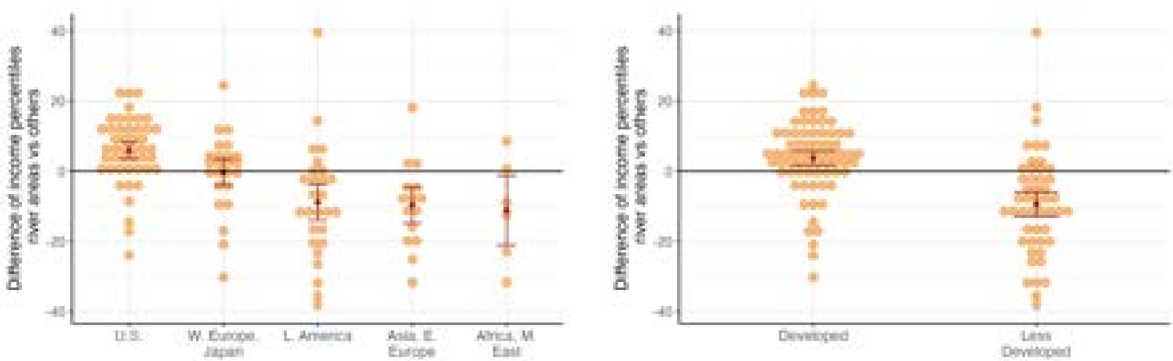


(a) By Regions

(b) By Development Status

Notes: Differences in average income percentile between hilly neighborhoods and nonhilly neighborhoods, as defined in Section 2. Emulates Figure 5, but focuses only on hills. Panel (a) by region; Panel (b) groups cities by development status. We also plot the average value and its 95% confidence interval.

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



(a) By Regions

(b) By Development Status

Notes: Differences in average income percentile between neighborhoods that are near a river, meaning within 100 meters of a natural waterway. Emulates Figure 5, but focuses only on rivers. Panel (a) by region; Panel (b) groups cities by development status. We also plot the average value and its 95% confidence interval.

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

City	Country	Difference	Region	Development Status
João Pessoa	Brazil	-35.2	L. America	Less Developed
Damascus	Syrian Arab Republic	-32.3	Africa, M. East	Less Developed
Dhaka	Bangladesh	-31.6	Asia, E. Europe	Less Developed
Toulouse	France	-30.2	W. Europe, Japan	Developed
Lima	Peru	-29.2	L. America	Less Developed
Novo Hamburgo	Brazil	-26.0	L. America	Less Developed
Managua	Nicaragua	-25.2	L. America	Less Developed
Lahore	Pakistan	-25.1	Asia, E. Europe	Less Developed
Belém	Brazil	-23.3	L. America	Less Developed
Dar es Salaam	U.R. of Tanzania: Mainland	-22.9	Africa, M. East	Less Developed
Natal	Brazil	-21.8	L. America	Less Developed
Vila Velha	Brazil	-21.5	L. America	Less Developed
Maceió	Brazil	-20.4	L. America	Less Developed
Londrina	Brazil	-20.4	L. America	Less Developed
Colombo	Sri Lanka	-20.3	Asia, E. Europe	Less Developed
Phnom Penh	Cambodia	-19.4	Asia, E. Europe	Less Developed
Newcastle upon Tyne	United Kingdom	-19.3	W. Europe, Japan	Developed
Curitiba	Brazil	-17.7	L. America	Less Developed
Recife	Brazil	-17.4	L. America	Less Developed
Florianópolis	Brazil	-16.8	L. America	Less Developed

(a) Bottom 20 Cities

City	Country	Difference	Region	Development Status
Campinas	Brazil	39.6	L. America	Less Developed
Honolulu	United States	30.7	U.S.	Developed
Las Vegas	United States	29.4	U.S.	Developed
Concord	United States	25.1	U.S.	Developed
Bradenton	United States	22.9	U.S.	Developed
Cleveland	United States	22.2	U.S.	Developed
Dà Nang	Viet Nam	21.9	Asia, E. Europe	Less Developed
Atlanta	United States	21.9	U.S.	Developed
Los Angeles	United States	21.3	U.S.	Developed
Austin	United States	21.1	U.S.	Developed
Marseille	France	19.9	W. Europe, Japan	Developed
San Jose	United States	16.4	U.S.	Developed
Houston	United States	16.2	U.S.	Developed
Orlando	United States	15.8	U.S.	Developed
Málaga	Spain	15.7	W. Europe, Japan	Developed
Buffalo	United States	15.5	U.S.	Developed
Bakersfield	United States	15.4	U.S.	Developed
Seattle	United States	15.1	U.S.	Developed
Sacramento	United States	15.0	U.S.	Developed
Albuquerque	United States	15.0	U.S.	Developed

(b) Top 20 Cities

Notes: A list of the top and bottom 20 cities, ranked by the difference in average income percentiles between neighborhoods that are hilly or near a river and those that are not (as indicated by the column "Difference"), as defined in Section 2.

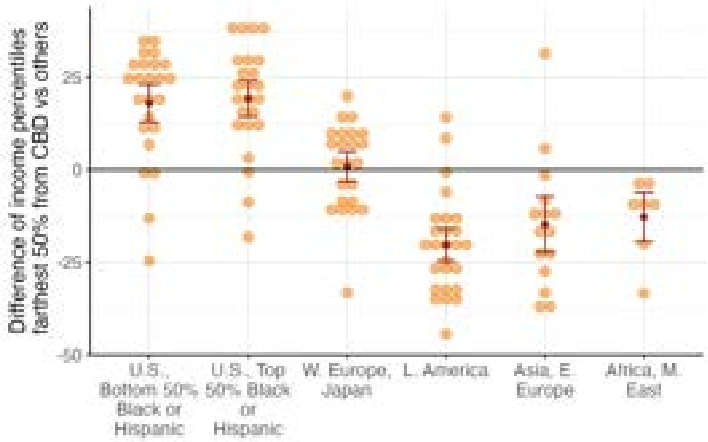
Table B.4: Residential Income and Hills/Rivers: By Country

Country	Difference	Cities	Region	Development Status
Syrian Arab Republic	-32.3	1	Africa, M. East	Less Developed
Bangladesh	-31.6	1	Asia, E. Europe	Less Developed
Peru	-29.2	1	L. America	Less Developed
Nicaragua	-25.2	1	L. America	Less Developed
Pakistan	-25.1	1	Asia, E. Europe	Less Developed
U.R. of Tanzania: Mainland	-22.9	1	Africa, M. East	Less Developed
Sri Lanka	-20.3	1	Asia, E. Europe	Less Developed
Cambodia	-19.4	1	Asia, E. Europe	Less Developed
Kenya	-13.9	2	Africa, M. East	Less Developed
Myanmar	-12.3	1	Asia, E. Europe	Less Developed
Japan	-11.3	1	W. Europe, Japan	Developed
Brazil	-9.8	25	L. America	Less Developed
Côte d'Ivoire	-8.9	1	Africa, M. East	Less Developed
Malaysia	-7.5	1	Asia, E. Europe	Less Developed
Lao People's DR	-6.5	1	Asia, E. Europe	Less Developed
Philippines	-5.9	2	Asia, E. Europe	Less Developed
Indonesia	-5.3	1	Asia, E. Europe	Less Developed
D.R. of the Congo	-2.1	1	Africa, M. East	Less Developed
Egypt	-1.7	1	Africa, M. East	Less Developed
France	-1.2	7	W. Europe, Japan	Developed
Viet Nam	-0.3	3	Asia, E. Europe	Less Developed
United Kingdom	1.0	9	W. Europe, Japan	Developed
Romania	1.6	1	Asia, E. Europe	Less Developed
Spain	2.7	7	W. Europe, Japan	Developed
China	2.8	1	Asia, E. Europe	Less Developed
United States	9.5	48	U.S.	Developed

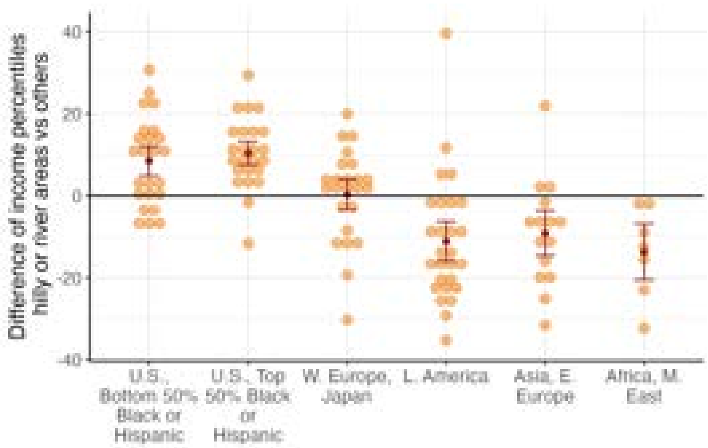
Notes: A list of countries, ranked by the difference in average income percentiles between neighborhoods that are hilly or near a river and those that are not (as indicated by the column "Difference"), as defined in Section 2.

B.3. Separating U.S. Cities by Racial Minority Shares

Figure B.7: Residential Income: Separating U.S. Cities by Racial Minority Shares



(a) Suburban-Urban Income Gap

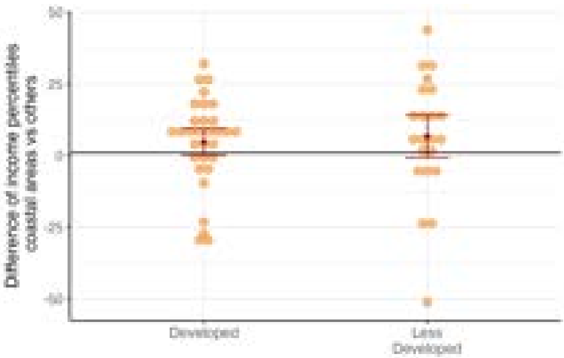


(b) Income Premiums in Hills and Rivers

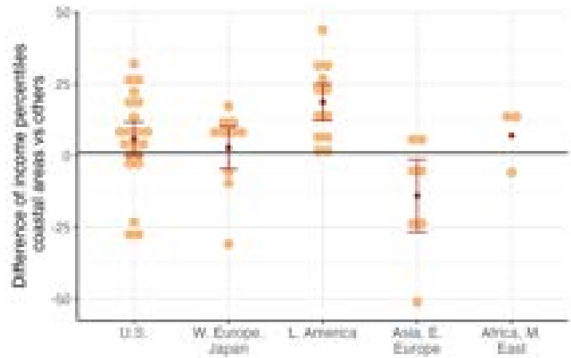
Notes: The panels display the difference in average income percentiles between suburban and urban core neighborhoods for each city, where suburban areas are defined as the neighborhoods containing the 50% of the population located farthest from the city center, and urban core areas are defined as the rest. Each dot represents a city. Emulates Figures 4 and 5, except that we divide the United States between cities with above and below median shares of racial minorities (Black or Hispanic).

B.4. Other Statistics

Figure B.8: Residential Income and Coasts



(a) By Development Status



(b) By Regions

Notes: The figures show the difference in average income percentiles between neighborhoods that are within 100 meter from coasts and those that are not. Each dot represents a city. Panel (a) groups them by region; Panel (b) groups cities by development status. In both panels, we report the group means along with 95% confidence intervals.

Table B.5: Average Household Size in Less Developed Cities

	Household Size			
	(1)	(2)	(3)	(4)
Suburban	0.27			0.24
	(0.21)			(0.19)
Hilly		0.13		0.05
		(0.08)		(0.05)
River			0.18	0.13
			(0.16)	(0.12)
City Fixed Effects	X	X	X	X
Unique Cities	26	26	26	26
Observations	5,851	5,851	5,851	5,851

*Notes: Regression results of average household size in less developed cities. The unit of observation is a neighborhood with a positive average income. We weight observations by the fraction of residents in each neighborhood for each city, such that the regression assigns equal weight to each city. Standard errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.*

Table B.6: Employment Status in Less Developed Cities

	Working			
	(1)	(2)	(3)	(4)
Suburban	0.01			0.01
	(0.01)			(0.01)
Hilly		−0.02		−0.02
		(0.01)		(0.01)
River			0.01	0.01
			(0.01)	(0.01)
City Fixed Effects	X	X	X	X
Unique Cities	26	26	26	26
Observations	5,851	5,851	5,851	5,851

Notes: Regression results of the dummy for working (as opposed to unemployed, nonemployed, or students) in less developed cities, analogous to Table B.5.

Table B.7: Average Age in Less Developed Cities

	Average Age			
	(1)	(2)	(3)	(4)
Suburban	-1.37^{***}			-1.29^{***}
	(0.40)			(0.37)
Hilly		-0.26		0.14
		(0.87)		(0.78)
River			-0.83^{***}	-0.54^{***}
			(0.21)	(0.17)
City Fixed Effects	X	X	X	X
Unique Cities	26	26	26	26
Observations	5,851	5,851	5,851	5,851

Notes: Regression results of the average age in less developed cities, analogous to Table B.5.

Table B.8: Years of Schooling in Less Developed Cities

	Years of Schooling			
	(1)	(2)	(3)	(4)
Suburban	-0.61^{**}			-0.50^{**}
	(0.19)			(0.16)
Hilly		-0.57		-0.38
		(0.44)		(0.41)
River			-0.47^{**}	-0.33^{*}
			(0.15)	(0.16)
City Fixed Effects	X	X	X	X
Unique Cities	10	10	10	10
Observations	2,273	2,273	2,273	2,273

Notes: Regression results of the years of schooling, analogous to Table B.5.

Table B.9: Spatial Patterns of Population Density

Dependent Variable:	Log population density			
Model:	(1)	(2)	(3)	(4)
Variables				
$\text{Developed}_c \times \text{Suburban}_{j,c}$	-0.76***			-0.74***
	(0.05)			(0.05)
$\text{Less Developed}_c \times \text{Suburban}_{j,c}$	-0.93***			-0.83***
	(0.08)			(0.07)
$\text{Developed}_c \times \text{Hilly}_{j,c}$		-0.86***		-0.77***
		(0.13)		(0.11)
$\text{Less Developed}_c \times \text{Hilly}_{j,c}$		-0.55***		-0.48***
		(0.11)		(0.08)
$\text{Developed}_c \times \text{River}_{j,c}$			-0.60***	-0.55***
			(0.06)	(0.05)
$\text{Less Developed}_c \times \text{River}_{j,c}$			-0.73***	-0.57***
			(0.08)	(0.06)
Difference: Less Developed$_c$ vs Developed$_c$				
$\text{Suburban}_{j,c}$	-0.17*			-0.09
	(0.09)			(0.09)
$\text{Hilly}_{j,c}$		0.31*		0.29**
		(0.17)		(0.13)
$\text{River}_{j,c}$			-0.13	-0.02
			(0.10)	(0.08)
Observations	50,004	50,004	50,004	50,004
Unique Cities	121	121	121	121
City FE	✓	✓	✓	✓
Weight by neighborhood pop within city	✓	✓	✓	✓

*Notes: Analysis similar to Table 2 using population density, as opposed to income as the outcome variable. The top panel reports the results of Regression (1). The bottom panel reports the differences in the coefficients between developed and less developed cities. The unit of observation is a neighborhood with a positive average income. We weight observations by the fraction of residents in each neighborhood for each city, such that the regression assigns equal weight to each city. Standard errors are clustered at the city level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels.*

C. Appendix for Commuting Costs and Job Access

C.1. Commuting Costs

Table C.1: Estimated Commuting Semielasticity to Road Distance in Less Developed Cities

City	Country	Commuting Semielasticity (km)
Chengdu	China	0.69 (0.03)
Phnom Penh	Cambodia	0.66 (0.04)
Lahore	Pakistan	0.60 (0.03)
Hanoi	Viet Nam	0.56 (0.02)
Kinshasa	D.R. of the Congo	0.54 (0.04)
Vientiane	Lao People's DR	0.46 (0.03)
Yangon	Myanmar	0.43 (0.02)
Cebu City	Philippines	0.41 (0.03)
Cairo	Egypt	0.40 (0.02)
Mombasa	Kenya	0.40 (0.03)
Dhaka	Bangladesh	0.39 (0.03)
Manila	Philippines	0.38 (0.03)
Ho Chi Minh City	Viet Nam	0.36 (0.01)
Jakarta	Indonesia	0.31 (0.01)
Abidjan	Côte d'Ivoire	0.31 (0.01)
Managua	Nicaragua	0.30 (0.02)
Nairobi	Kenya	0.30 (0.03)
Dar es Salaam	U.R. of Tanzania: Mainland	0.28 (0.02)
Lima	Peru	0.28 (0.01)
Dà Nang	Viet Nam	0.27 (0.04)
Bucharest	Romania	0.25 (0.01)
Belém	Brazil	0.20 (0.01)
Colombo	Sri Lanka	0.19 (0.01)
Kuala Lumpur	Malaysia	0.17 (0.01)
Damascus	Syrian Arab Republic	0.06 (0.02)

Notes: Estimated commuting semielasticity to road distance in kilometers using PPML estimator of Specification (2). Parentheses indicate the standard errors, where the standard errors are clustered in two ways by origins and by destinations.

Table C.2: Estimated Commuting Semielasticity to Road Distance in Western Europe and Japan

City	Country	Commuting Semielasticity (km)
Marseille	France	0.30 (0.03)
Lyon	France	0.22 (0.01)
Nottingham	United Kingdom	0.21 (0.01)
Leeds	United Kingdom	0.20 (0.01)
Newcastle upon Tyne	United Kingdom	0.20 (0.01)
Liverpool	United Kingdom	0.20 (0.01)
Sheffield	United Kingdom	0.20 (0.01)
Birmingham	United Kingdom	0.20 (0.01)
Toulouse	France	0.19 (0.01)
Manchester	United Kingdom	0.18 (0.00)
Bordeaux	France	0.17 (0.01)
Lille	France	0.17 (0.01)
London	United Kingdom	0.17 (0.00)
Paris	France	0.16 (0.00)
Nice	France	0.15 (0.01)
Bristol	United Kingdom	0.15 (0.02)
Tokyo	Japan	0.14 (0.00)

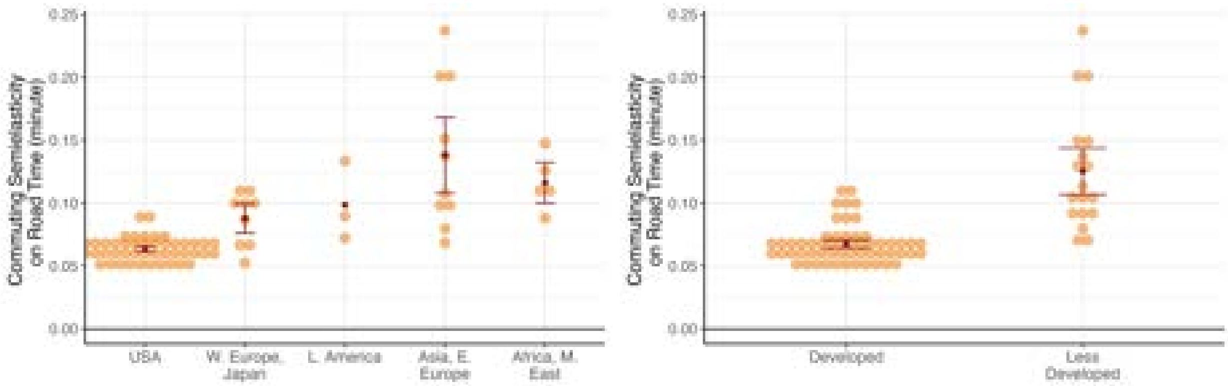
Notes: Estimated commuting semielasticity to road distance in kilometers using PPML estimator of Specification (2). Parentheses indicate the standard errors, where the standard errors are clustered in two ways by origins and by destinations.

Table C.3: Estimated Commuting Semielasticity to Road Distance in the United States

City	Country	Commuting Semielasticity (km)
Pittsburgh	United States	0.17 (0.01)
Boston	United States	0.16 (0.00)
Providence	United States	0.15 (0.01)
Bridgeport	United States	0.14 (0.00)
Philadelphia	United States	0.13 (0.00)
New Orleans	United States	0.13 (0.01)
Portland	United States	0.13 (0.00)
New York	United States	0.12 (0.00)
Tucson	United States	0.12 (0.01)
Virginia Beach	United States	0.12 (0.01)
Buffalo	United States	0.12 (0.01)
Honolulu	United States	0.12 (0.01)
Concord	United States	0.11 (0.01)
Washington D.C.	United States	0.11 (0.00)
St. Louis	United States	0.11 (0.00)
Baltimore	United States	0.11 (0.00)
Minneapolis	United States	0.11 (0.00)
Austin	United States	0.11 (0.00)
Tampa	United States	0.11 (0.00)
Denver	United States	0.11 (0.00)
Atlanta	United States	0.11 (0.00)
Fresno	United States	0.11 (0.01)
Bradenton	United States	0.11 (0.01)
Kansas City	United States	0.11 (0.00)
Cincinnati	United States	0.10 (0.01)
Orlando	United States	0.10 (0.00)
Milwaukee	United States	0.10 (0.00)
Louisville	United States	0.10 (0.01)
Indianapolis	United States	0.10 (0.00)
Sacramento	United States	0.10 (0.00)
Chicago	United States	0.10 (0.00)
San Antonio	United States	0.10 (0.00)
Albuquerque	United States	0.10 (0.01)
Omaha	United States	0.10 (0.01)
Cleveland	United States	0.10 (0.00)
Oklahoma City	United States	0.10 (0.00)
Dallas	United States	0.10 (0.00)
Seattle	United States	0.10 (0.00)
Salt Lake City	United States	0.09 (0.01)
Columbus	United States	0.09 (0.00)
Los Angeles	United States	0.09 (0.00)
Bakersfield	United States	0.09 (0.01)
Las Vegas	United States	0.09 (0.00)
Miami	United States	0.09 (0.00)
San Jose	United States	0.09 (0.00)
Detroit	United States	0.08 (0.00)
Houston	United States	0.08 (0.00)
Phoenix	United States	0.08 (0.00)

Notes: Estimated commuting semielasticity to road distance in kilometers using PPML estimator of Specification (2). Parentheses indicate the standard errors, where the standard errors are clustered in two ways by origins and by destinations.

Figure C.1: Estimated Semielasticity of Commuting to Road Travel Time (Minutes)

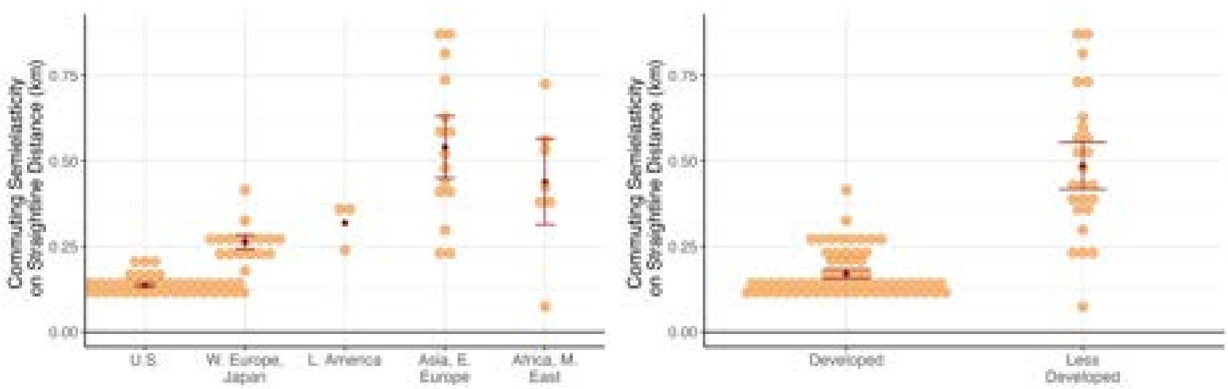


(a) Regions

(b) Development Status

Notes: The panels show the estimated semielasticity of commuting to road travel time using the PPML estimator of Specification (2). *Emulates Figure 6, where we replace road distance in the independent variable with road travel time (in minutes), where road travel time is defined by the road distance from OSRM times the average traffic speed for each city using Google Maps API (Akbar et al., 2023b).*

Figure C.2: Estimated Semielasticity of Commuting to Straightline Distance (km)

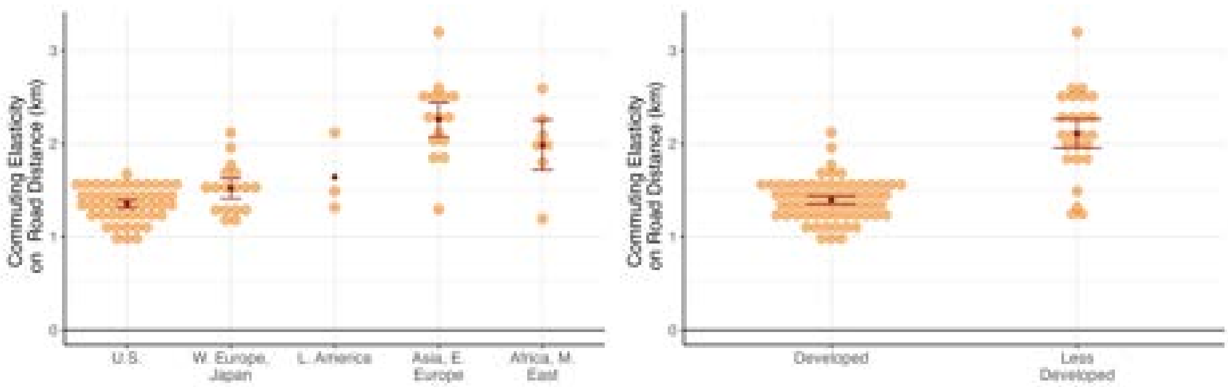


(a) By Regions

(b) By Development Status

Notes: The panels show the estimated semielasticity of commuting to straightline distance using the PPML estimator of Specification (2). *Emulates Figure 6, where we replace road distance with straightline distance.*

Figure C.3: Estimated Elasticity of Commuting to Road Distance

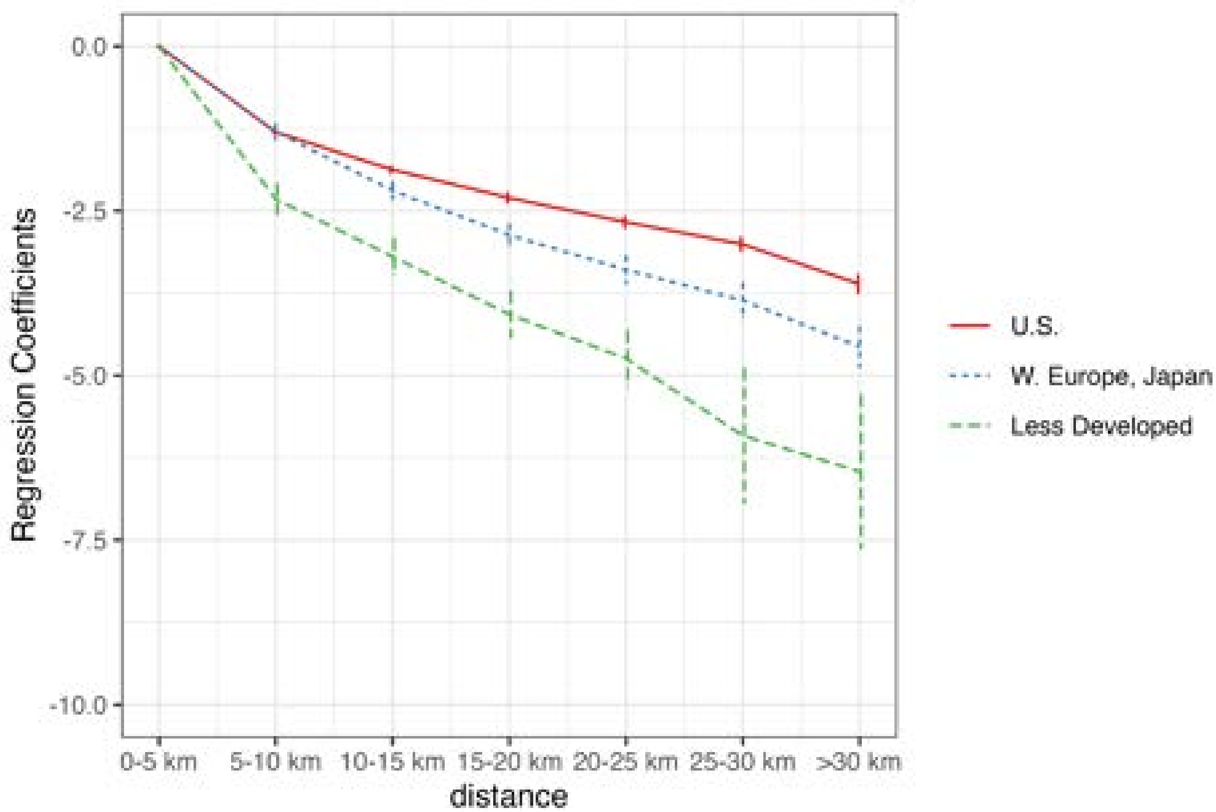


(a) By Regions

(b) By Development Status

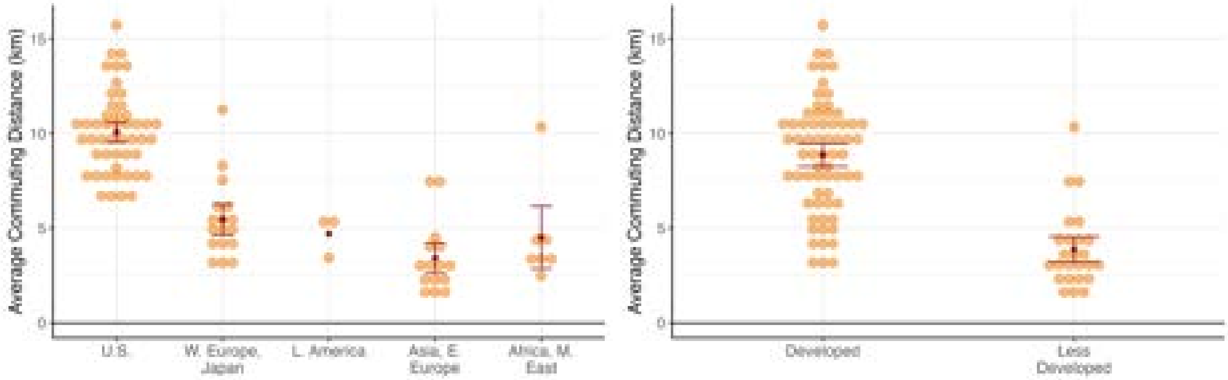
Notes: The panels show the estimated elasticity of commuting to road distance using the PPML estimator of Specification (2)*. Emulates Figure 6, where we replace the road distance in the independent variable with its log transformation.*

Figure C.4: Nonparametric Gravity Regression Results



Notes: Estimated results of a version of Specification (2) *using PPML estimator, where we replace the linear road distance in the independent variable with dummies of distance bins of 5-10, 10-15, 15-20, 20-25, 25-30, and over 30 kilometers, where we exclude 0-5 kilometer as an omitted baseline category. We estimate this specification for each city, and present the mean and 90% confidence intervals of the mean estimates within each of the three sets of countries.*

Figure C.5: Average Commuting Distances (km)



(a) By Regions

(b) By Development Status

Notes: The figures show the average road distances between the home and work locations. Each dot represents an estimate for each city. Panel (a) groups them by region, while Panel (b) groups cities by development status.

Table C.4: Commuting Semielasticity, Speed, and Modes

	Dependent variable:		
	log Commuting Semi-Elasticity		
	(1)	(2)	(3)
Speed Index (log scale)	-1.86^{***}		-0.21
	(0.14)		(0.32)
Prvivate Car		-1.34^{***}	-1.21^{***}
		(0.08)	(0.22)
Constant	-1.74^{***}	-0.96^{***}	-1.04^{***}
	(0.04)	(0.06)	(0.13)
Observations	70	70	70
R^2	0.73	0.81	0.81

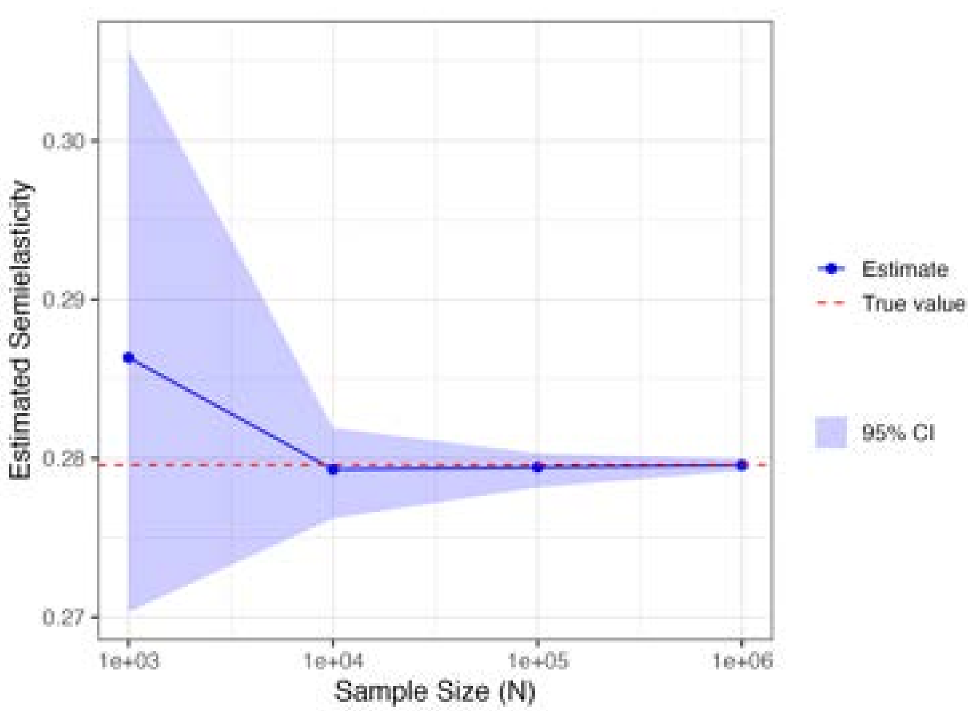
Notes: This table shows the regression results of the log of estimated commuting semielasticities from Specification (2) on "speed index" from Akbar et al. (2023b), which measures log-point differences in average road speed across cities using Google Maps API, and on the fraction of commuters by private car. We measure the latter value using our travel surveys whenever they are available, and for other cities, we use the data constructed by Prieto-Curiel and Ospina (2024) based on various surveys and administrative data. We restrict to cities where both of these datasets are available.

C.2. Small Sample Properties of Commuting Semi-elasticity Estimates

In this appendix, we assess how the sampling rates of travel surveys may affect the estimates of commuting semielasticities through a Monte Carlo simulation. Specifically, we use the fitted commuting gravity (2) from Lima (with 388 survey zones) as the true data-generating process, and we simulate random samples following this data-generating process. We vary the number of commuters to draw ($N = 10^3, 10^4, 10^5, 10^6$). For each N, we sum up all commuters across all location pairs, and estimate the same commuting gravity equation (2). We repeat this process 20 times for each N and draw a 95% confidence interval of the estimated semielasticities.

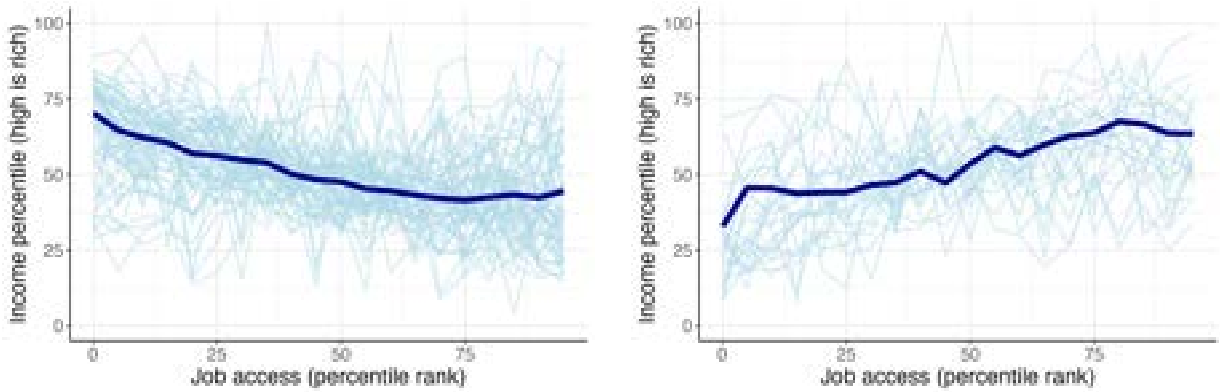
We find that the statistical uncertainty quickly diminishes as the sample size increases. Even with $N = 1000$, the mean is 0.29 relative to the assumed true value of 0.28, with confidence intervals ranging tightly from 0.27 to 0.30. With $N = 10000$—still smaller than the sample sizes in the travel surveys in our dataset (Appendix Table A.1, A.2, and A.3), the bias and variance become almost negligible. We therefore conclude that sampling-driven statistical uncertainty is minimal in our empirical setting.

Figure C.6: Small Sample Properties of Commuting Semi-elasticity Estimates



C.3. Job Access

Figure C.7: Residential Income and Job Access, by Development Status

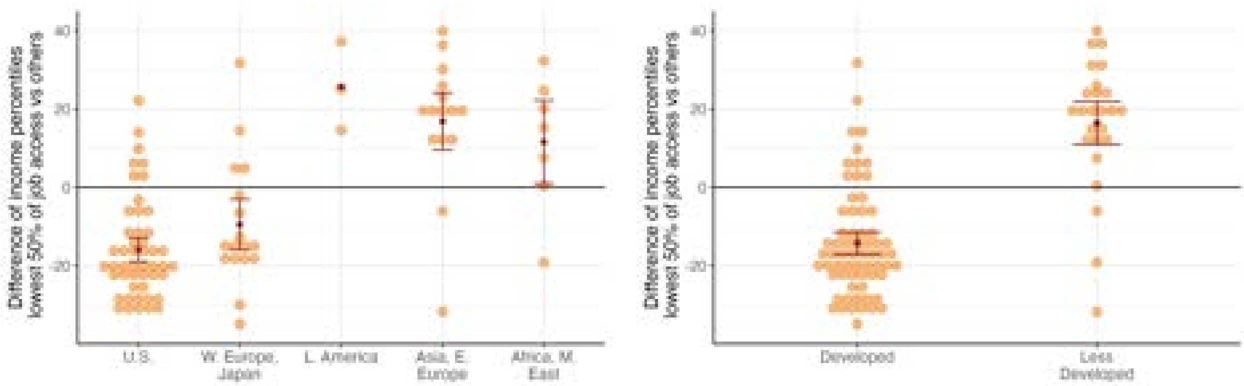


(a) Developed Cities

(b) Less Developed Cities

Notes: The figures show the relationships between the percentiles of estimated job access (equation 3) within each city and average neighborhood residential income percentile for developed cities (Panel a) and less developed cities (Panel b), instead of by region in Figure 8. Each light line represents a single city, and averages are highlighted in bold.

Figure C.8: Residential Income and High-Job-Access Neighborhoods



(a) By Regions

(b) By Development Status

Notes: The figures display the difference in average income percentiles between high and low job access neighborhoods for each city, where high job access is defined by above median job access neighborhoods. Each dot represents a city. Panel (a) groups them by region, while Panel (b) groups them by development status. In both panels, we also report the group averages and their 95% confidence intervals.

Table C.5: Regression Results of Job Access and Work Location Fixed Effects

Dependent Variables:	Job access (home FE)	Area-adjusted work location FE
Model:	(1)	(2)
Variables		
$\text{Developed}_c \times \text{Suburban}_{j,c}$	-0.64***	-0.69***
	(0.04)	(0.06)
$\text{Less Developed}_c \times \text{Suburban}_{j,c}$	-1.6***	-1.8***
	(0.13)	(0.12)
$\text{Developed}_c \times \text{Hilly}_{j,c}$	-0.19***	-0.94***
	(0.05)	(0.13)
$\text{Less Developed}_c \times \text{Hilly}_{j,c}$	-0.83***	-1.1***
	(0.23)	(0.21)
$\text{Developed}_c \times \text{River}_{j,c}$	-0.09***	-0.15***
	(0.02)	(0.04)
$\text{Less Developed}_c \times \text{River}_{j,c}$	-0.50***	-0.66***
	(0.11)	(0.12)
Difference: Less Developed$_c$ vs Developed$_c$		
$\text{Suburban}_{j,c}$	-0.96***	-1.1***
	(0.14)	(0.14)
$\text{Hilly}_{j,c}$	-0.64***	-0.20
	(0.23)	(0.25)
$\text{River}_{j,c}$	-0.41***	-0.51***
	(0.11)	(0.13)
Observations	36,522	36,499
Unique Cities	90	90
City FE	✓	✓

Notes: The results of regression (1), where the outcome variables are estimated origin fixed effects from the commuting gravity equation (2) (Column 1); and destination fixed effect, net of log area (Column 2), where the area adjustment is applied to offset the mechanical effect that the destination fixed effects proportionally increase in neighborhood area size (Kreindler and Miyauchi, 2023). In our quantitative model, Column (1) corresponds to expected wage rates at residential location $\overline{w}_{j,c}$, and Column (2) corresponds to productivity $A_{j,c}$.

D. Appendix for Model and Quantitative Analysis

D.1. Model Fit

Table D.1 demonstrates that the estimated model closely replicates key patterns in the spatial distribution of income across U.S. cities. The table presents a version of regression (1), where the odd-numbered columns report results using model-predicted log residential income, and the even-numbered columns use observed income data. In the independent variable, $\text{JobAccess}_{j,c}$ is the estimated job access in Section 4. We instrument $\text{JobAccess}_{j,c}$, $\text{JobAccess}_{j,c} \times \text{Hilly}_{j,c}$ and $\text{JobAccess}_{j,c} \times \text{River}_{j,c}$ by $\widetilde{\text{JobAccess}}_{j,c}$, $\widetilde{\text{JobAccess}}_{j,c} \times \text{Hilly}_{j,c}$, and $\widetilde{\text{JobAccess}}_{j,c} \times \text{River}_{j,c}$, where $\widetilde{\text{JobAccess}}_{j,c}$ is constructed analogously as in Section 4, except we replace actual road distances for the estimation of equation (2) with bilateral straight-line distances, consistent with the moment condition used for the model estimation (Section 6.1).

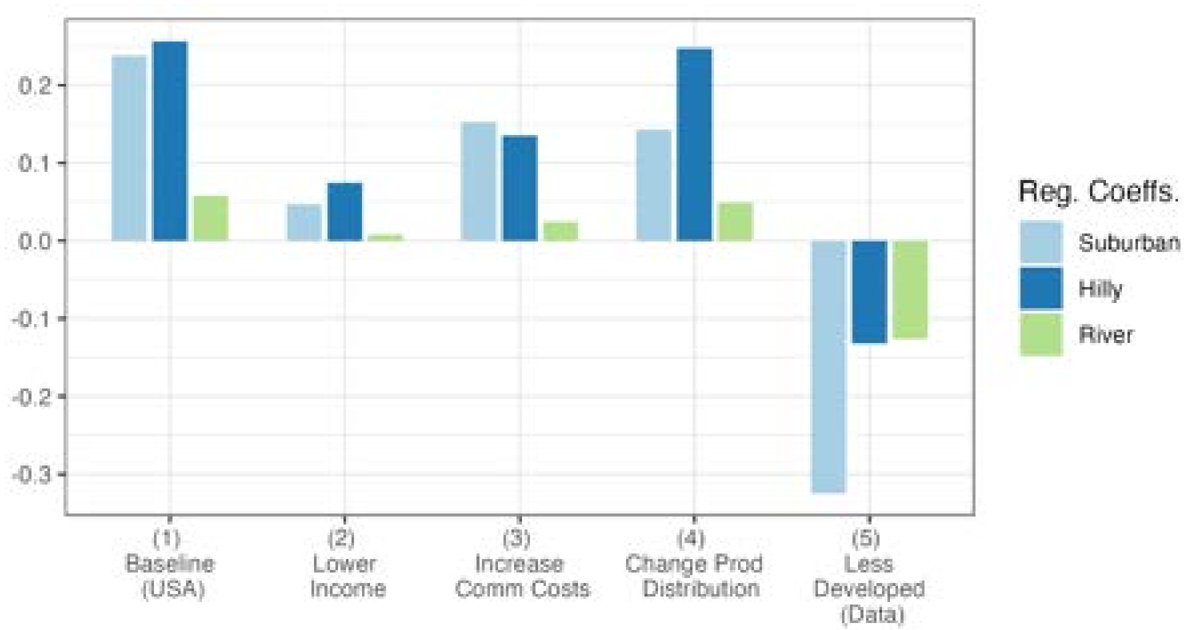
Columns (1) and (2) show that the model successfully replicates the elevated average residential income in suburban, hilly, and river-adjacent neighborhoods. Columns (3) and (4) capture the unconditional negative relationship between residential income and job access, consistent with the pattern illustrated in Section 4. Finally, Columns (5) and (6) add the interaction terms between job access and geographic features. While the model's regression coefficients do not exactly match those from the data—due in part to overidentifying restrictions in the GMM estimation—the overall patterns are well aligned.

Table D.1: Model Fit to U.S. cities

	log Residential Income$_{j,c}$					
	Model	Data	Model	Data	Model	Data
	(1)	(2)	(3)	(4)	(5)	(6)
Suburban$_{j,c}$	0.24	0.24			0.30	0.23
	(0.01)	(0.03)			(0.01)	(0.04)
Hilly$_{j,c}$	0.26	0.28			0.29	0.29
	(0.01)	(0.05)			(0.01)	(0.05)
River$_{j,c}$	0.06	0.07			0.08	0.07
	(0.004)	(0.02)			(0.003)	(0.02)
JobAccess$_{j,c}$			−0.43	−0.82	0.47	−0.12
			(0.08)	(0.19)	(0.05)	(0.21)
JobAccess$_{j,c}$ × Hilly$_{j,c}$					0.43	0.45
					(0.07)	(0.26)
JobAccess$_{j,c}$ × River$_{j,c}$					0.21	0.14
					(0.03)	(0.14)
City Fixed Effects	X	X	X	X	X	X
Unique Cities	48	48	48	48	48	48
Observations	27,117	27,117	27,117	27,117	27,117	27,117

D.2. Additional Figures and Tables for Quantitative Analysis

Figure D.1: Spatial Residential Income Distribution of U.S. Cities: Separate Counterfactual for Lowering Income, Increasing Commuting Costs, and Changing Productivity Distribution



Notes: This figure displays the estimated coefficients on the suburban, hilly, and river indicators from the regression specification (1), using our data and under our model calibration. Emulates Figure 11, except that we run counterfactuals columns (2)-(4) separately, instead of cumulatively.

Table D.2: Estimated $\{\beta_1, \beta_2, \beta_3\}$ to Rationalize the Income Distribution in Other Developed Cities

Model	Suburban (β_1)	Hilly (β_2)	River (β_3)
Baseline Estimates (USA)	0.90	1.03	0.26
Estimates to Fully Rationalize Non-U.S. Developed Cities	0.66	0.69	0.14

Notes: First row reports the estimated $\{\beta_1, \beta_2, \beta_3\}$ using U.S. cities as reported in Table 4. Second row reports the estimated $\{\beta_1, \beta_2, \beta_3\}$ to fully rationalize the differences in the income premiums of suburban, hilly, and river neighborhoods, after accounting for the overall productivity differences, commuting cost differences, and differences in productivity premiums in those areas, as described further in Section 6.2.

D.3. Heterogeneity of Commuting Costs and Spatial Productivity Distribution by Income Groups

In our baseline analysis, we abstracted from income-related heterogeneity in commuting costs and wage distributions. However, in U.S. cities, disparities in transportation modes and commuting costs across income groups have been identified as one potential driver of residential sorting by income (Glaeser et al., 2008; Su, 2022). In this subsection, we assess the quantitative relevance of this channel.

To do so, we extend our model from Section 5 to allow commuting costs and wages to depend on individuals' earning potential s. Specifically, we now let commuting costs $\tau_{jn,c}(s)$ and wages $w_{n,c}(s)$ vary with s. We retain the assumption that idiosyncratic preferences over work locations are drawn from an i.i.d. Fréchet distribution with shape parameter $\theta(s)$, which is common across s. Under this setting, the probability that a worker with earning potential s living in neighborhood j commutes to job location n is given by:

$$\lambda_{jn,c}(s) = \frac{\left(\tau_{jn,c}(s)^{-1} w_{n,c}(s)\right)^{\theta(s)}}{\sum_{\ell}\left(\tau_{j\ell,c}(s)^{-1} w_{\ell,c}(s)\right)^{\theta(s)}}. \tag{D.1}$$

We also follow Section 4 that the commuting cost $\tau_{jn,c}$ is a power function of road distance between neighborhoods j to n such that $\log\tau_{jn,c}(s) = \tilde{\kappa}_c(s) \times \text{RoadDistance}_{jn,c}$, where $\tilde{\kappa}_c(s)$ can depend on s. Under this assumption, the commuting gravity equation (11) holds separately for each earning potential s:

$$\log\lambda_{jn,c}(s) = \theta(s)\log w_{n,c}(s) - \tilde{\kappa}_c(s)\theta(s)\times\text{RoadDistance}_{jn,c} - \log\sum_{\ell}\left(\tau_{j\ell,c}(s)^{-1} w_{\ell,c}(s)\right)^{\theta(s)}. \tag{D.2}$$

If we observe the commuting flows by earning potential s, we can estimate the empirical analog of this equation using a PPML estimator for each earning potential s, analogously as equation (2):

$$\log\mathbb{E}\left[\lambda_{jn,c}(s)\right] = \psi_{n,c}(s) - \kappa_c(s)\text{RoadDistance}_{jn,c} + \eta_{j,c}(s), \tag{D.3}$$

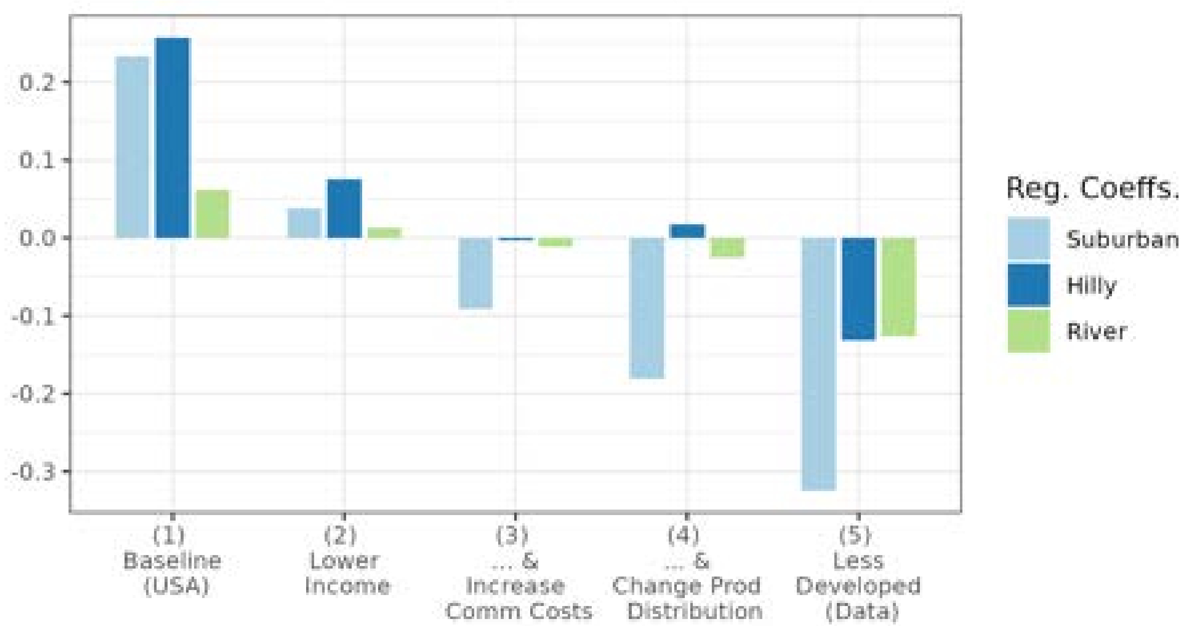
where $\psi_{n,c}(s) \equiv \theta(s)\log w_{n,c}(s)$ is the workplace fixed effects, $\kappa_c(s) \equiv \tilde{\kappa}_c(s)\theta(s)$, and $\eta_{j,c}(s) \equiv -\log\sum_{\ell}\left(\tau_{j\ell,c}(s)^{-1} w_{\ell,c}(s)\right)^{\theta(s)}$ is the origin fixed effects.

A challenge in estimating this equation is that we do not directly observe earning potentials s in our data. While some travel survey data provide information about variables such as education, it is not comprehensive, and it is also difficult to create a proxy that is consistent across countries. To deal with this issue, we divide our samples based on the realized income. Through the lens of our model, realized income is a product of earning potential s and the expected wage rates at the residential location $\overline{w}_{j,c}(s)$. Therefore, if the variance of earning potential s is much larger than the spatial variation of wage rates $\overline{w}_{j,c}(s)$, this strategy effectively splits the samples with high- and low-earning-potential households within each city.

Figure 12 reports the estimated commuting semielasticities for developed cities (U.S. cities and Tokyo; commuting data by income are not available for the United Kingdom and France) and for less developed cities. Consistent with previous studies, we find larger commuting semielasticities among low-income groups (0.11) than high-income groups (0.10) in developed cities. However, this difference is *more* pronounced in less developed cities, with 0.42 for low-income groups than 0.32 for high-income groups. These findings suggest that, while these forces may contribute to the sorting of low-income households toward central areas in both developed and less developed cities, they are unlikely to account for the observed disparity between the two groups of cities.

Using this calibrated model, we run the same counterfactual simulations as before, except that we change the commuting costs and spatial productivity distribution for each s. Consistent with the observations above, we find that changing commuting costs and productivity distributions to the levels of less developed cities generates slightly smaller effects on the spatial income distribution compared to our baseline scenario (Figure D.2). Therefore, the heterogeneity across earning potential s in commuting costs and spatial productivity distribution does not explain the differences in spatial income distribution. At the same time, our main conclusion remains: differences in aggregate income levels, commuting costs, and spatial productivity distributions across cities jointly account for the main observed gap in spatial income distributions between U.S. and less developed cities.

Figure D.2: Unpacking Spatial Income Distribution Gap: U.S. vs. Less Developed Cities, Using Model with Heterogeneous Commuting Costs and Wage Distribution across Earning Potential



Notes: A version of Figure 11, where we use the extended model to incorporate heterogeneity in commuting costs and spatial productivity distribution across s. We use the same parameters as in our baseline model (Table 4), except that we separately calibrate commuting costs and productivities across earning potential groups s, as estimated using Specification (D.3); see Figure 12 and Appendix Table D.3 for those estimates. We also use the common parameter $\theta(s) = \theta$.

Table D.3: Regression Results of Estimated Origin and Destination Fixed Effects by Income Groups

Dependent Variables:	Area-adj Work FE (High Earner)	Area-adj Work FE (Low Earner)	Job Access (High Earner)	Job Access (Low Earner)
Model:	(1)	(2)	(3)	(4)
Variables				
$\text{Developed}_c \times \text{Suburban}_{j,c}$	-0.63***	-0.63***	-0.61***	-0.60***
	(0.06)	(0.07)	(0.05)	(0.05)
$\text{Less Developed}_c \times \text{Suburban}_{j,c}$	-1.5***	-1.6***	-1.3***	-1.4***
	(0.12)	(0.11)	(0.09)	(0.10)
$\text{Developed}_c \times \text{Hilly}_{j,c}$	-1.0***	-1.1***	-0.20***	-0.20***
	(0.15)	(0.15)	(0.06)	(0.06)
$\text{Less Developed}_c \times \text{Hilly}_{j,c}$	-0.87***	-1.0***	-0.73***	-1.0***
	(0.32)	(0.34)	(0.23)	(0.31)
$\text{Developed}_c \times \text{River}_{j,c}$	-0.30***	-0.37***	-0.15***	-0.17***
	(0.05)	(0.05)	(0.02)	(0.02)
$\text{Less Developed}_c \times \text{River}_{j,c}$	-0.60***	-0.62***	-0.41***	-0.49***
	(0.09)	(0.10)	(0.09)	(0.10)
Difference: Less Developed_c vs Developed_c				
$\text{Suburban}_{j,c}$	-0.92***	-1.0***	-0.69***	-0.83***
	(0.13)	(0.13)	(0.10)	(0.11)
$\text{Hilly}_{j,c}$	0.18	0.03	-0.53**	-0.83***
	(0.35)	(0.37)	(0.24)	(0.31)
$\text{River}_{j,c}$	-0.30***	-0.25**	-0.25***	-0.32***
	(0.10)	(0.11)	(0.09)	(0.10)
Observations	31,548	31,924	31,955	31,955
Unique Cities	73	73	73	73
City FE	✓	✓	✓	✓
Weight by neighborhood pop within city	✓	✓	✓	✓
Subset	✓	✓	✓	✓

Notes: The results of regression (1), where the outcome variables are estimated destination fixed effects from the commuting gravity equation (D.3), net of log area (Columns 1-2) and the estimated origin fixed effects (Columns 3-4). Odd columns report the results of high-income groups, and even columns report the results of low-income groups, where high- and low-income groups are defined by above or below the city-specific median income.

D.4. Distributional Effects of Overall Productivity Increase

In this section, we analyze the distributional welfare effects of a uniform productivity increase within the city. Specifically, using our model calibrated to U.S. cities, we compute welfare gains from a uniform increase in productivity—from the levels observed in less developed cities to the U.S. level, corresponding to a 2.5 log-point rise—as analyzed in Section 6.2. We examine how this aggregate productivity improvement translates into welfare gains across households, disaggregated by earning potential and residential location. We measure these gains using an equivalent variation (EV) metric that asks: "Given the existing U.S. distribution of population and housing prices, how much income would a household be willing to give up to avoid a citywide drop in productivity to the level of low-income cities, assuming no change in their residential location choice?" Following Baqaee and Burstein (2023), it is composed of two additive terms: (i) (uniform) changes in labor income across locations and household types, and (ii) location- and type-specific changes in expenditure-adjusted housing costs.

Our model predicts that this welfare measure varies across households due to nonhomothetic preferences, which induce shifts in spatial population distribution and generate uneven changes in housing costs. In a special case where we shut down nonhomotheticity (i.e., $\epsilon = 1$ and $\rho \to 0$), the welfare effects are uniform for all households, because wages and housing costs change uniformly across locations.

Figure D.3 shows the distribution of equivalent variation (EV), in log points, across households by residential location and earning potential. The average EV is approximately 2.3 log points, both for high-earning and low-earning potential groups. This value is somewhat below the assumed 2.5 log point increase in overall productivity. This gap reflects the fact that rising housing costs partially offset the benefits of higher productivity, abstracting from income gains to landowners.

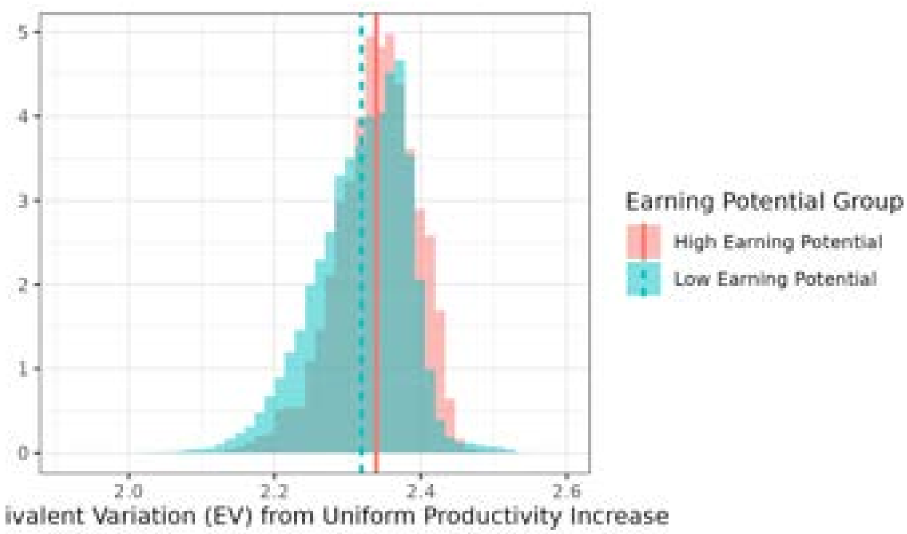
The finding of similar average welfare gains across groups reflects the interplay of two opposing forces: (i) low-earning-potential households devote a larger share of income to housing, which tends to lower their EV, and (ii) they are more likely to reside in central urban areas with better job access in high-income (U.S.) cities, where housing costs rise less in response to a uniform productivity increase due to sorting. Our results suggest that the two forces roughly dominate.

We also find substantial dispersion in EVs across residential locations within each earning potential group. This reflects the spatial variation in housing cost changes induced by nonhomothetic preferences. As the overall productivity rises, the housing costs in suburban, hilly, and river areas increase. This implies that lower-earning-potential households who live in those areas tend to have lower welfare gains.[34]

Taken together, these findings highlight that the evolution of spatial income distribution during economic development has important implications for the distribution of welfare gains across households.

[34] Table D.4 reports the regression results of the EVs with the neighborhood characteristics for each earning potential group.

Figure D.3: Equivalent Variations (EV) from Uniform Productivity Increase



Notes: The distribution of EVs, in log points, across households by residential location and earning potential, to increase the overall productivity from low-income-city level to high-income-city level (as observed in the U.S. cities).

Table D.4: Spatial Variations of Equivalent Variations (EV) from Uniform Productivity Increase

	Dependent variable:			
	EV (High Earning Potential)		EV (Low Earning Potential)	
	(1)	(2)	(3)	(4)
Suburban		-0.046^{***}		-0.062^{***}
		(0.004)		(0.004)
Hilly		-0.045^{**}		-0.039
		(0.018)		(0.025)
River		-0.007^{***}		-0.013^{***}
		(0.003)		(0.003)
High Work Access		0.024^{***}		0.025^{***}
		(0.003)		(0.004)
Constant	2.339^{***}	2.367^{***}	2.319^{***}	2.328^{***}
	(0.003)	(0.005)	(0.003)	(0.005)
Number of cities	48	48	48	48
Observations	27,117	27,117	27,117	27,117
R^2	0.000	0.337	-0.000	0.369

Notes: Regression of EVs, in log points, across households by residential location and earning potential, to increase the overall productivity from low-income-city level to high-income-city level (as observed in the U.S. cities). "High Work Access" proxies the neighborhoods with above-median work access for each city.