Economic Development and the Spatial Distribution of Income in Cities

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Abstract

We draw on new granular data from cities around the world to study how the spatial distribution of income within cities varies with development. We document that in less developed countries, average incomes of urban residents decline monotonically in distance to the city center. In developed economies, by contrast, household incomes are mostly increasing in distance to the city center. We also show that urban neighborhoods in hills and near rivers are poorer than average in the developing world and richer than average in developed countries. We explain these facts in a spatial model in which neighborhoods within cities differ in productivity, natural amenities, transportation infrastructure, and residential infrastructure. Households have non-homothetic preferences and vary in earning potential. Natural amenities raise the desirability of a neighborhood but only with sufficient residential infrastructure. Quantitative analysis of the model can replicate the empirical patterns for cities across the development spectrum.

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1. Introduction

Economic development goes hand in hand with urbanization. Around two in five Americans lived in urban areas at the turn of the twentieth century, and today it is four in five. The spatial distribution of income *within* cities has also been transformed over this period. In the late nineteenth century, the richest residents of U.S. cities lived in or near city centers, with poorer households residing further out on the peripheries. Nowadays, the locus of residential wealth within U.S. cities has shifted to suburbs, with poorer households much more likely to be concentrated near city centers (Wheaton, 1977; Glaeser, Kahn, and Rappaport, 2008; Baum-Snow and Hartley, 2020; Lee and Lin, 2018). Poorer inner cities, and richer suburbs, are now a defining feature of American cities.

Outside of the U.S. experience, less has been systematically documented about the spatial distribution of income within cities. Europeans are quick to point out that cities like London or Paris have greater concentrations of high-income residents living near city centers, suggesting that U.S. cities may be exceptional among developed nations. In the developing world, a lack of household income data at a fine level of geographic detail within cities has hampered measurement. Many of the poorest urban residents in developing world cities are concentrated in slum areas, yet the location of slums does not seem to be systematically related to the distance to city centers (Marx, Stoker, and Suri, 2013).[1]

In this paper, we draw on new fine-grained geographic data from a large cross-section of cities around the world to document how the spatial distribution of income within cities varies with development. Our data come from two main sources. The first is a set of travel surveys collected by Japan's International Cooperation Agency (JICA) for use in planning urban infrastructure projects. The surveys, which are new to the economics literature, record the location, demographic characteristics, income, and daily travel activities of a representative survey of households in each city. The surveys cover an average of 75,000 households per city and span 21 large developing world cities such as Lima, Nairobi, and Manila. The second main data source is population censuses that contain comparable fine-grained geographic data on household income and demographic characteristics. We have such geographically aggregated data for all major cities in Brazil, the United States, England, France and Spain. We merge these data with neighborhood-level information on geographic characteristics such as average slope and distance to rivers. Our final data set covers 129 cities, 82 from developed countries and 47 from less developed countries, and comprises a total of 123,000 distinct urban locations ("neighborhoods").

[1]For example, the Kibera slum in Nairobi and Nima slum in Accra are within walking distance of their city centers, whereas Soweto in Johannesburg and Paraisopolis in Sao Paulo are 25 kilometers from theirs.

We begin our analysis by asking how average neighborhood income varies with the distance from the city centers. A location's distance relative to its city center has long been the focus of urban models, since city centers are the nexus of urban production and employment activities (though certainly not the only workplaces).

In our main specification we measure the city center using satellite estimates of building heights and night lights, as well as road density, and we measure the distance in kilometers from the city center to the centroid of each neighborhood. In each city we measure household income using standard survey questions about household income from the previous month. To maximize the comparability of income data across cities, we express the average income in each neighborhood as a percentile relative to all other neighborhoods in the same city.

We find that in developing world cities, average incomes decline linearly with distance to city centers. Taking an average across developing world cities, incomes in the city center are around the 67th percentile relative to the rest of the city. This falls to the 30th percentile in neighborhoods furthest from the city center. In the United States, income gradients are mostly U-shaped, with incomes declining sharply as one moves away from the city centers and then rising steadily as one moves into suburban areas. European cities generally have flatter gradients, with less variation in average income levels across space than in U.S. cities. Overall, though, gradients in the United States and Europe are relatively similar when compared to developing countries, with no signs of steeply declining gradients among our cities in poorer countries. Simple t-tests strongly reject the null hypothesis that income-density gradients are the same on average in developed and less developed economies.

We next ask how incomes in urban areas vary with the presence of natural amenities. We focus on hilly vs non-hilly areas, close proximity to rivers, and close proximity to the ocean. Natural amenities are of interest because, in principle, many households prefer the view, recreation opportunities, or micro-climate offered in steeper terrain or by waterways. Yet natural amenities may be more challenging places for urban development as well. The cost of providing roads, piped water, and electricity is greater higher up on slopes, and natural disasters like mudslides may have more serious consequences in the absence of investments in mitigation measures like retaining walls and proper drainage. Waterways can fill up with trash if there are not adequate waste removal systems in places.

Along this dimension as well, we find stark differences between cities in developed and developing countries. In developing world cities, we document that average incomes are significantly lower than average in hilly areas or in close proximity to rivers. In contrast, we find the opposite to be true in developed country cities, where average incomes are substantially *higher* in hilly areas and near rivers. Residents living in hilly urban areas in developed countries earn about 30 percent higher income on average than their counterparts in the rest of the city. Urban households living on hills in poorer countries have incomes about 20 percent *lower* on average than households in non-hilly areas. The premium is about 10 percent for rivers in developed countries, and negative 10 percent for developing world cities. Interestingly, we find no significant differences for oceans. Wealthy residents are more likely to leave near the ocean in both developed and developing world cities, and though income levels near the ocean are relatively higher in the developed world, the difference is statistically insignificant.

In simple descriptive regressions, we show that distance to city center and hilliness are both significant negative predictors of average neighborhood income in less developed countries when controlling for the other. Similarly, both are significant positive predictors of average income in developed countries. We find that these patterns are robust to alternative weighting schemes, including weighting each neighborhood by its population or weighting all countries equally in the regressions. The patterns are still present when adding controls for cardinal direction from the city center (Heblich, Trew, and Zylberberg, 2021), neighborhood area, and distance to the ocean.

To explain these findings we build an urban model in which households are heterogeneous in income levels and choose where to locate. Locations vary in transportation infrastructure, which governs transport speed across space, and residential infrastructure, which represents publicly provided features like sewers and electricity. Locations also vary exogenously in their amenities, and some locations are "hilly," which we model as having higher amenities but higher costs of providing residential and transportation infrastructure. Household preferences are non-homothetic and feature relatively larger housing expenditures for poorer residents.

Our theory shows three fundamental forces that shape the residential location patterns across income groups. First is the commuting cost. Residents incur higher commuting costs away from the central business district (CBD) and in hilly regions, depending on the efficiency of the commuting technology within the city. Second is the residential infrastructure. The level of residential infrastructure may deteriorate away from CBD or in hilly regions depending on the governments' efficiency in providing residential infrastructure. Third is the natural amenity. Places in hilly regions or away from CBD have a better view or green area. The attractiveness of the residential location is shaped by these three forces. Furthermore, in residential locations where the attractiveness is high, rents are also higher. Therefore, under non-homothetic preference in housing, more attractive residential locations are dominated by richer households, which shape the income sorting patterns within a city.

Our theory predicts several alternative explanations for the differential income sorting patterns between cities in developed and developing countries. In developing world cities, the quality of transportation infrastructure may be low, decreasing the attractiveness of the locations away from CBD or in hilly regions. Furthermore, the quality of residential infrastructure, such as clean water and electricity, may be dis-proportionally worse in locations away from CBD or in hilly regions, if governments have low state capacity to supply residential infrastructure in remote areas. Under non-homothetic preference, this implies that poorer residents sort into locations away from CBD or in hilly regions in poorer cities. As the efficiency of commuting technology increases, or as the efficiency in residential infrastructure away from CBD and hilly regions increases, or if the income level rises so that the non-homotheticity of housing becomes less relevant, this sorting pattern becomes less pronounced. Finally, if the efficiency of commuting technology and the residential infrastructure away from CBD and hilly regions are sufficiently high, income sorting patterns flip; richer residents instead sort into locations away from CBD and in hilly regions in poorer cities, as we empirically document for the case with developed country cities.

In work in progress, we quantify the roles of these four channels by simulating two cities, developed and less developed, in our model. Comparing income sorting patterns of rich and poor residents in the two cities, we find that the model does a good job replicating the actual income-distance gradients that we observe in rich countries, as well as the relatively higher average income in hilly areas. We then explore three main counterfactuals. The first two raise state capacity to supply residential and transportation infrastructure, respectively to remote areas to the level of a developed country. Due to greater provision of both types of infrastructure a substantial number of richer households shift locations from urban centers to peripheral and hilly regions, with poorer households become more represented near the city center. However residential infrastructure appears to be more salient in explaining income sorting relative to transport infrastructure. The second counterfactual raises average income levels to that of our representative developed city but holds state capacity fixed at it's low level. This leads to little change in income sorting patterns, however increased average income significantly reduces inequality, while infrastructure improvements do not. Our simulations thus far suggest that the bulk of the observed differences in spatial income distributions across cities can be explained by lower ability to construct residential infrastructure in developing world cities.

Our paper builds on a growing body of work studying how cities in developed and developing countries systematically differ. It is well known, for example, that population density in cities is higher in the developing world than in developed countries (see e.g. Henderson and Turner, 2020). Chauvin, Glaeser, Ma, and Tobio (2017) show that the size distribution of cities in China and India contains fewer very large cities than city size distributions in richer countries. Akbar, Duranton, Couture, and Storeygard (2022) document that travel speeds are worse in poor countries than rich ones. None of these studies analyze income gradients within cities across the development spectrum, as we do.

Studies of income gradients within cities have focused primarily on historical patterns in currently developed countries. Couture, Gaubert, Handbury, and Hurst (2024) argue that rising incomes for wealthy U.S. households led to increased demand for amenities in urban city centers that led to displacement or higher cost of living for lower-income households. Margo (1992) argues that half of the post-war suburbanization of the United States is due to the interaction of income growth and non-homothetic preferences, where richer households demand greater living space. Baum-Snow (2007) shows that the construction of radial highways leading to the urban core played an important role in the decentralization of U.S. cities, and Baum-Snow, Brandt, Henderson, Turner, and Zhang (2017) find a similar pattern for roads and railways in Chinese cities.

To our knowledge, there are no previous studies of income gradients across developing world cities. We embrace the vision of Bryan, Glaeser, and Tsivanidis (2020), who argue that more research should be devoted to studying developing world cities, since they are the fastest growing parts of the planet. Alonso (1964) cites case studies of Bangalore and Guatemala City finding that poorer residents tended to live on the outskirts of town, but did have enough evidence to make systematic comparisons between poor and richer countries. Gollin, Kirchberger, and Lagakos (2021) draw on comparable surveys from Africa to study how various measures of living standards vary with population density, but their comparisons are about urban versus rural areas rather than neighborhoods within cities. Henderson, Squires, Storeygard, and Weil (2018) study the distribution of economic activity with countries using night lights as a proxy, though these data do not allow one to separate population density from income per capita within cities.

Our work also contributes to a large literature on the effects of transport and public utility infrastructure in developing cities. Zárate (2021), Tsivanidis (2023), and Balboni et al. (2020) study the distributional impacts of transportation, finding negligible to pro-poor aggregate effects. Ashraf et al. (2021) and Franklin (2021) explore impacts of water access and improved housing more broadly, finding improved health and labor market participation, respectively. This work studies concrete interventions in isolated contexts. Our project contrasts with this literature by exploring large differences in state capacity at large, between a developed and less developed cities around the world, rather than single well defined interventions in isolated locations.

Further work will progress in two directions. First, we will continue to leverage our unique data sources to accurately estimate the value to residents of public utilities, transport access, and sensitivity to rents. With this estimates in hand, we will use our model to generate sharp predictions on income sorting for the cities in our sample. Second, we will work to endogenize infrastructure levels through a characterization of the government's objective function. This change will enable us to isolate state capacity as the key difference between developed and less developed cities, allowing us to explore how differences in urban governance, such as tax collection and construction expertise, affect both the shape of cities and residential welfare.

2. Data and Empirical Findings

We begin by describing our data sources and how we use them to construct measures of income at the neighborhood level, among other variables. We then summarize our findings for income-distance gradients and income levels by hilliness.

2.1. Data Sources

Surveys conducted by the Japanese International Cooperation Agency Our data from developing countries come mostly from household travel surveys conducted by the Japanese Development Agency (JICA) as part of research for transportation projects that they funded. Surveys are representative of the cities in question and contain an average of around 75,000 households. The surveys cover 21 cities including, for example, the African cities of Maputo and Nairobi, the South Asian cities of Dhaka and Karachi, the East Asian cities of Hanoi and Viangchan, and the Latin American cities of Lima and Managua. Figure A1 presents a map of all cities included in our analysis. Appendix Table A1 contains a complete list of the cities and years in our data.

The unique feature of the JICA surveys is their fine spatial resolution. We match each household to small geographic neighborhoods, which are on average 6km^2 in area. On average, there are 156 neighborhoods to a city. Barring Brazil, which we include in our analysis, there are few administrative sources allowing researchers to analyze income from developing countries at such a fine spatial level.

JICA conducted their surveys over the course of 20 years, between 1995 and 2015, and questionnaires and sampling strategies are not perfectly standardized across time or context. For all surveys, we generate a household-level measure of annual income through either reported household income or individual income aggregated to the household-level. We further aggregate households to the level of neighborhood. Figure A2 plots our measure of annual household income for cities against GDP-per-capita for the same country-year of that city's survey, derived from Penn World Tables. Fit is imperfect, the correlation between the two measures 0.53, though statistically significant at the 1 percent level. As our goal is to analyze the distribution of income *within* cities, rather than compare across cities, we choose as our primary income measure a neighborhood's rank within a city, with 100 representing the richest neighborhood and 0 the poorest. This measure also corresponds to that used by Lee and Lin (2018), who also analyze income distribution within US cities.

Additionally, due to differences in the sampling strategies between surveys, we do not rely on the number of surveys conducted in a given neighborhood to measure it's residential population. Rather, our estimates for the population of neighborhoods in cities with JICA surveys are derived from 2015 LandScan population distributions (Bright et al., 2016). While this measure is imperfect, our primary specification does not incorporate the populations of neighborhoods.

Administrative data Our analysis also includes dis-aggregated census data from Brazil, Spain, France, UK, USA, measured between 2008 and 2019. We include all such data that reported (or allowed us to measure) average income at a fine grained level of geographic detail within cities. The cities and years coming from censuses are also reported in Appendix Table A1.

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

City centers City centers are constructed using a combination of (1) VIIRS Nighlights data from the Colorado School of Mines (2) Building volumes data from the World Settlement Footprint project (3) Road network density derived Open Street Maps, and (4) City locations from Open Street maps. For the first three sources, we performed kernel smoothing to find three points with the brightest nighlights, maximum building volume, and road network density, respectively. With four city center candidates in hand, choose "city center" to be the most central of these locations — the point closest to all the others.

City boundaries To generate city boundaries, and ensure we exclude rural areas, we use the World Settlement Footprint's "Built Up Areas" data set. For each city center, we include all neighborhoods which are both within 25km of a city center and and include only areas which intersect with "built up area". We end up with 127,000 polygons (neighborhoods) from 18 countries.

In deciding whether to include neighborhoods containing non-built up areas, we face a trade-off between mistakenly including rural households, which are likely to poorer than their urban counterparts (especially in developing countries), and mistakenly excluding citizens living on the urban periphery but who are a part of the city's non-agricultural economy. In cities drawn from administrative sources, this error is negligible due to the small size of neighborhoods. In cities drawn from JICA surveys, with larger neighborhoods, this trade-off is more severe. Figure A3 shows JICA-defined neighborhoods in red and urban boundaries for two cities in our data, Viangchan, Laos and Colombo, Sri Lanka. As shown in Panel (a), omitting polygons who intersect with non-urban areas would significantly reduce city coverage and throw away many urban households. In Colombo, panel (b), the exclusion of boundary neighborhoods would be less detrimental, both due to the size of the built-up area and the average size of polygons. Our findings are robust to the inclusion of urban-rural border neighborhoods (our primary specification) and only including neighborhoods contained entirely within the built up area.

Elevation and slopes To determine whether a neighborhood is "hilly", we 30m×30m elevation estimates as part of Amazon Web Services Terrain Tiles global datasets (Larrick et al., 2020). Slope is calculated through the average change in elevation across 4 adjacent 30m by 30m grids (Hijmans, 2024). A neighborhood is "hilly" if it's average slope is greater than 5 degrees.[2]

To illustrate our data, Figure 1 plots maps of Los Angeles and Lima, which in some ways are representative cities of developed and less developed countries, and which share broadly similar geography. Both are located between the Pacific Ocean and large mountain ranges, for example, and both have similar average temperatures.[3]

The dot in each image represents the center of the city, and the surrounding circle has a radius of 10 km. As a preview of results below, notice the circle in Los Angeles contains many dark blue neighborhoods, poorer than average. The circle in Lima, on the other hand, contains many light blue neighborhoods, richer than average. In Los Angeles, the hilly areas of Laurel Canyon and Beverly Hills, to the northwest of the the city center, report very high incomes. In Lima, *Los Olivos*, corresponding to the lighter blue area to the northwest of the center just outside the 10km radius, is a middle class area contained in the valley between two poor hillsides on either side.

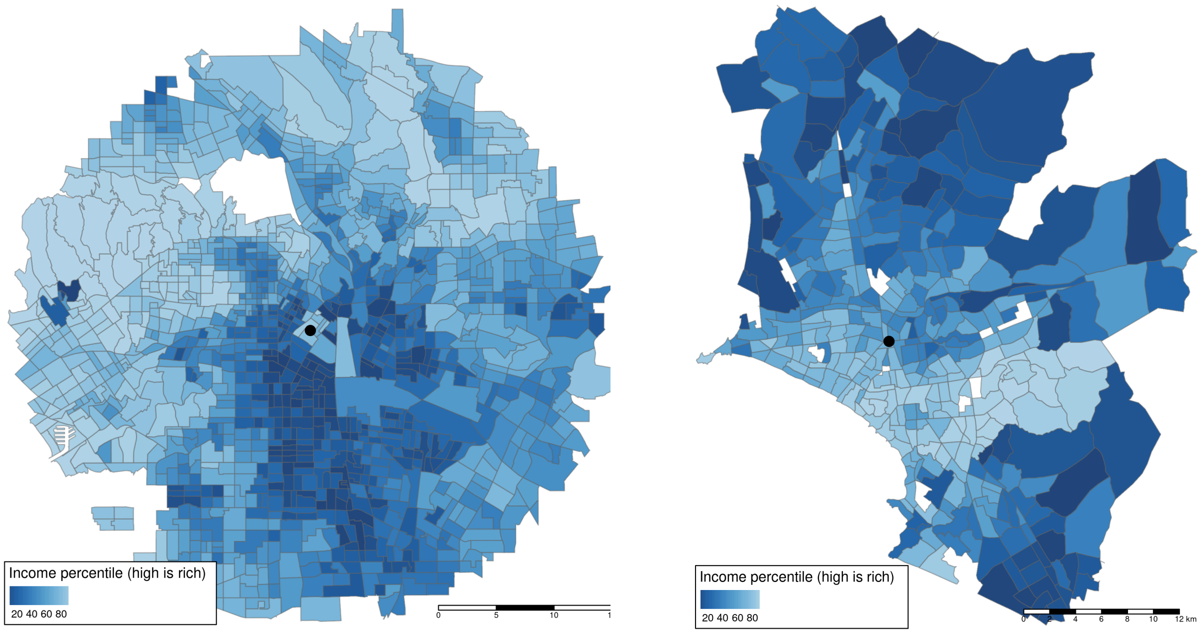
2.2. Income-Distance Gradients

Figure 2 shows the relationship between distance from city center and average income at the neighborhood level. We bin neighborhoods based on distance to the city center and, for each

[2]This measure differs from that of Lee and Lin (2018), who use a hilliness threshold of 15 degrees. We believe this difference derives from our distinct method of calculating slope. Among urban census tracks in the USA, 5.6% register as hilly according to our measure, compared to 6.3% reported by Lee and Lin (2018)

[3]Missing income areas in Los Angeles correspond to Griffith Observatory in the northwest of the city, LAX in the southwest, as well as miscellaneous industrial areas. Similarly, missing income areas in Lima correspond to parks, industrial areas, and military installations.

Figure 1: Income by Neighborhood in Los Angeles and Lima



(a) Los Angeles

(b) Lima

distance bin, take the average income-rank for neighborhoods. Each light line represents a single city, while averages are highlighted in bold.

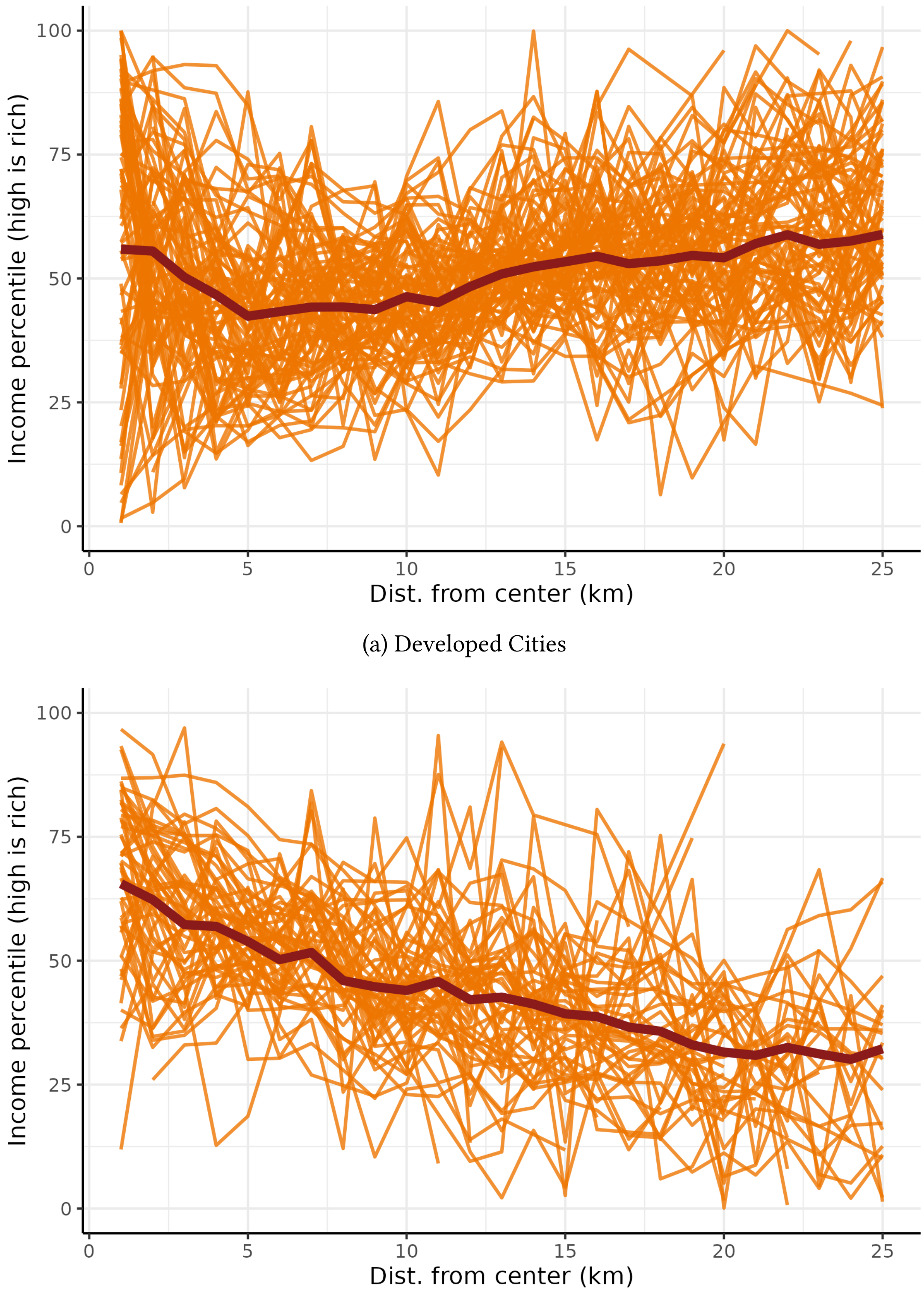
Panel (b) of Figure 2 shows in less developed countries income has a strong negative monotone relationship with distance to the city center: Areas close to the city center have an average income rank of 67 percentile points, while at the outskirts of the city this falls to 30 percentile points. Panel (a) shows this does not hold in developed countries. Unlike the steady downward trend of income in poor cities, income follows a U-shape with distance to city center. On average, city centers are relatively wealthy, but income quickly declines within a short distance from the CBD. After reaching it's nadir at around 5 kilometers from the city center, income climbs from 42 percentile points to 62 percentile points. Despite the U-shape, the slope of the line for cities in developed countries, Panel (a), is 0.6,. The slope of the line for cities in less developed countries, Panel (b) is -1.4. Both are statistically significant at the 1 percent level.

In Table 1 we demonstrate this relationship statistically. For each city c, we run a regression at the neighborhood (n)-level

$$\text{Income rank (High rich)}_{nc} = \beta_{0c} + \beta_{1c} \times \text{Log Distance}_{nc} + \epsilon_{nc}$$

This process generates collection of 129 income gradients, one for each city in our sample. We

Figure 2: Neighborhood Average Income and Distance from City Center



(a) Developed Cities

(b) Less Developed Cities

analyze whether the distribution of these gradients is different between our 47 less developed cities and 82 developed cities.

In Column 1 of Panel A of Table 1 we assess whether (1) income gradients in rich and poor countries are different from zero and (2) income gradients in rich and poor countries are different from one another, accomplished through a city-level regression of income gradient on the development status of a city and corresponding Wald test. In Column 2 of Panel A we perform the same comparisons on the median of the distribution of income gradients, accomplished analogously through a quantile regression and bootstrapped standard errors.

In Panel B of Table 1, we divide the city into two groups: Neighborhoods who cumulatively comprise the 25% of households furthest from the city center, and neighborhoods who comprise the inner 75% of population, and take the ratio of incomes of the outer group to incomes of the inner group. Unlike the distance measure used in Figure 2 and Panel A of Table 1, this measure is robust to differences in the geographic size of cities. Some geographically small cities have no neighborhoods further than 15km, but for all cities it is possible to divide the population of a city into further and nearer groups. As in Panel A, we compare the mean and median of this income ratio using OLS and quantile regression, respectively.

The results of Table 1 re-affirm the visual trend of Figure 2. Income gradients in developed cities are positive and significantly different than zero. In the median developed city, a 1% increase in distance to city center corresponds to a roughly 5 percentile point increase in income rank. This effect is small relative to the large and negative income gradients found in developing cities, where the median correlation between distance and income percentile is -13.5.

In Panel B we show results are robust to a geography-agnostic definition of distance. Results are even more striking. In the average developed city, the 25% of residents furthest from the city center have 126 percent the income of closer residents. In the average developing city, by contrast, peripheral residents have only 71 percent the income of their interior neighbors. We interpret the results in Panel B to mean our results are not being driven by differences in the aggregate population density of cities, robustness we explore more systematically in Section 2.5.

2.3. Income and Hilliness

Next, we explore how hilliness affects the distribution of income differently in rich vs poor cities. Figure 3 shows histograms of the ratio of income between hilly and non-hilly areas across cities in our sample. Cities with no hilly areas, such as Dallas, TX, and Dhaka, Bangladesh, are omitted, leaving us with 89 cities, 53 developed and 36 less developed.

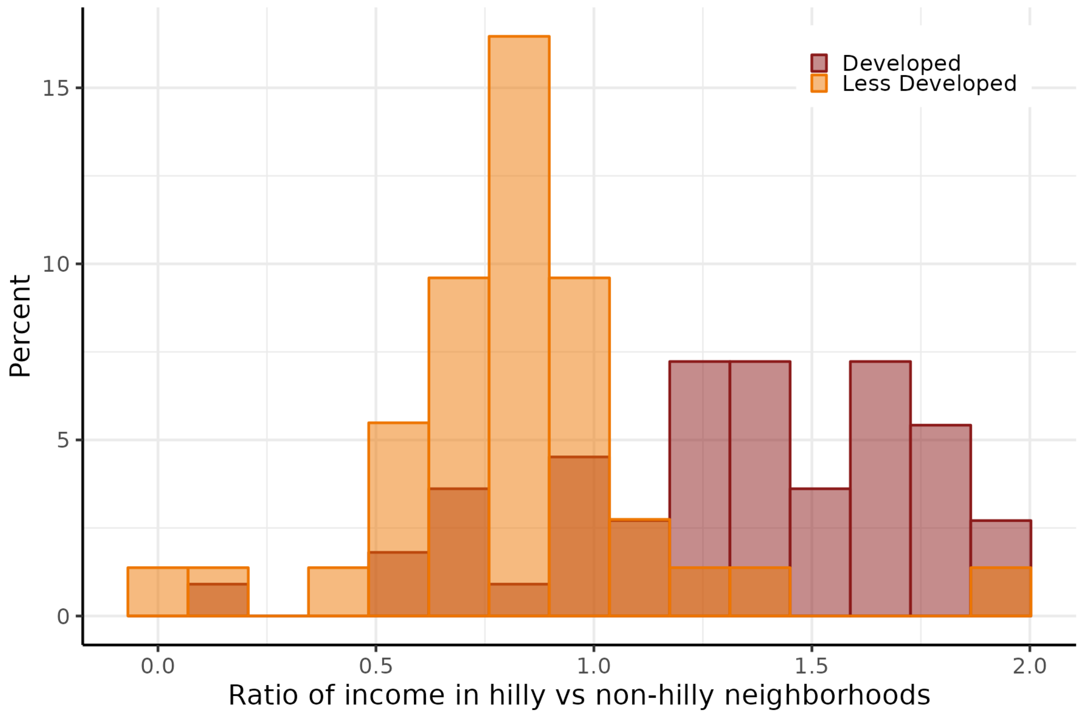
Figure 3 visually demonstrates our second key fact: In developed cities, hilly areas are richer

Table 1: Income Gradients within Cities: Summary Statistics

Development status	Mean (1)	Median (2)
Panel A: Coefficient on log distance to city center		
Developed	4.56^{***}	3.86^{**}
Less Developed	-11.7^{***}	-12.4^{***}
Difference	-16.2^{***}	-16.3^{***}
Panel B: Ratio of income, furthest 25% of population to others		
Developed	1.22^{***}	1.18^{***}
Less Developed	0.709^{***}	0.665^{***}
Difference	-0.508^{***}	-0.517^{***}

Note: Panel A reports the mean and median slope coefficients from a regression of the income percentile of a neighborhood on that neighborhood's log distance to the city center. The first row runs these regressions only for cities in developed countries, and the second row does so only for cities in less developed countries. The third row reports the difference and *t*-test of differences in means. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels. Panel B reports the mean and median ratios of the income percentile in the neighborhoods comprising the furthest 25 percent of population relative to other (closer) neighborhoods. The first and second rows are for cities in developed and less-developed countries, and the last row is the difference and *t*-test of the difference in means and medians.

Figure 3: Relative Incomes of Hilly Neighborhoods



than non-hilly areas. By contrast, in less developed cities, hilly areas are poorer. In the developed world, 79 percent of cities have income ratios above one, meaning hilly neighborhoods are richer than non-hilly ones. In the developing world, the opposite is true: 83 percent of cities have income ratios *less* than one.

Table 2 demonstrates this fact statistically. For each of 89 cities with hills in our sample, we calculate two statistics, (1) the coefficient from a regression of income rank on a hilliness dummy, and (2) the ratio of income between hilly to non-hilly areas. With these city-level statistics in hand, we compare values between developed and less developed cities in a method analogous to that of Table 1: Values in Column 1 derive from an OLS regression and associated Wald test, while Values in Column 2 derive from a quantile regression.

Table 2 shows income is highly segregated by hilliness in both developed and less developed cities. Panel A demonstrates in developed cities, incomes are 15 percentile points higher in hilly relative to non-hilly areas, while in less developed cities, they are 10 percentile points *lower*. Magnitudes in Panel B are larger. In the median developed city, the percentile of income in hilly areas is 1.36 times the percentile of income in non-hilly areas. In the median developing city, hilly areas are only 85% as rich as non-hilly areas.

Table 2: Hilliness and Income within cities: Summary Statistics

Development status	Mean (1)	Median (2)
Panel A: Coefficient on hilly dummy		
Developed	14.9^{***}	16.2^{***}
Less Developed	-9.66^{***}	-7.89^{***}
Difference	-24.6^{***}	-24.1^{***}
Panel B: Ratio of income in hilly areas to others		
Developed	1.32^{***}	1.35^{***}
Less Developed	0.810^{***}	0.836^{***}
Difference	-0.508^{***}	-0.512^{***}

Note: Panel A reports the mean and median slope coefficients from a regression of the income percentile of a neighborhood on that whether a neighborhood is hilly. The first row runs these regressions only for cities in developed countries, and the second row does so only for cities in less developed countries. The third row reports the difference and t-test of differences in means. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels. Panel B reports the mean and median ratios of the income percentile in hilly vs non-hilly neighborhoods. The first and second rows are for cities in developed and less-developed countries, and the last row is the difference and t-test of the difference in means and medians.

2.4. Pooling cities to learn about average effects

Sections 2.2 and 2.3 demonstrate developed and less developed cities have opposite income sorting patterns across distance and hilliness, respectively. Table 3 tests these separate findings jointly through a neighborhood-level regression of the form

$$\begin{aligned}\text{Income percentile}_{nc} = \gamma_{0d} \times \text{Log distance}_{nc} + \gamma_{1d} \times \text{Log Distance} \times \mathbf{1}(\text{Developed}_{nc}) \\ + \gamma_{0h} \times \text{Hilly}_{nc} + \gamma_{1h} \times \text{Hilly}_{nc} \times \mathbf{1}(\text{Developed}_{nc}) + \mathbf{1}_c + nu_{nc}\end{aligned}$$

That is, we allow slopes on distance and hillinesss to differ based on development status, and include city-fixed effects. Our weighting scheme treats neighborhoods in a city as identical, and in aggregate each city has a total weight of one. The second panel of Table 3 shows the difference in slopes for Distance and hilliness between developed and less developed cities. We show separate slope estimates for rich and poor countries (meaning there is no need to add coefficients together). Differences in slopes between developed and less developed countries are calculated through a Wald test.

Columns (1) and (2) in Table 3 re-confirm our earlier findings using the new specification. In developed countries, neighborhoods far from the city center and in hills are rich, while in less developed countries, neighborhoods far from the center and in hills are poor. Column 3, our preferred specification, shows these two effects are distinct. Magnitudes on distance and hilliness are unchanged even with the inclusion of the other. In developed countries, a one percent increase in distance from the city center is associated with a 4.5 percentile point increase in income. In the developing world, this same increase in distance is associated with an 11.5 percentile point *decrease* in income. Hilly areas in developing countries have 7.2 percentile points lower income than comparative non-hilly areas. In developed countries, by contrast, hilly areas have 13.5 pecentile points higher income.

2.5. Robustness

To assess sensitivity of our results to alternative specifications, we focus on two main avenues. First, we explore alternative modeling choices to the neighborhood-level regressions of Table 3. Second, we expand our geographic aggregation to explore distance and hilliness gradients by continent, rather than by development status.

Table 3: Neighborhood-level analysis

Dependent Variable:	Income percentile (high is rich)				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Developed × Log dist. from center	3.78***				3.70***
	(1.23)				(1.24)
Less Developed × Log dist. from center	-11.5***				-11.2***
	(1.25)				(1.24)
Developed × Hilly		13.4***			13.2***
		(3.32)			(3.17)
Less Developed × Hilly		-8.72***			-7.49***
		(1.83)			(1.87)
Developed × < 100m from river			3.85***		3.36***
			(1.14)		(1.10)
Less Developed × < 100m from river			-6.30***		-5.25***
			(1.80)		(1.58)
Developed × < 100m from coast				12.5***	12.2***
				(3.38)	(3.17)
Less Developed × < 100m from coast				7.45***	6.63***
				(2.41)	(2.49)
Difference in slopes: Developed vs Developing					
Log dist. from center	-15.2***				-14.9***
	(1.75)				(1.75)
Hilly		-22.1***			-20.7***
		(3.79)			(3.68)
< 100m from river			-10.1***		-8.61***
			(2.13)		(1.92)
< 100m from coast				-5.05	-5.53
				(4.14)	(4.03)
Weight	Cities equal	Cities equal	Cities equal	Cities equal	Cities equal
Subset	Full	Full	Full	Full	Full
Fixed-effects					
City	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	117,355	117,355	117,355	117,355	117,355
R^2	0.048	0.016	0.011	0.012	0.064
Within R^2	0.041	0.009	0.004	0.005	0.058

Note: Regressions are at the neighborhood-level. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels. The dependent variable in all regressions is the income rank of a neighborhood. In all columns, weights are such that each city is given equal aggregate weight and within a city neighborhoods have equal weight. In the top panel, each row indicates a separate slope by group. Differences in slopes, presented in the second panel, calculated via a Wald test.

2.5.1. Robustness of neighborhood-level regressions

This section treats the specification used in Column (3) of Table 3, a neighborhood-level regression testing jointly whether distance and hilliness gradients vary with development status, as our modeling baseline. We explore five key departures from this specification.

Inclusion of controls Table A2 Column (1) controls for whether a neighborhood's centroid is within 1km from the coast, either the ocean or a great lake, reflecting the notion that these neighborhoods may be inherently desirable (Lee and Lin, 2018), and city centers frequently lie near the coastline. Column (2) includes controls for the quadrant of a neighborhood relative to the city center, reflecting the notion that weather patterns, lead some regions of cities to have higher amenity value than others (Heblich et al., 2021). Column (3) controls for a neighborhood's area, addressing concerns that a high number of small neighborhoods drive results. In all cases, the effects of controls are allowed to vary by city. The findings of A2 are not qualitatively different from those of our main specification in 3.

Alternative approaches to neighborhood weighting Figure A3 explores sensitivity to alternative weighting schemes. In Column (1), we construct weights such that all cities have neighborhood weights summing to one, as in our main specification, but within cities, neighborhoods with larger population are assigned higher weight, reflecting a concern that sparsely populated rich or poor neighborhoods drive results. Findings in Column (1) are qualitatively identical to those in our main specification. In Column (2), we weight neighborhoods such that each *country* is assigned equal weight, while within countries cities are treated equally. In Column (3) we combine the approaches of Columns (1) and (2), such that countries are treated equally, while within a city neighborhoods with larger population receive larger weight.

Table A3, Columns (2) and (3) shows our estimated effects on distance in the developed countries are largely driven by income sorting in the United States. Income gradients appear flat in developed cities when the 55 US cities collectively have equal weight compared to the 8 Spanish, 8 French, and 11 British cities. Similarly, in less developed countries, the estimated effects in our main specification are partially driven by Brazil, but are still qualitatively robust to the country-level weighting. The estimated income gradient with distance declines in magnitude by from -11.7 to -6.2, but is still negative and statistically significant. Importantly, across both country-level weighting schemes we can reject the hypothesis that poor and rich countries have equal income gradient.

The estimated effect on hilliness and income also changes with the new weighting scheme, although, although qualitatively, differences are smaller. The coefficient on hilliness in developed countries ceases to be statistically significant, but remains large in magnitude. Across both weighting schemes, we can reject the hypothesis that income sorting by hilliness is the same between developed and less developed countries.

We view this robustness exercise as highly conservative. First, by reducing weight on a high number of cities, we dramatically reduce our effective sample size. Second, there is no a priori reason to treat countries as equal units of analysis when our distinction of interest is between developed and less developed cities.

Alternative sampling frames Table A4 shows robustness to alternative definitions of the city. As illustrated by Figure A4, few people in France and Spain live further than 10km from the city center. In Columns (1) and (2), we restrict attention to neighborhoods within 15 and 20km from the city center, respectively. In Column (3) we include only neighborhoods fully contained in the "Built up areas" urban boundary, omitting those neighborhoods who straddle the border.

Results are virtually unchanged for less developed countries. However Columns (1) and (3) show distance gradients in developed countries are sensitive to the inclusion of far-out areas, while the hilliness gradients remain unchanged. We conclude rich households beyond 15km appear to drive some of the distance effects found in our main specification. In all cases, we confidently reject the hypothesis that distance and hilliness gradients are equal between developed and less developed countries.

Alternative income measures The outcome in our main specification is income rank, ranging from 0 to 100. In Column (1) of Table A5, we use neighborhood log income as our outcome measure. City fixed effects, employed in all specifications presented, capture differences in income levels across cities. Results are robust to this difference in outcome measure. A one percent increase in distance from the city center is associated with a .07 percent increase in income in developed cities, while in less developed cities a one percent increase in distance from the city center corresponds to a .29 percent *decrease* in income. Column (2) shows results are qualitatively unchanged when the outcome is a neighborhoods income as a fraction of mean income for the city as a whole.

In Column (3) we normalize a neighborhood's income with respect to all other neighborhoods in the city, generating a z-score. In developed cities, hilly areas are on average .5 standard deviations higher in income relative to non-hilly areas, while in developing cities, hilly areas are .1 standard deviations lower. Across all specifications, the difference between developed and less developed cities, for both distance and hilliness gradients, are consistent with results in our main specification.

Alternative distance measures Table A6 shows robustness to alternative measures of distance from the city center. In Columns (1) and (2), we ask whether people further from the city center have higher incomes than those near the city center — purely relative income sorting. This contrasts with our main specification, which asks if individuals far from the city center, in objective terms, have higher incomes than those near the city center. Column (1) simply ranks neighborhoods by distance from the city center, with rank ranging from 0 to 100. Column (2) uses a population-weighted ranking. A neighborhoods "distance" is the percent of total city population living closer to the city center than the centroid of that neighborhood, and ranges from 0 to 100. Results are robust to these purely relative distance schemes.

Finally, Column (3) uses distance from the city center in km, rather than log distance as in our main specification. An extra kilometer further from city center leads to a .9 percentile rank increase in income in developed cities, and a -1.9 percentile rank decrease in income in less developed cities. We can reject equality of effects between developed and less-developed countries.

3. A Model of Income Sorting in the City

In this section, we develop a simple model that accounts for the income sorting patterns presented above. Our model is a simple extension of a monocentric urban model (Alonso, 1964; Mills, 1967; Muth, 1968). We extend these models to incorporate non-homothetic preference following Couture et al. (2024).

Primitives and agents Cities differ in terms of four different fundamental productivities. First is the productivity of the final goods sector, denoted by A^F. Second is the productivity of the housing supply sector, denoted by A^H. Third is the efficiency of transportation technology, denoted by A^T. Fourth is the decay of the level of residential infrastructure as a function of the travel cost to the city center, denoted by A^R. Broadly speaking, cities in the developing world can be thought to have lower values of A^F, A^H, A^T,and A^R than cities in the developed world, and these differences in turn cause different patterns of income sorting in the two regions.

A city is organized as a line segment of an interval $[-1,1]$. Production occurs only at $j = 0$ (the midpoint), which we call the central business district (CBD). Every worker must commute to the CBD, and no worker lives in this center location. The left side of CBD ($[-1,0)$) 'hilly" and the right side of the CBD is "flat". Generally, it will be harder to construct residential infrastructure (e.g. water, electricity lines) and harder to travel across the hilly area, yet the hilly also provides natural amenities, such as views and clean air. We formalize this intuition below.

There are two types of workers $s \in \{L,H\}$, distinguished by their endowment of efficiency units of labor in final goods production. We assume that the total population size of type s workers is given by $\bar{l}^s$, and normalize the aggregate population size such that $\bar{l}^L + \bar{l}^H = 1$. The efficiency unit of labor for type H workers is one, and that of type L workers is $0 < \eta < 1$. Competitive firms at CBD produce a homogeneous product that is freely traded within a city by using a linear production technology $y = A^F L$, where A^F is the total factor productivity (TFP) and L is the efficiency unit of labor. Taking the output goods as numeraire, wages of workers of type $s \in \{L, H\}$ are given by

$$w^s = A^F \eta^{\mathbb{I}[s=L]}. \tag{1}$$

Household preferences Households preferences of household ω (of either type $s \in \{L, H\}$) living in location j is given.

$$U_{j,\omega}(h_j, c_j) = \left(\frac{h_j - \underline{h}}{\alpha}\right)^{\alpha} \left(\frac{c_j}{1-\alpha}\right)^{1-\alpha} \tau_j^{-1} B_j^R B_j^N \varepsilon_{j,\omega}, \tag{2}$$

where h_j is consumption of housing, c_j is consumption of the final good, τ_j is the utility commuting cost from residential location j to the CBD, B_j^N is the natural amenity of location j, B_j^R is the residential infrastructure of location j. $\underline{h} > 0$ represents a "minimum needs" housing consumption, and $0 < \alpha < 1$ represents the preferences towards housing consumpion. Finaly, $\varepsilon_{j,\omega}$ represents a household-specific idiosyncratic preference shock unique to household ω and location j. Following the convention of urban equilibrium models, we assume that $\varepsilon_{j,\omega}$ follows i.i.d., Frechet distribution with shape parameter θ.

Costs and benefits of distance and hills We introduce several parametric assumptions about τ_j, B_j^N, and B_j^R. First, we assume the commuting cost from residential location j is increasing in absolute distance from the CBD and is more costly in hilly areas.

$$\tau_j = \exp\left(\frac{D_j + \delta \times \mathbb{I}[j < 0]}{A^T}\right), \tag{3}$$

where $D_j = |j|$ is the geographic distance between location j and the CBD, and $\delta \geq 0$ is the parameter that governs the additional cost associated moving across the hilly area ($[-1, 0)$). Together $D_j + \mathbb{I}[j < 0]A^T$ constitute the "geographic friction" of construction in location j. As stated above, A^T, represents the transport technology of the city: commuting to the CBD is less costly in cities with high A^T. Next, we assume that residential infrastructure B_j^R takes the following form:

$$B_j^R = \exp\left(-\frac{D_j + \delta \times \mathbb{I}[j < 0]}{A^R}\right), \tag{4}$$

where A^R denotes the rate of decay of residential infrastructure as a function of location j's geographic friction. This feature captures the notion that, in low-income cities, the government has limited ability to supply suitable residential structures (e.g., electricity, sewage) in residential locations far from the CBD and in hilly areas. Notice δ in Equation 4 appears also in Equation 3. That is, we assume the increased difficulty of constructing transportation infrastructure in hilly areas is the same as when constructing residential infrastructure in hilly areas. Finally, we assume that the natural amenity B_j^N takes the following form:

$$B_j^N = \exp\left(\beta D_j + \zeta \times \mathbb{I}[j < 0]\right), \tag{5}$$

where $\beta \geq 0$ captures an increase in residential amenities as one moves away from the CBD (e.g., green spaces), and $\zeta \geq 0$ is a parameter that governs the natural amenity associated with hilly areas (e.g., nice view of the city). Since these terms jointly enter in the utility function ((2)), we define the attractiveness of the location B_j^* as follows:

$$B_j^* = \tau_j^{-1} B_j^R B_j^N. \tag{6}$$

Location decisions and consumption choices We now describe households' decisions. Households first decide their residential locations after observing $\varepsilon_{j,\omega}$. They then make consumption decisions for $\{h_j, c_j\}$ subject to the budget constraint. *Given* residential choice j, the household consumption decision for a worker of type s is given by

$$\max_{h_j, c_j} \quad \left(\frac{h_j - \underline{h}}{\alpha}\right)^{\alpha} \left(\frac{c_j}{1-\alpha}\right)^{1-\alpha} B_j^* \varepsilon_{j,\omega} \tag{7}$$
$$s.t. \quad c_j + r_j h_j \leq w^s$$

where r_j is the rent per efficiency unit of housing available at location j. Assuming that $w^s > r_j h_j$ for all j, meaning minimum housing consumption is met for both types of workers, the solution to this problem is given by

$$h_j^s = \alpha \left(\frac{w^s - r_j \underline{h}}{r_j}\right) + \underline{h}, \tag{8}$$

$$c_j^s = (1-\alpha)\left(w^s - r_j \underline{h}\right), \tag{9}$$

Therefore, the indirect utility of residing in location j is given by

$$v_{j,\omega}(h_j, c_j) = V(w^s, r_j, B_j^*)\varepsilon_{j,\omega}, \qquad V(w^s, r_j, B_j^*) = \left(\frac{w^s}{r_j} - \underline{h}\right) r_j^{1-\alpha} B_j^*. \tag{10}$$

Using properties of the Frechet distribution of $\varepsilon_{j,\omega}$, equilibrium population of type-s workers at location j is given by

$$l_j^s = \pi_j^s \bar{l}^s, \qquad \pi_j^s = \frac{V(w^s, r_j, B_j^*)^{\theta}}{\sum_{\ell} V(w^s, r_{\ell}, B_{\ell}^*)^{\theta}}, \tag{11}$$

where π_j^s denotes the probability that workers of type s choose to live in location j.

Housing production We assume that there is a competitive housing sector that supplies housing at each location j using lands owned by absentee landlords. The inverse housing supply function is given by

$$r_j = \frac{1}{A^H}\left(H_j\right)^{\gamma}, \tag{12}$$

where H_j is the aggregate housing consumption at location j, γ is the inverse of housing supply elasticity, and A^H is the parameter that governs the efficiency unit of housing supply, including the level of the residential infrastructure of the city. The housing market clearing implies that

$$H_j = \sum_{s\in\{L,H\}} l_j^s h_j^s. \tag{13}$$

Equilibrium The competitive equilibrium consists of the population distribution $\{l_j^s\}$, consumption decisions $\{h_j^s, c_j^s\}$, wages $\{w^s\}$, and rents $\{r_j\}$ such that workers maximize consumption choices conditional on location choice (Equations 8 and 9), workers optimally choose locations (Equation 11), and the housing production market clears (Equations 12 and 13).

Welfare of low and high-skill workers Our model permits straightforward parametrization of expected welfare for low and high-skilled workers. Using properties of the exreme value distribution of $\epsilon_{\omega j}$, workers' idiosyncratic preference shocks over neighborhoods, welfare of worker type s, $\mathbb{W}^s$ can be expressed

$$\mathbb{W}^s = \Gamma\left(\frac{\theta-1}{\theta}\right)\left(\sum_j V\left(w^s r_j, B_j^*\right)^{\theta}\right)^{\frac{1}{\theta}} \tag{14}$$

where $\Gamma(\cdot)$ is the Gamma function and $V(\cdot)$, defined in Equation 10, represents the indirect utility of working in location j for a worker of type s, without taking into account the idiosyncratic preference shock.

3.1. Patterns of Income Sorting within a City

This section outlines the model's prediction of the patterns of income sorting within cities. In particular, we analyze how the final goods productivity of the city, A^F, the efficiency of the housing supply, A^H, the efficiency of commuting technology, A^T, and the efficiency of residential infrastructure supply per geographic friction, A^R, shape the location decisions of low and high-skill residents.

To facilitate our analysis, we first provide the following lemma that shows that the income sorting patterns are summarized by the rent of location j:

Lemma 1. *If $w^L < w^H$, $\underline{h} > 0$, and $\alpha > 0$,*

$$\frac{\partial}{\partial r_j} \frac{V(w^H, r_j, B_j^*)}{V(w^L, r_j, B_j^*)} < 1. \tag{15}$$

Lemma 15 shows that, although all types of workers prefer to live in locations with a lower rent, workers with lower income levels (type L) are more elastic in their residential location decisions to increases in rent. This lemma implies that, given an equilibrium, the average income of residents in location j is higher if the rent of the location r_j is higher, and rent is a sufficient statistic for income sorting.

We now provide comparative statics on income sorting patterns within a city. Define the average income of location j as:

$$\overline{w}_j = \frac{l_j^L w_j^L + l_j^H w_j^H}{l_j^L + l_j^H}. \tag{16}$$

Furthermore, define the derivative of the average income with respect to the distance to CBD:

$$\nabla \overline{w}_j = \frac{\partial \overline{w}_j}{\partial D_j}. \tag{17}$$

If $\nabla \overline{w}_j < 0$, average income is increasing in distance to CBD, as we we have shown is the case for cities in the developed world. Conversely, if $\nabla \overline{w}_j > 0$, the average income is decreasing in distance to CBD, as we have shown is the case for cities in the developing world. . The following propositions provide conditions under which these sorting patterns emerge in our model.

Proposition 1 (Income gradients)**.** *Under $\beta < \frac{1}{A^T} + \frac{1}{A^R}$, and finite A^F and A^H*

(i) $\nabla \overline{w}_j < 0$, i.e., average income decrease as a function of the distance to CBD.

(ii) Within this parameter region, the negative income gradient becomes smaller in magnitude with respect to A^F, A^H, A^T, and A^R.

$$\frac{\partial}{\partial A^F} \nabla \overline{w}_j > 0, \quad \frac{\partial}{\partial A^H} \nabla \overline{w}_j > 0, \quad \frac{\partial}{\partial A^T} \nabla \overline{w}_j > 0, \quad \frac{\partial}{\partial A^R} \nabla \overline{w}_j > 0. \tag{18}$$

The first part of the proposition shows that, under the sufficiently low values of $\{A^T, A^R\}$, such that the amenity value of living far from the city is outweighed by the commuting cost and low residential infrastructure, average income decreases as a function of the distance to CBD.

The second part of the proposition shows that, as the city increases its four fundamental productivity values, the degree of this income sorting becomes less pronounced. These patterns are consistent with the patterns for developing country cities, in comparison to developed country cities, as we documented in Section 2.

We also show that, if the commuting technology A^T and the efficiency of residential infrastructure supply with respect to geographic friction A^R are sufficiently high, the model can predit upward-sloping income as a function of the distance to CBD. This pattern is consistent with the patterns in developed countries as documented in Section 2.

Proposition 2 (Distance to CBD in High-Income Cities)**.** *Under $\beta > \frac{1}{A^T} + \frac{1}{A^R}$ and finite value of A^F and A^R, for a location j in regular region ($j \in [0,1]$), $\nabla \overline{w}_j > 0$, i.e., the average income increases as a function of the distance to CBD.*

In this parameter space, the amenity value of living far from the city center outweighs the long commutes and low residential infrastructure. As a consequently, regions far from the city center are relatively more populated with high-skill workers.

Finally, we provide a comparative statics regarding hilly region.

Proposition 3 (Hilly Regions)**.** *Consider locations $j > 0$ in flat region and $-j < 0$ in hilly region which are equidistant to CBD ($D_j = D_{-j}$). Assume finite values of A^F and A^H. If $\frac{\zeta}{\delta} < \frac{1}{A^T} + \frac{1}{A^R}$, then $\overline{w}_j > \overline{w}_{-j}$, and otherwise $\overline{w}_j < \overline{w}_{-j}$.*

Therefore, under sufficiently low level of A^T and A^H relative to the amenity in hilly region γ relative to its geographic friction δ, the average income of residents in hilly region is lower than regular regions. As the commuting technology A^T and the efficiency of residential structure per geographic friction A^H increase, this pattern flips. These patterns are consistent with the patterns we document in developing and developed country cities as documented in Section 2.

4. Quantitative Analysis

4.1. Parametrization and parameter choices

Table 4 summarizes the parameter choices used in a simple simulation of our model. For this exercise, we simulate the income and hilliness gradients for a representative less developed city and a representative developed city. The two cities are identical except for three technology parameters, A^T and A^R, and A^F, which govern the commuting technology efficiency, rate of decay of the infrastructure in hills and far from the city center, and overall income levels of the city. Below, we describe the reasoning behind each choice.

Productivities: A^T, A^R, A^F, and A^H We set A^T as follows. Presume it takes 30 minutes to commute from the outer city to the CBD in the flat area of the rich city, and the equivalent trip in the hilly area takes 1 hour. Following the findings of Akbar et al. (2023), we let the less developed city have speeds 2/3 that of the developed city. Because τ_j, is measured in utility terms, A^T must also account for the dis-utility of time. Using the parametrization $e^{\kappa \text{Hours of travel time}}$, Ahlfeldt et al. (2015) finds $\kappa \approx 0.9$. This generates

$$A^T_{\text{Developed}} = 2.2, \qquad \delta = 1, \qquad A^T_{\text{Less developed}} = 1.66$$

When set A^R according to the heuristic that, in the developed country, residential infrastructure is 95 percent as nice at the outer periphery. This captures the intuition that, in developed cities households across the entire city have approximately equal electricity and sewage access. In less developed cities, by contrast, we set A^R such that the residential infrastructure outer periphery of the city is only 60% that of the city center. Consequently, we set

$$A^R_{\text{Developed}} = 20, \qquad A^R_{\text{Less developed}} = 2$$

The relative residential infrastructure of hilly areas is determined by δ, set above. Using the value $\delta = 1$, our assumptions choices of A^R imply the distant, hilly areas in the developed city feature 90 percent the infrastructure level of the city center. In the less developed city, hilly distant areas have only 36 percent the residential infrastructure.

Finally we set final goods productivity A^F to be 1 in the developed city and 0.75 in the less-developed city.

$$A^F_{\text{Developed}} = 1, \qquad A^F_{\text{Less developed}} = 0.75$$

Housing construction productivity, A^H, is equal to one in both cities, for convenience.

Amenity value of distance and hills: β and ζ To select β, the amenity value of living far from the city center, such that living on the periphery is twice as nice as in the city center, generating a value of $\beta = 0.7$. Recall this valuation does not account for commuting time or residential infrastructure, which enter separately into the worker's utility.

Similarly we allow for the hilly area to be twice as valuable to the worker as the non-hilly area, generating $\zeta = 0.7$. Combined, β and γ imply the utility value of living in a distance, hilly area (not accounting for public infrastructure) is four times that of living in adjacent to the city center, in both the developed and less developed cities.

Table 4: Parameter choices for Developed and Less Developed countries

Description	Parameter (1)	Less developed (2)	Developed (3)
Final goods productivity	A^F	**0.75**	**1.0**
Housing sector productivity	A^H	1.0	1.0
Transport productivity	A^T	**1.66**	**2.2**
Residential infrastructure productivity	A^R	**2.0**	**20.0**
Difficulty of building in hills	δ	1.0	1.0
Amenity value of living far from center	β	0.7	0.7
Amenity value of living in hills	ζ	0.7	0.7
Consumption share of housing	α	0.25	0.25
Minimum housing consumption	$\underline{h}$	1.0	1.0
Frechet shape parameter	θ	6.0	6.0
Relative productivity of low-skill workers	η	0.5	0.5
Inverse housing construction elasticity	γ	0.33	0.33
Population	l^H	0.5	0.5

Frechet shape parameter: θ Following Ahlfeldt et al. (2015), we set θ, which governs the heterogeneity of individual-level preference shocks, to 6.

Housing consumption and production: α, γ Following Ahlfeldt et al. (2015), we set α, the consumption share of housing, to 0.25. Also following Ahlfeldt et al. (2015), we set the inverse elasticity of housing construction to 0.33.

Population: l^H **and** η For simplicity, we allow equal numbers of high- and low-skill residents, letting $l_h = 0.5$. Additionally, we let low-skill workers be half as productive as high-skill workers, meaning $\eta = 0.5$.

While intuitive, our parameter choices also neatly divide the developed and less developed cities according to the predictions for income gradient by distance (Proposition 2) and hilliness (Proposition 3). According to the parameters values outlined in Table 4, the developed city will feature positive gradients for distance and hilliness, and the less developed city will feature negative gradients for distance and hilliness, consistent with the facts described in Section 2. To examine the exact magnitudes and shapes of these gradients, however, we must simulate the model.

4.2. Simulation Results

We present the empirical implications of our model, generated through a numerically solved equilibrium, in three steps. Figure 4 describes the difference in primitives between the developed and less developed cities. Figure 5 demonstrates the implications of these primitives for the location choices of low and high-skill workers, which in turn foreshadows Figure 6, demonstrating our model's implications income sorting by distance and hilliness.

To start, Figure 4 shows the fundamental, exogenous, differences between the developed and less developed cities. On the x-axis of Figure 4, and all following figures, are neighborhoods, indexed $j \in [-1,0)$ for the hilly region and $j \in (0,1]$ for the flat region. On the y-axis of Panel (a) is the τ_j, the utility-adjusted transportation cost of neighborhood j. In both cities, it is more costly to commute from the edges of the city, but this cost gradient is steeper in the less developed city compared to the developed one.

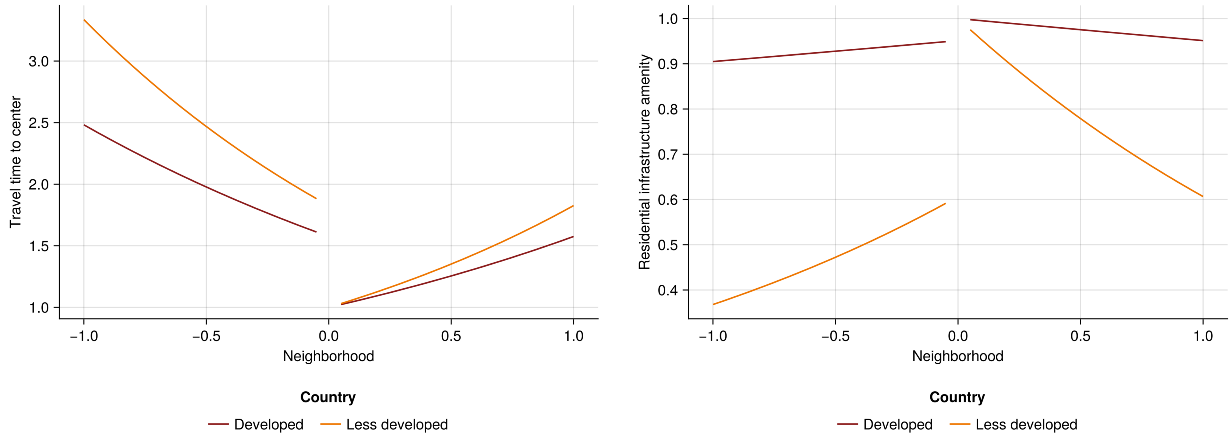
Panel (b) shows residential infrastructure, B_j^R, in the developed and less developed cities. In the developed city, residential infrastructure is highest in the city center, but stays roughly constant throughout the city. In the developed city, by contrast, residential infrastructure is equal to that of the developed country in the city center (a feature of our functional form assumptions), and declines rapidly with distance from the city center. In the developing city, residential infrastructure drops off significantly as one crosses from the flat to hilly areas.

Next, in Figure 5 we examine the implications of these differences in fundamental differences in τ_j and B_j^R for the residential location choices of workers in each city. Panel (a) shows the fraction of low-skill workers living in each location in our city, corresponding to π^L as defined in Equation 11. In the developed city, low-skill workers live everywhere in the city, with slightly fewer workers in distant, hilly areas. In contrast, the less developed city features large income segregation. Almost no low-skill workers live in the center of the flat area, choosing instead to live in hilly areas near the center of the city and flat areas far from the city center.

Panel (b) of Figure 5 examines analogous location decisions for high-skill residents (π^H). In the developed city, high-skill workers live far from the city center, and are more concentrated in hilly distant neighborhoods. In the less developed city, high-skill in workers congregate in the flat area near the CBD, with very few workers elsewhere.

Finally, Figure 6 demonstrates our model can correctly emulate the facts described in Section 2. It shows the average income of each neighborhood j, $\overline{w}_j$ (Equation 16), relative to the average income of the city at large. Starting with distance, Figure 6 demonstrates average income increasing with distance from the city center, as we showed to be the case in developed cities in Panel (a) of Figure 2. In contrast, average income is *decreasing* with distance from the city center in the less

Figure 4: Costs of geographic frictions in Developed and Less developed Countries



(a) Transportation cost

(b) Residential infrastructure

developed city, as we demonstrated was true in Panel (b) of Figure 2. Moreover, Figure 2 shows the gradient is smaller in developed cities compared to less developed ones. Our simulations in 6 correctly replicate this finding.

Turning to hilliness, 6 correctly predicts average incomes in hills to be higher in the developed city and lower in the less developed city. We conclude our parsimonious model correctly captures the two key facts in the data.

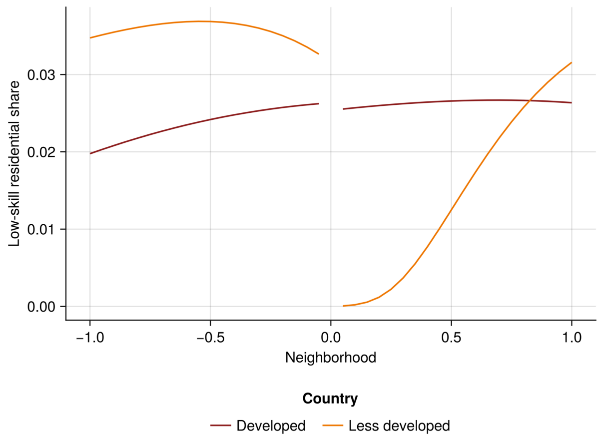
4.3. Counterfactual analysis

In a final analysis, we explore which difference in fundamental productivity is most important in generating the observed distance and hilliness gradients. Additionally, we undertake preliminary welfare analysis to explore how each productivity term affects the relative welfare of high- and low-skill residents.

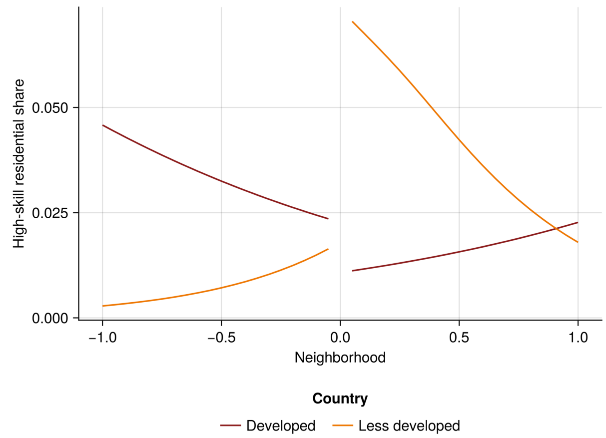
4.4. Counterfactual Distance and Hilliness Gradients

Recall there are three differences between the developed and less developed cities: The developed city has higher final goods productivity A^F, higher transport productivity, A^T, and higher residential infrastructure productivity A^R. Table 5 takes as a starting point the less developed city, and raises each productivity in turn to uncover the magnitude of the changes in income and hilliness gradients.

Figure 5: Residential location between Developed and Less developed cities



(a) Low-skill workers



(b) High-skill workers

Figure 6: Income gradients in Developed and Less developed cities

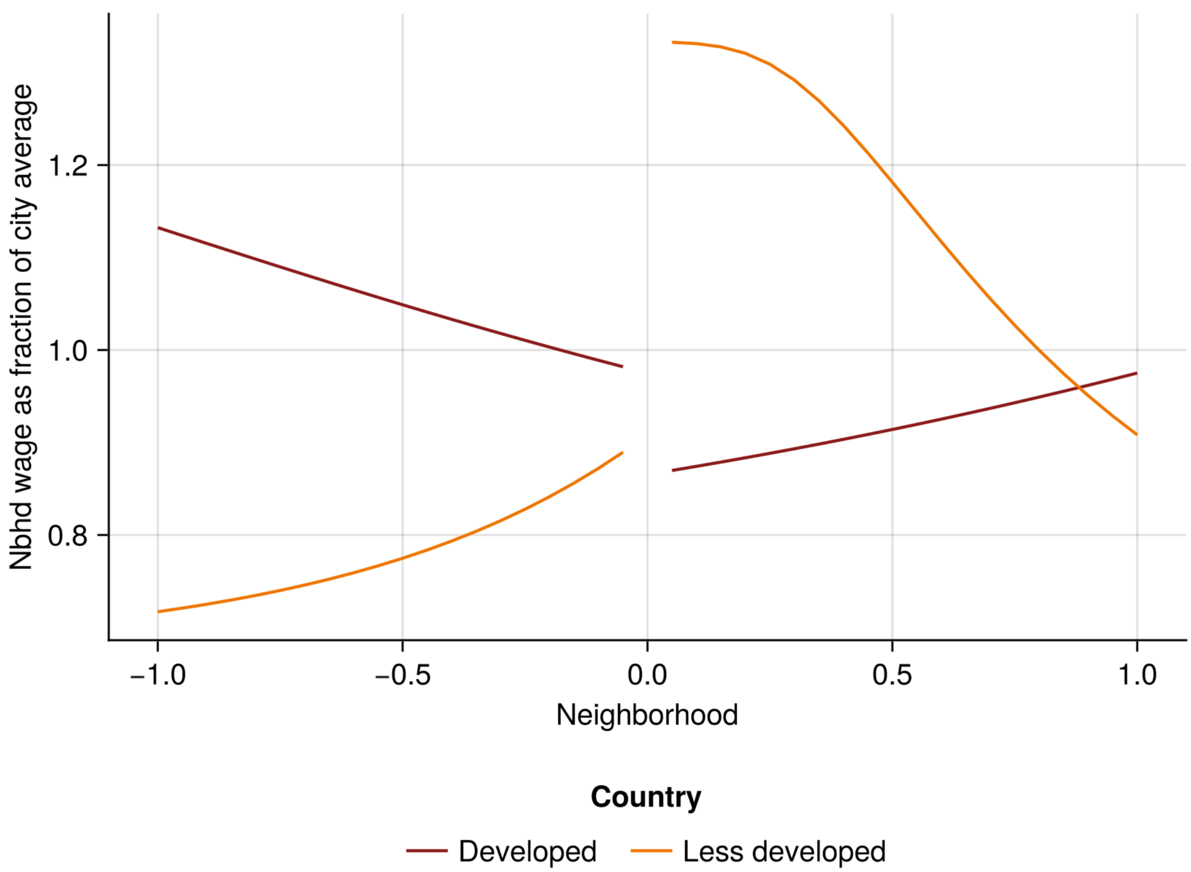


Table 5: Counterfactual gradients

Country	Distance gradient (1)	Hilliness ratio (2)
Developed	0.05	1.15
Less developed	-0.11	0.68
Less developed, high A^T	-0.09	0.75
Less developed, high A^R	0.02	1.06
Less developed, high A^F	-0.08	0.77

Column (1) of Table 5 runs the simple descriptive regression for each simulated city c

$$\log D_{jc} = \beta_c \times \log \overline{w}_{jc} + \epsilon_{jc}$$

and reports separate β_c for each city. Column (2) reports the ratio of hilly and non-hilly areas for each city. The first two rows of Table 5 correspond to the simulated cities outlined in Table 4. They show, as expected, a positive distance distance gradient and a hilliness ratio above one in the developed city, and a negative distance gradient and hilliness ratio below one in the less developed city.

In the bottom three rows, we raise A^T, A^R and A^F of the less developed city, respectively to that of the developed city. Beginning with the third row of Table 5, in line with Propositions 2 and 3, the low value of $A^R_{\text{Less developed}}$ drives our income sorting results. When A^R in the less developed city is set to the value of 20, as in the developed city, both distant and hilly areas become relatively more valuable and the less developed city resembles the developed one. Continuing on to rows (4) and (5), while the predictions of Proposition 1 hold, that the magnitude of income sorting decreases with productivities, under our calibrations, these effects are modest.

4.5. Counterfactual Welfare

In Table 6, we employ our model-derived estimate of worker welfare, presented in Equation 14, and calculate welfare for each counterfactual explore in Table 5. We normalize all welfare measures with respect to that of high-skill workers in the developed country. Columns (1) and (2) present the welfare of the low and high-skill workers, respectively. Column (3) presents the relative welfare of the two groups.

Results of Table 6 present the interesting result that though differences in A^R between the two nations are responsible for differences in income sorting (Table 5), A^R has little effect on the relative

Table 6: Counterfactual welfare

Country	Welfare low-kill (1)	Welfare high-skill (2)	Ratio (3)
Developed	0.26	1.0	0.26
Less developed	0.05	0.36	0.13
Less developed, high A^T	0.06	0.41	0.14
Less developed, high A^R	0.08	0.56	0.14
Less developed, high A^F	0.14	0.55	0.26

welfare of the low and high-skill groups. That is, both groups benefit equally from improvements to residential infrastructure. The final row of Table 6 shows the only counterfactual policy which significantly reduces the welfare gap between high and low-skill workers is an increase in final sector productivity A^F.

Through the lens of our model, this effect has a straightforward explanation: In the less developed city (Row 2), a high number of low-skill workers consume housing only slightly above their minimum needs. As a consequence, higher incomes allow workers to purchase more final consumption goods at a high marginal utility. Nonetheless, even with incomes at that of a developed city, the welfare of residents in Less developed, high A^F city (Row 5) is still only 50% that of those in the developed city, underscoring the importance of public infrastructure for aggregate welfare.

5. Conclusion So Far

This paper draws on unique geo-located survey data from developing countries around the world, in conjunction with a host of fine-grained administrative data to document two new facts about the spatial sorting of income in developed and developing cities.

We show the gradient of income with respect to distance from the city center is strongly negative in developing cities. In the developing world, relatively well-off individuals are congregated in the city center, while the poor are more likely to live towards the periphery of the city. We show this does not hold in cities in the developed world, where income gradients range from zero to positive. Hills also divide incomes in opposite ways between developed and developing cities. In the developed world, hilly areas are significantly richer than non-hilly areas, while in the less developed world, they are significantly poorer.

We develop a simple model urban model, in the spirit of Alonso (1964), to account for these facts. Our model allows for residential amenities, transportation infrastructure productivity, and residential infrastructure productivity to vary with distance to the city center and hilliness. These features, combined with non-homothetic preferences over housing consumption, and heterogenous workers, generate rich predictions on income sorting within a city. We conclude steeper gradients in state capacity with distance from the city center in less developed countries, that is, how easily governments can construct sewage and electricity lines close to the city center compared to the periphery, reproduces our observed sorting patterns. Our model also permits straightforward welfare analysis. In our model, while improvements in residential infrastructure drive differences sorting patterns throughout the city as well as large differences in aggregate welfare, they have little impact on the relative welfare of high compared to low earning residents.

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Online Appendix

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A. Details on Data Construction

Table A1: List of all Cities in Data

City	Country	Avg. Nbhd size (km^2)	Num. of Nbhds	Year
		Cities surveyed by JICA		
Belem	Brazil	4.58	91	2000
Bucharest	Romania	7.55	75	1998
Cairo	Egypt	3.40	387	2001
Colombo	Sri Lanka	3.20	273	2013
Da Nang	Viet Nam	7.37	50	2008
Damascus	Syrian Arab Republic	18.2	74	1998
Dhaka	Bangladesh	10.6	86	2009
Dhaka	Bangladesh	9.44	135	2014
Hanoi	Viet Nam	3.73	241	2005
Hanoi	Viet Nam	5.91	190	2014
Ho Chi Minh	Viet Nam	6.54	224	2003
Karachi	Pakistan	6.00	167	2011
Kuala Lumpur	Malaysia	9.71	194	1999
Lahore	Pakistan	7.93	178	2010
Lima	Peru	2.69	370	2003
Managua	Nicaragua	2.66	92	1998
Manila	Philippines	3.16	208	1996
Mombasa	Kenya	5.87	32	2015
Nairobi	Kenya	6.37	88	2005
Nairobi	Kenya	5.79	102	2013
Viang Chan	Lao People's DR	9.02	33	2007
		Brazilian Cities *Income source: 2010 Census* *Neighborhood definition: Census block (Setor)*		
Aracaju		0.428	895	
Belo Horizonte		0.145	5730	
Belém		0.329	1862	
Brasília		0.384	1704	
Campinas		0.285	1964	
Curitiba		0.242	2992	
Florianópolis		0.293	817	
Fortaleza		0.136	3537	

Table A1: (continued)

City	Country	Avg. Nbhd size (km^2)	Num. of Nbhds	Year
Goiânia		0.376	2210	
João Pessoa		0.211	1097	
Maceió		0.345	1053	
Manaus		0.327	2334	
Maringá		0.485	637	
Natal		0.371	657	
Porto Alegre		0.170	2801	
Recife		0.187	3827	
Ribeirão Prêto		0.221	851	
Rio de Janeiro		0.0652	11336	
Salvador		0.194	3672	
Santos		0.146	2177	
Serra		0.153	1703	
Sorocaba		0.511	740	
São José dos Campos		0.320	1158	
São Luís		0.363	1281	
São Paulo		0.0707	22250	
Teresina		0.471	1035	
French Cities *Income source: 2019 INSEE Tax Statistics (Median income)* *Neighborhood definition: IRIS*				
Bordeaux		1.10	226	
Lille		0.577	362	
Lyon		0.572	403	
Marseille		0.762	374	
Nantes		1.34	169	
Paris		0.357	3373	
Strasbourg		0.669	147	
Toulouse		1.02	213	
Spanish Cities *Income source: 2021 Instituto Nacional de Estadística* *Neighborhood definition: Sección*				
Barcelona		0.292	2534	
Bilbao		0.392	692	

Table A1: (continued)

City	Country	Avg. Nbhd size (km^2)	Num. of Nbhds	Year
Las Palmas		0.470	326	
Madrid		0.393	3679	
Málaga		0.883	548	
Sevilla		0.700	684	
Valencia		0.640	1106	
Zaragoza		1.95	481	
UK Cities *Income source: 2018 Office of Statistics Tax Data* *Neighborhood definition: "Small Areas" (MSOA)*				
Birmingham		3.87	340	
Bristol		10.2	85	
Gateshead		3.63	107	
Harrogate		4.19	220	
Hove		3.78	55	
Liverpool		4.46	166	
London		1.80	1021	
Manchester		4.46	306	
Nottingham		5.55	83	
Portsmouth		4.66	93	
Rotherham		7.96	102	
USA Cities *Income source: Aggregated American Community Survey* *Neighborhood definition: Census Block*				
Albuquerque		7.30	157	
Atlanta		3.86	330	
Austin		4.84	197	
Bakersfield		15.0	90	
Baltimore		2.58	417	
Boston		2.32	496	
Buffalo		3.78	191	
Chicago		1.04	1024	
Cincinnati		3.58	213	
Cleveland		2.37	435	
Columbus		4.71	298	

Table A1: (continued)

City	Country	Avg. Nbhd size (km^2)	Num. of Nbhds	Year
Dallas		3.33	508	
Denver		3.20	506	
Detroit		1.72	669	
Fort Worth		5.52	286	
Fresno		7.32	148	
Honolulu CDP		2.96	141	
Houston		3.45	563	
Indianapolis		6.49	256	
Kansas City		4.61	299	
Las Vegas		3.04	441	
Los Angeles		1.29	1476	
Louisville		5.37	215	
Memphis		4.74	134	
Miami		2.28	470	
Milwaukee		3.04	337	
Minneapolis		3.42	498	
New Orleans		3.12	308	
New York		0.441	2358	
Newark		1.80	593	
Oakland		2.57	289	
Oklahoma City		5.13	229	
Omaha		4.10	179	
Orlando		5.72	208	
Philadelphia		1.88	695	
Phoenix		3.26	498	
Pittsburgh		2.81	305	
Portland		4.44	373	
Providence		4.17	153	
Riverside		4.38	393	
Sacramento		5.17	292	
Salt Lake City		7.77	193	
San Antonio		4.01	315	
San Diego		2.81	401	
San Francisco		1.56	260	
San Jose		3.44	374	
Santa Ana		2.65	501	

Figure A1: Locations of Cities in our Data Set

Table A1: (continued)

City	Country	Avg. Nbhd size (km^2)	Num. of Nbhds	Year
Seattle		3.07	313	
St. Louis		4.84	293	
Tacoma		5.07	192	
Tampa		4.12	257	
Tucson		6.12	163	
Tulsa		5.50	154	
Virginia Beach		4.42	256	
Washington		2.14	692	

B. Robustness

Figure A2: Comparison between income from JICA survey and GDP Per Capita

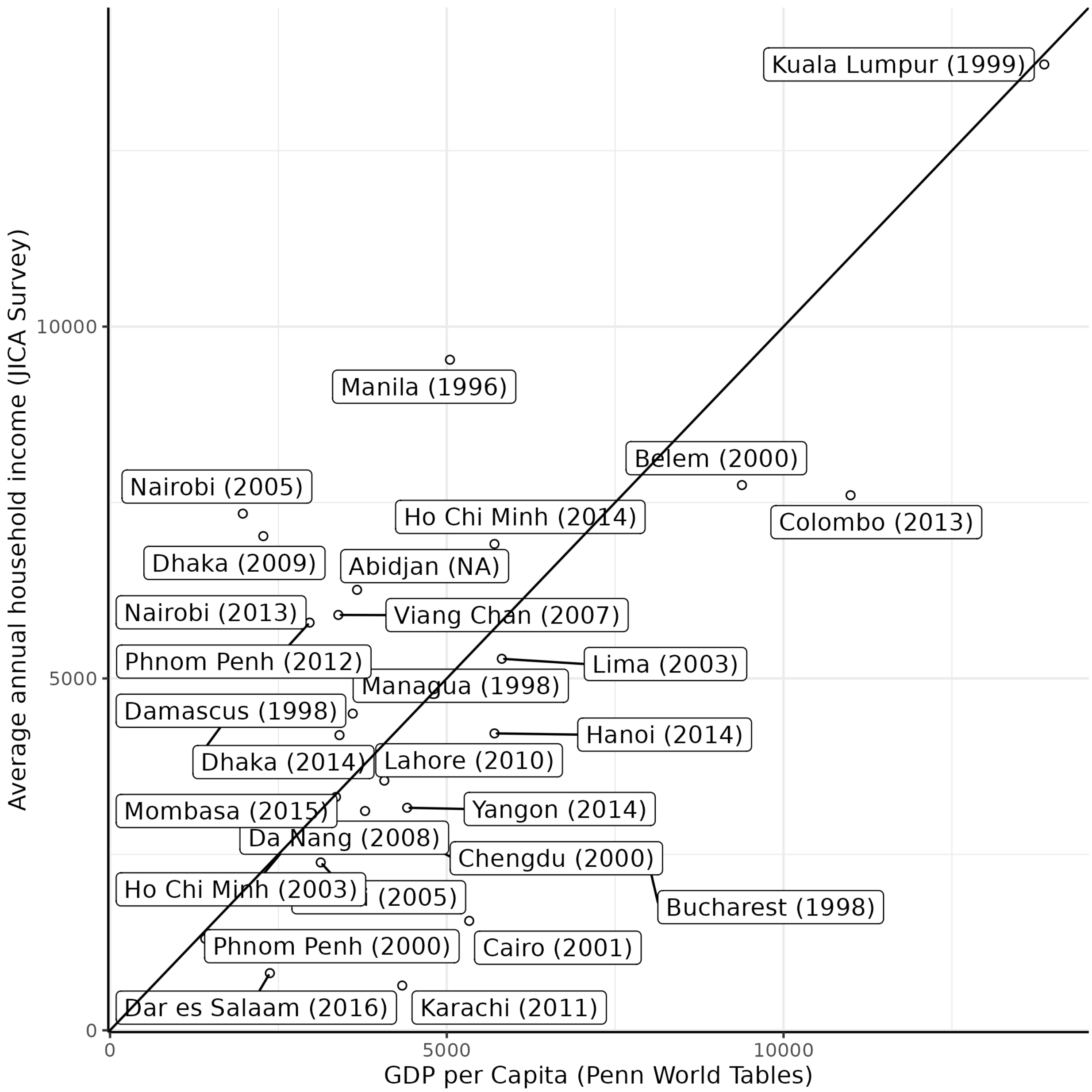
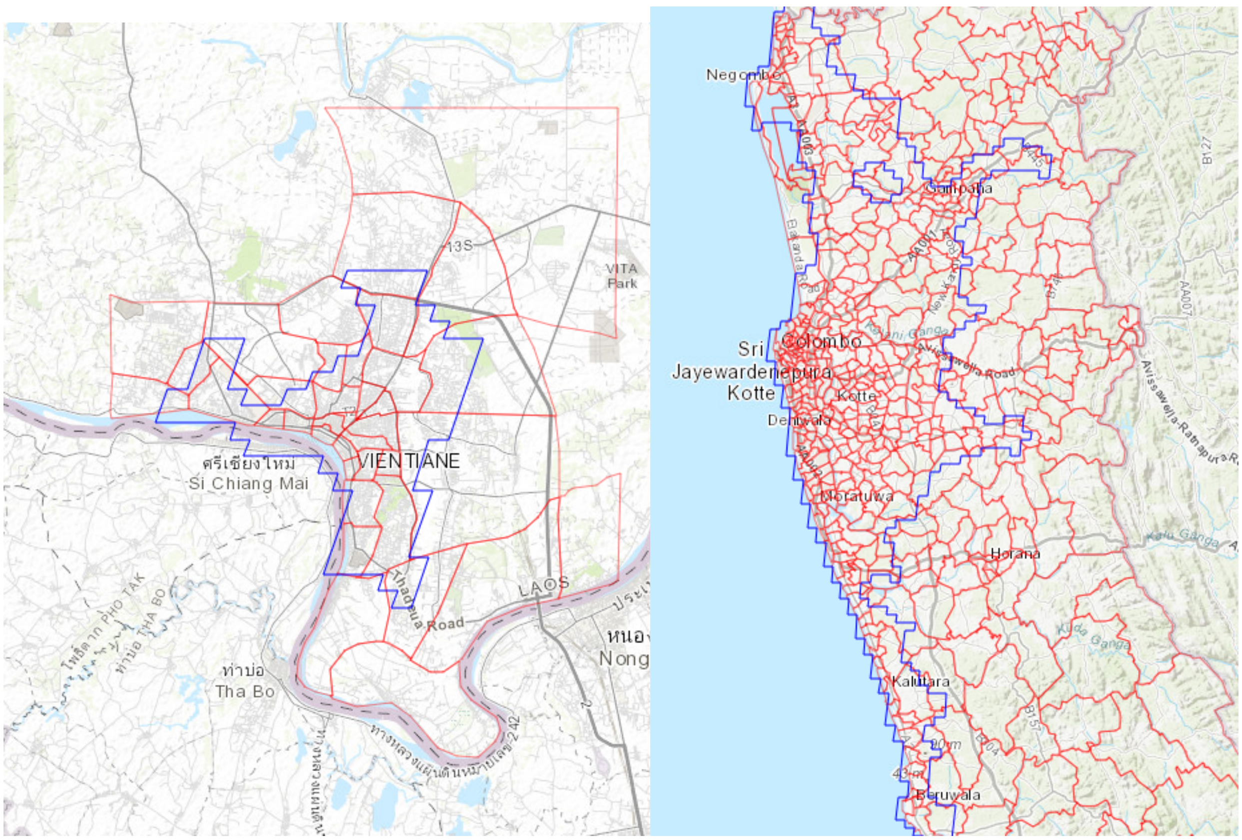


Figure A3: Neighborhoods (red) and Built up Area (blue) in Vianghan and Colombo



(a) Viangchan, Laos

(b) Colombo, Sri Lanka

Figure A4: Population distribution with distance from center

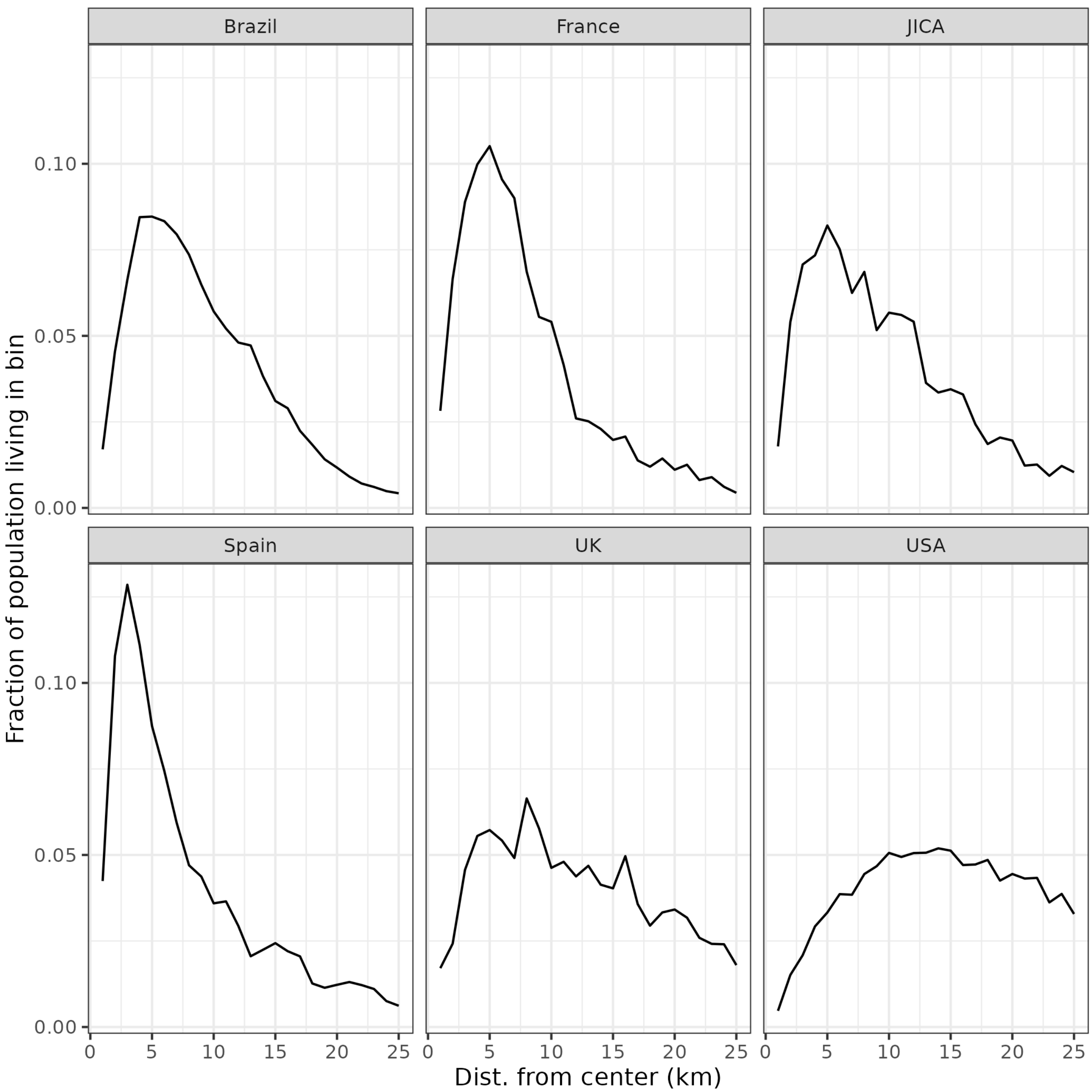


Table A2: Neighborhood-level regressions: Inclusion of controls

Dependent Variable:	Income percentile (high is rich)	
Model:	(1)	(2)
Variables		
Developed × Log dist. from center	4.09***	2.38*
	(1.29)	(1.23)
Less Developed × Log dist. from center	-10.9***	-10.5***
	(1.32)	(1.16)
Developed × Hilly	10.0***	12.1***
	(2.90)	(3.24)
Less Developed × Hilly	-7.70***	-8.58***
	(1.83)	(1.38)
Developed × < 100m from river	3.42***	1.37
	(0.998)	(1.14)
Less Developed × < 100m from river	-4.04**	-4.26***
	(1.58)	(1.44)
Developed × < 100m from coast	9.70***	11.3***
	(2.62)	(3.31)
Less Developed × < 100m from coast	6.77***	5.99***
	(2.17)	(2.26)
Difference in slopes: Developed vs Developing		
Log dist. from center	-15.0***	-12.9***
	(1.85)	(1.70)
Hilly	-17.7***	-20.7***
	(3.43)	(3.52)
< 100m from river	-7.46***	-5.63***
	(1.87)	(1.84)
< 100m from coast	-2.93	-5.32
	(3.40)	(4.01)
Weight	Cities equal	Cities equal
Subset	Full	Full
Fixed-effects		
City	Yes	Yes
Varying Slopes		
NE (City)	Yes	
SW (City)	Yes	
NW (City)	Yes	
Polygon Area (City)		Yes
Fit statistics		
Observations	117,355	117,355
R^2	0.186	0.095

Table A3: Neighborhood-level regressions: Alternative weighting schemes

Dependent Variable:	Income percentile (high is rich)		
Model:	(1)	(2)	(3)
Variables			
Developed × Log dist. from center	4.34***	-0.320	0.411
	(1.33)	(1.35)	(1.35)
Less Developed × Log dist. from center	-12.0***	-6.84***	-8.21***
	(1.33)	(1.30)	(1.14)
Developed × Hilly	13.2***	5.30	5.38
	(3.17)	(4.12)	(3.97)
Less Developed × Hilly	-8.40***	-4.72	-9.52***
	(1.97)	(4.05)	(3.63)
Developed × < 100m from river	3.49***	3.95***	3.88**
	(1.10)	(1.46)	(1.56)
Less Developed × < 100m from river	-3.66**	-5.78***	-3.76*
	(1.52)	(2.08)	(1.99)
Developed × < 100m from coast	11.6***	8.76**	8.15**
	(2.97)	(4.22)	(3.88)
Less Developed × < 100m from coast	7.03***	3.17	5.69
	(2.36)	(4.95)	(5.22)
Difference in slopes: Developed vs Developing			
Log dist. from center	-16.4***	-6.52***	-8.62***
	(1.88)	(1.87)	(1.77)
Hilly	-21.6***	-10.0*	-14.9***
	(3.73)	(5.78)	(5.38)
< 100m from river	-7.15***	-9.73***	-7.64***
	(1.88)	(2.54)	(2.53)
< 100m from coast	-4.54	-5.59	-2.46
	(3.79)	(6.50)	(6.51)
Weight	Cities equal, Nbhd pop	Countries equal	Countries equal, Nbhd pop
Subset	Full	Full	Full
Fixed-effects			
City	Yes	Yes	Yes
Fit statistics			
Observations	117,355	117,355	117,355
R^2	0.072	0.053	0.070
Within R^2	0.060	0.041	0.049

Note: Regressions are at the neighborhood-level. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels. The dependent variable in all regressions is the income rank of a neighborhood. In Column (1), neighborhood weight reflects it's fraction of total residential population. In Column (2) weights sum to one within each country. Column (3) combines the weighting schemes in Column (1) and (2). In the top panel, each row indicates a separate slope by group. Differences in slopes, presented in the second panel, calculated via a Wald test.

Table A4: Neighborhood-level regressions: Alternative samples

Dependent Variable:	Income percentile (high is rich)			
Model:	(1)	(2)	(3)	(4)
Variables				
Developed × Log dist. from center	0.063	2.20*	-9.80**	3.70***
	(1.24)	(1.23)	(4.13)	(1.24)
Less Developed × Log dist. from center	-10.1***	-10.8***	-11.7***	-8.32***
	(1.32)	(1.29)	(1.92)	(1.83)
Developed × Hilly	9.77***	11.6***	-0.841	13.2***
	(3.56)	(3.34)	(10.9)	(3.17)
Less Developed × Hilly	-7.67***	-7.43***	-5.79	0.111
	(1.84)	(1.93)	(4.71)	(5.82)
Developed × < 100m from river	3.36**	3.64***	-0.725	3.36***
	(1.31)	(1.16)	(3.76)	(1.10)
Less Developed × < 100m from river	-5.50***	-5.34***	-8.76**	-5.12**
	(1.61)	(1.62)	(3.35)	(2.00)
Developed × < 100m from coast	12.8***	12.3***	16.1***	12.2***
	(3.56)	(3.20)	(3.86)	(3.17)
Less Developed × < 100m from coast	7.07***	6.77***	-3.93	5.24
	(2.21)	(2.39)	(9.07)	(3.87)
Difference in slopes: Developed vs Developing				
Log dist. from center	-10.1***	-13.0***	-1.88	-12.0***
	(1.81)	(1.78)	(4.56)	(2.21)
Hilly	-17.4***	-19.0***	-4.95	-13.1**
	(4.01)	(3.86)	(11.9)	(6.63)
< 100m from river	-8.86***	-8.98***	-8.04	-8.48***
	(2.07)	(1.99)	(5.04)	(2.28)
< 100m from coast	-5.72	-5.49	-20.0**	-6.91
	(4.19)	(4.00)	(9.86)	(5.00)
Weight	Cities equal	Cities equal	Cities equal	Cities equal
Subset	<15km from CBD	<20km from CBD	Only fully urban areas	No Brazil
Fixed-effects				
City	Yes	Yes	Yes	Yes
Fit statistics				
Observations	84,151	104,105	2,283	39,505
R^2	0.068	0.060	0.366	0.046
Within R^2	0.045	0.052	0.102	0.037

Note: Regressions are at the neighborhood-level. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels. The dependent variable in all regressions is the income rank of a neighborhood. In all columns, weights are such that each city is given equal aggregate weight and within a city neighborhoods have equal weight. In the top panel, each row indicates a separate slope by group. Differences in slopes, presented in the second panel, calculated via a Wald test.

Table A5: Neighborhood-level regressions: Alternative income measures

Dependent Variables:	Log nbhd average income	Ratio to mean income	Income z-score
Model:	(1)	(2)	(3)
Variables			
Developed × Log dist. from center	0.055***	0.022	0.050
	(0.019)	(0.019)	(0.040)
Less Developed × Log dist. from center	-0.258***	-0.314***	-0.400***
	(0.033)	(0.040)	(0.044)
Developed × Hilly	0.214***	0.250***	0.538***
	(0.047)	(0.056)	(0.120)
Less Developed × Hilly	-0.204***	-0.161***	-0.121**
	(0.044)	(0.048)	(0.055)
Developed × < 100m from river	0.056***	0.060***	0.126***
	(0.015)	(0.016)	(0.036)
Less Developed × < 100m from river	-0.089***	-0.077**	-0.151***
	(0.028)	(0.035)	(0.056)
Developed × < 100m from coast	0.199***	0.238***	0.471***
	(0.048)	(0.059)	(0.116)
Less Developed × < 100m from coast	0.245***	0.418***	0.465***
	(0.056)	(0.106)	(0.094)
Difference in slopes: Developed vs Developing			
Log dist. from center	-0.313***	-0.337***	-0.450***
	(0.0379)	(0.0445)	(0.0593)
Hilly	-0.417***	-0.410***	-0.659***
	(0.0648)	(0.0739)	(0.132)
< 100m from river	-0.145***	-0.137***	-0.277***
	(0.0320)	(0.0386)	(0.0671)
< 100m from coast	0.0460	0.180	-0.00604
	(0.0733)	(0.121)	(0.149)
Weight	Cities equal	Cities equal	Cities equal
Subset	Full	Full	Full
Fixed-effects			
City	Yes	Yes	Yes
Fit statistics			
Observations	117,339	117,355	117,355
R^2	0.809	0.072	0.058
Within R^2	0.053	0.072	0.058

Note: Regressions are at the neighborhood-level. ***, ** and * indicate statistical significance at the 1-percent, 5-percent and 10-percent levels. In all columns, weights are such that each city is given equal aggregate weight and within a city neighborhoods have equal weight. In the top panel, each row indicates a separate slope by group. Differences in slopes, presented in the second panel, calculated via a Wald test.

Table A6: Neighborhood-level regressions: Alternative distance measures

Dependent Variable:	Income percentile (high is rich)		
Model:	(1)	(2)	(3)
Variables			
Developed × Dist. to center, neighborhood percentile rank	0.140***		
	(0.030)		
Less Developed × Dist. to center, neighborhood percentile rank	-0.311***		
	(0.033)		
Developed × Dist. from center, population percentile rank		0.143***	
		(0.030)	
Less Developed × Dist. from center, population percentile rank		-0.318***	
		(0.031)	
Developed × Dist. from center (km)			0.725***
			(0.145)
Less Developed × Dist. from center (km)			-1.83***
			(0.198)
Difference in slopes: Developed vs Developing			
Dist. to center, neighborhood percentile rank	-0.450***		
	(0.0452)		
Dist. from center, population percentile rank		-0.461***	
		(0.0436)	
Dist. from center (km)			-2.55***
			(0.246)
Weight	Cities equal	Cities equal	Cities equal
Subset	Full	Full	Full
Fixed-effects			
City	Yes	Yes	Yes
Fit statistics			
Observations	117,355	117,355	117,355
R^2	0.058	0.062	0.058
Within R^2	0.051	0.055	0.051

Note: Regressions are at the neighborhood-level. The dependent variable in all regressions is the income rank of a neighborhood. In all columns, weights are such that each city is given equal aggregate weight and within a city neighborhoods have equal weight. In the top panel, each row indicates a separate slope by group. Differences in slopes, presented in the second panel, calculated via a Wald test.