The monocentric city model worldwide: Rent, density, and transportation cost gradients in 734 cities[1]

Bernhard Nöbauer[2]
University of Lausanne

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Abstract

I use the monocentric city model to relate urban rent and density gradients to a third gradient describing transportation costs. I estimate rent gradients for 734 cities worldwide using internationally comparable data on Airbnb properties. The average elasticity of rent to distance from the city center is -0.06. Rent gradients are less pronounced in cities that are smaller or located in upper-middle-income countries. Density gradients are steeper than rent gradients in most cities. Combining the two types of gradients, I estimate the elasticity of transportation costs to distance from the city center to be 0.3 on average. Taken together, the two estimates imply a concave transportation cost function. While I precisely match the Duranton and Puga (2022) urban cost estimate of 0.07 for the United States, my global estimate of 0.3 suggests that the US is an outlier, with transportation costs being less sensitive to distance than elsewhere.

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[2] Departement of Economics, Faculty of Business and Economics (HEC Lausanne), University Of Lausanne, 1015 Lausanne, Switzerland; bernhard.noebauer@bluewin.ch.

1 Introduction

The monocentric city model illustrates stylized facts about cities and provides intuition on how rents, transportation costs, and living space are interrelated. It has a long tradition, is typically the first model that is taught in university courses on urban economics, and still possesses importance within and beyond the field (Duranton and Puga, 2015). Nevertheless, the empirical evidence related to the monocentric city model is comparatively scarce. This paper helps fill this gap by estimating rent and density gradients for 734 cities worldwide. To do this, I use internationally consistent data, including data about short-term rental properties from Airbnb. The paper then uses the structure of the monocentric city model to relate these two gradients to infer information about the urban transportation cost gradient.

Transportation costs are one of the most relevant factors in the study of cities. The inherent advantage of cities is proximity. Being physically close to other people allows individuals to exchange knowledge and goods, sustain infrastructure, host events, and engage with one another. If traveling from A to B would cost neither time nor money, cities might not exist. Given that it is costly, people face a trade-off between being closer to advantageous locations versus having cheaper unit costs of housing. But how should we represent transportation costs in economic models?

A common simplifying assumption is to model transportation costs as being linear in distance, implying that the monetary and non-pecuniary costs of traveling 10 km are twice as high as those of traveling 5 km. One example of this are iceberg trade costs. In contrast, I come to the conclusion that most cities feature concave transportation costs, implying that travelling a distance twice as long is less than twice as costly. The average elasticity of transportation costs with regard to distance is around 0.3, while the linear case would suggest an elasticity of 1. This suggests that the monetary and non-pecuniary costs of traveling 10 km are in fact only 30% higher as those of traveling 5 km. Intuitive explanations for concave transportation costs include higher congestion and more frequent public transport stops in more central parts of a city, as well as fixed costs in order to get to a bus stop or into the car. While transportation costs are concave for the overwhelming majority of cities, the elasticity varies considerably across and within countries.

Instead of directly measuring transportation costs for one particular mode of transportation as e.g. in Akbar et al. (2021), I infer them from market prices and location choices that are structurally connected by the monocentric city model. I use a standard version of this model and amend it with the assumption that rents and population density both follow a log-log relationship with distance. I show empirically that this functional form is considerably more robust to the precise delineation of cities than a log-linear relationship, which is the other option commonly used in the corresponding empirical literature. This setup results in the transportation cost gradient being equal to the difference between the rent gradient and the density gradient. I estimate these two gradients for a worldwide cross-section of cities.

Duranton and Puga (2015) note that "the empirical knowledge accumulated on the monocentric urban model and its extensions remains limited" and that "[the] literature has often struggled to provide evidence of negative gradients for the unit price of housing" (p. 523). The available studies are based on an individual city or one single country at most. Examples include Gupta et al. (2022) for the United States, Combes et al. (2018) for France, or Ding and Zhao (2014) and Li and Wan (2021) for Beijing. For a long time, there existed simply no internationally comparable data for rents or house prices on an object-level basis, as is needed for such an analysis.[1]

To my knowledge, the only other project that estimates rent gradients on a global scale is the recent work by Liotta et al. (2022), who use data from different real estate websites for 192 cities worldwide. They estimate the elasticity of rental prices (and population density) on income net of transportation costs. In comparison to their work, this paper relies on real estate data from a single internationally consistent source. Moreover, I use a first-stage hedonic regression to separate out the effect of various property-level characteristics. This is important, as properties close to the city center might be quite different from properties on the outskirts. If the former are more expensive, we want to know to which extent this is due to the more central location, and to which extent these properties have more rooms or nicer amenities. In contrast, if they are smaller and have less amenities, this might imply an underestimation of the effect of distance. Finally, Liotta et al. (2022) aggregate their rental data on the grid cell level, while I work directly with the coordinates of the objects.

I find an average rent gradient of -0.064, implying a 0.64% increase in price for every 10% increase in distance. Contrasting my estimates for different subsamples with the empirical literature mentioned above, I find them to be roughly comparable. Combes et al. (2018) report that house price gradients decrease in city size in France. I confirm this finding for most countries (that have at least 10 cities in my sample), with the notable exception of countries in Latin America. Moreover, rent gradients are flatter in cities in upper-middle-income countries and in cities situated near a major water body.

The monocentric city model predicts negative rent and density gradients. If these predictions hold, the density gradient needs to be steeper than the rent gradient to yield a sensible transportation cost function in my setting, i.e. one that features positive transportation costs that are increasing in distance. This is indeed the case for 89% of cities, with an average density gradient of -0.356. Combining the two gradients yields an average transportation cost gradient of about 0.3, implying decreasing marginal transportation costs.

This average value masks considerable heterogeneity. For example, the average among French cities is 0.47, while the average among cities in the United States is 0.07. The latter precisely matches the urban cost estimate that Duranton and Puga (2022) obtain when performing a similar exercise for cities in the United States, although they disregard population density and focus solely on price. While the similarity between our estimates is reassuring for the robustness of the result for the US, my findings suggest that the United States is an outlier. Internationally,

[1] Data on Airbnb properties have been used extensively to research the effect of short-term rental objects on the long-term rental market (see, for example, Calder-Wang, 2021; Àngel Garcia-López et al., 2020; Barron et al., 2021). Almagro and Domínguez-Iino (2022) use such data to examine endogenous amenities and their distributional effects. Coles et al. (2018) briefly discuss rent gradients in the context of New York City. However, these papers are all concerned with an individual city or, at most, different cities in an individual country.

the average elasticity of transportation costs to distance is about four times higher. In the context of their model, this would imply considerably higher urban costs. However, even within the US, the average estimate masks substantial heterogeneity, with the elasticity of transportation costs being much higher in cities like New York, Boston, or Chicago.

The remainder of the paper is organized as follows: Section 2 specifies the theory, while Section 3 defines the cities and their centers. Sections 4, 5, and 6 present the results on rent gradients, density gradients, and transportation cost gradients, respectively. Section 7 provides a discussion, and section 8 concludes. Finally, the appendix contains a more in-depth description of my city definitions and auxiliary results.

2 Data and city definitions

The data on Airbnbs come from AirDNA, a company specialized in "short-term rental data and analytics".[2] They contain close to all properties that were advertised on Airbnb at least once between 01.01.2018 and 25.03.2019, over 9.4 million properties in total.[3] By combining information about days for which properties are rented with information about the properties' prices for these days, AirDNA is able to estimate the prices actually paid by customers. For every property, I have information about the average daily price over the twelve months before the date on which a property was last web scraped from the Airbnb website. I also have the coordinates of the location for each property, even though some of them are scrambled by at most 500 meters due to security concerns. Moreover, the data contain a substantial number of covariates, from the number of bedrooms to the presence of a hairdryer. All of these variables are available in an internationally standardized way. After dropping properties that were never rented over the period in question, my dataset still contains more than 3 million properties within the cities defined below.[4]

It is not straightforward to determine where a city ends and where its center is located. Different countries have different rules to set administrative boundaries. Official city delineations are, therefore, hardly comparable. Fortunately, there have been attempts to find internationally consistent definitions of cities on which I can build. A related and even harder question is the location of the city center. This information is crucial for my project, but research about it on an international scale is almost non-existent. This section summarizes the choices I make when defining the set of cities for this study. Appendix A provides more details.

I start with the open collaboration database OpenStreetMap, which is based on crowd intelligence, letting users set and change geographic tags themselves. My city definition starts with all city tags contained in OpenStreetMap. I spatially join them to the Urban Centre Database

[2] `https://airdna.co`, last accessed: 16.01.2023.

[3] To the best of my knowledge, AirDNA web scraped every single property from Airbnb once every three days. This implies that a small number of properties that appeared only briefly and were immediately removed or rented might not be part of the dataset.

[4] The raw dataset contains 9,419,495 observations. However, 2,354,445 of these properties were never reserved. I have to drop another 1,917 observations because their coordinates are missing. Afterwards, I can spatially join 3,093,755 properties with my city polygons. An additional 25,603 observations drop because of missing covariates (or a missing price in 1 case). In the end, 3,068,152 entries remain.

of the Global Human Settlement Layer project (Florczyk et al., 2019).[5] In a first step, I keep all city tags within an urban center with at least 300,000 inhabitants and at least 100 Airbnbs.[6] Figure A1a shows the city delineation and the distribution of the Airbnb properties for the example of Paris.

In some cases, urban center polygons contain multiple city tags. Using the city population counts from OpenStreetMap, I retain all city tags that are associated with a population count that amounts to at least 40% of the highest population count in the respective urban center.[7] This allows me, for example, to keep Kobe, Kyoto, and Osaka as different cities without having to split the urban center around Tokyo into 120 parts. Moreover, if several tags are close to each other (less than 7 km air-line distance between the individual tags), I only retain the tag that exhibits the largest population count among them. After defining the centers (see below), I follow Akbar et al. (2021) in how I split the urban areas with more than one remaining tag, by defining border points according to their distance to the different city centers, taking the population size of these centers into account (see Appendix A). Figure A2 presents the example of Den Haag and Rotterdam, an urban center that I split into two distinct cities.

To set the location of a city tag on OpenStreetMap, users are asked to place it "at the center of the city, like the central square, a central administrative or religious building or a central road junction".[8] The coordinates of those tags therefore offer a transparent and globally consistent definition of city centers. Together with a research assistant, I manually checked all city tags that remain at this stage. Unfortunately, there are some cities for which visual inspection using satellite images and street view from GoogleMaps suggests that they are not a good representation of the actual center. I use the coordinates from OpenStreetMap for my preferred specifications whenever they seem accurate. When they do not, I use the coordinates proposed by Google Maps, which we checked as well. If they also seem not to provide a suitable representation of the center of a given city, we propose our own best guess. Figure A3 presents a corresponding example in Rosario. I provide robustness checks in which I take the coordinates from OpenStreetMap or those from Google Maps to define all city centers.

My final sample contains 734 cities worldwide. Figure 1 illustrates their geographic distribution, while Figure A4 shows the number of cities by country.

3 Implications of the monocentric city model

The basis of this analysis is the monocentric city model. It was developed by Alonso (1964), Mills (1967), and Muth (1969), who formalized an idea that had been around at least since von Thünen (1826). The model assumes an exogenously given employment center on a homogenous

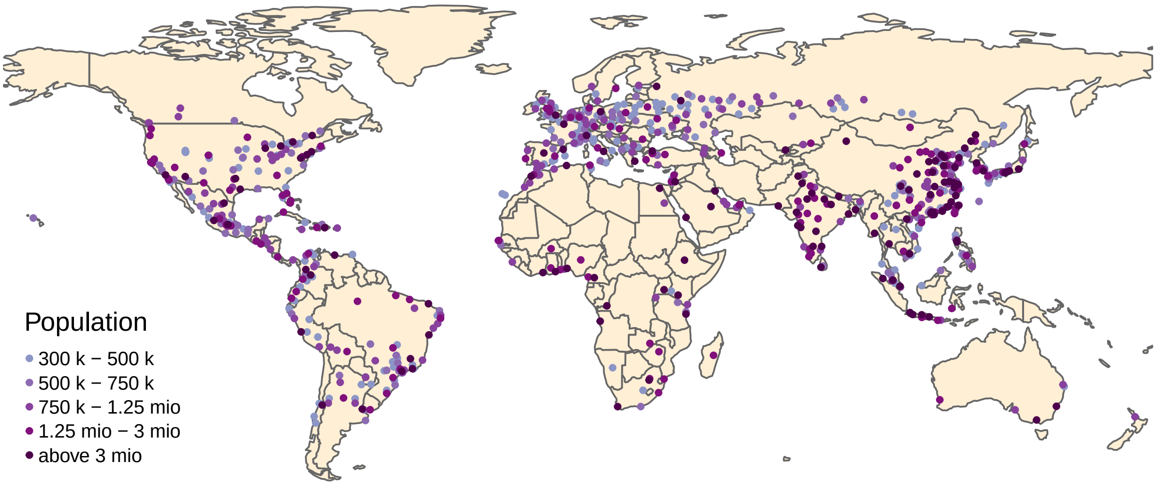
[5] Their definition results in some urban areas being very broad and containing multiple well-known cities, for example Oakland/San Francisco/San José or Kobe/Kyoto/Osaka. In some of these cases setting one city center for the whole urban center would be very tricky. I therefore decided against simply adopting the definition from Florczyk et al. (2019). I believe that combining it with data on cities from OpenStreetMap results in a set of cities that is better suited for this analysis.

[6] Not including Airbnbs that have never been rented during the study period and have therefore no information about the average rent charged.

[7] I complement missing population counts on OpenStreetMap with information from Wikipedia.

[8] `https://wiki.openstreetmap.org/wiki/Tag:place%3Dcity`, last accessed: 13.01.2023.

Figure 1: 734 cities in the sample



Note: The dots in this figure show the geographic distribution of the 734 cities in my sample. Their colors refer to the city's population size, with larger cities represented in darker shades. To be included in the sample, a city must have had a population of at least 300,000 inhabitants in 2015 and at least 100 Airbnb properties that were active between January 2018 and March 2019.

plain. People face transportation costs to move from their homes to the center. With very few additional assumptions, the model predicts decreasing house prices (the rent gradient), decreasing population densities (the density gradient), and increasing housing unit sizes as one moves from the city center to the periphery. The key prediction of the model is the Alonso-Muth condition:

$$R'(x) = -\frac{t'(x)}{h(x)} \; ; \tag{1}$$

where x denotes distance to the city center, $R(x)$ describes housing rents, $t(x)$ transportation costs, and $h(x)$ housing unit sizes. As the latter term describes an area, it will always be positive. While this paper deals with whether marginal transportation costs are linear, decreasing, or increasing in distance, they should certainly not be negative, which would imply that traveling longer distances is cheaper than shorter ones. Therefore both sides of eq. (1) are predicted to be negative. Economically, this signifies that housing units feature cheaper rents if they are farther away from the city center. Moreover, the rate at which housing units become cheaper in distance multiplied by their size is equal to the rate at which transportation costs become more expensive in distance. Gains through shorter transportation costs are compensated by higher housing costs, and vice versa. I use an extension of the baseline model that allows housing units to differ in size while I keep the assumption that all buildings have the same height.[9] In this

[9] Setting up the model in this way implies that flat sizes govern population density entirely. Considering a city where flat sizes increase with distance to the city center while building heights decrease, my formulation would predict even smaller flats in the central parts of the city and even larger flats towards the periphery. Allowing the height of buildings to vary is feasible from a theoretical perspective, but I lack access to appropriate data. However, due to regulations, assuming fixed building heights might not be further from reality for many cities than assuming fully flexible building heights driven by market forces.

case, the following equations hold, with $D(x)$ denoting population density:

$$D(x) = \frac{1}{h(x)} \; ; \tag{2}$$

$$R'(x) = -t'(x)D(x) \; . \tag{3}$$

The standard model predicts rents or housing prices to decrease with distance to the city center in a convex way (see Brueckner, 1987). Beyond that, the functional form of the rent gradient is not a priori clear. For (parametric) empirical estimation, however, an assumption has to be made. The most popular choices in the empirical literature are log-linear and log-log specifications, regressing log prices either on distance expressed in kilometers (or any other linear scale) or on the log of distance. The estimated parameter related to distance is called the rent gradient. The same considerations also hold for the relationship between distance and population density. For a more detailed exposition of the model see Brueckner (1987) or Duranton and Puga (2015).

Leveraging my data, I find that the log-linear assumption is more sensitive to the precise definition of cities. Figure 2 depicts this regularity for all cities with an Airbnb property further than 20 km from the city center. To construct the figure, I first recompute the rent gradients using subsets of Airbnbs within increasingly limited distances from the city center. This is equivalent to defining the cities more narrowly by imposing a maximal distance of the city fringe. I then consider the ratio between the average rent gradient for each subset and the average rent gradient computed with my preferred city definition specified below.

For the log-log specification, the cutoff distance does not alter the average rent gradient much, with a maximal deviation of 9%. However, when using a log-linear functional form, the placement of the city boundaries matters a lot. For example, suppose I limit cities to the area within 8 kilometers of the city centers. In that case, the average estimated rent gradient becomes almost 2.4 times as large compared to the case where I employ my preferred city definition. I, therefore, decide to proceed with a log-log specification.

Modeling the relations between rents and distance and between density and distance as log-log implicitly assumes that the underlying functions are

$$R(x) = Ax^b \; ; \tag{4}$$

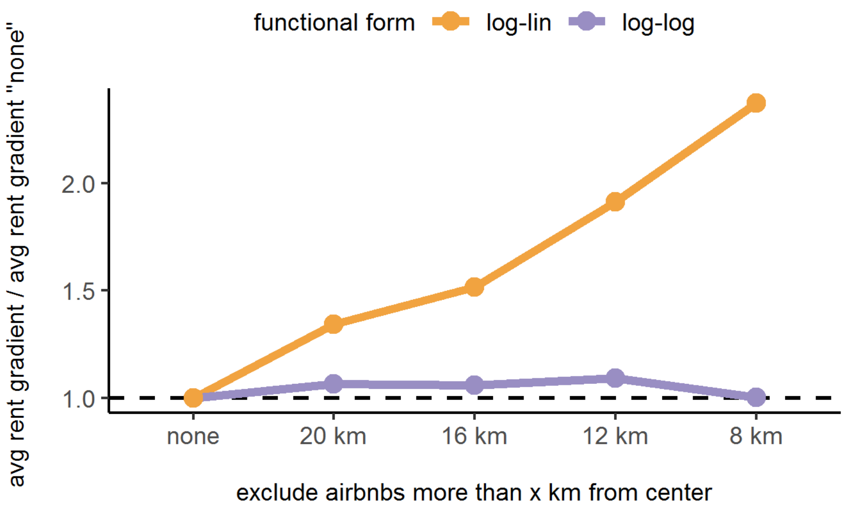
$$R'(x) = bAx^{b-1} \; ; \tag{5}$$

$$D(x) = Cx^d \; . \tag{6}$$

For details on the derivations, see Appendix B. Plugging eq. (5) and eq. (6) into equation (3) and solving for $t'(x)$ yields

$$t'(x) = -\frac{bA}{C}x^{b-d-1} \; . \tag{7}$$

Figure 2: Functional form and city definitions



Note: This figure compares 10 average regression coefficients. In all cases, I estimate rent gradients for all cities in the sample by regressing the log of hedonic prices of Airbnbs on a distance variable interacted with city indicators. For the purple points, I use the log of the distance to the city center as the variable of interest, while I use linear distance for the orange points. I then compute the average over all city rent gradients. All regressions include city fixed effects. I apply these two ways to compute gradients for five different samples. In the baseline version, I use all Airbnb properties. This specification is denoted as "none". Within each of the two functional forms, the coefficients are divided by the average gradients of this first specification. I then apply progressively stricter thresholds, excluding all objects that are more than 20, 16, 12, and finally 8 kilometers away from the city center. This is equivalent to defining more narrow city boundaries. For this figure I only use cities that have at least one property that is more than 20 kilometers away from the city center.

Furthermore, taking the integral of this term and imposing that $t(0) = 0$ (no transportation costs to travel to the center if you are already there) returns the transportation cost function

$$t(x) = -\frac{bA}{C(b-d)} x^{b-d} \tag{8}$$

or

$$t(x) = \phi x^{\theta} \; ; \tag{9}$$

where θ describes the elasticity of transportation costs and ϕ is a constant. In other words, taking a standard version of the monocentric city model and using log-log specifications to model the rent gradient and the density gradient, as is commonly done in the empirical literature, implies that transportation costs also follow a gradient. Moreover, the transportation cost gradient θ equals the difference between the rent gradient b and the density gradient d, which, to my knowledge, is a novel result.

The rent gradient and the density gradient are both predicted to be negative by the monocentric city model; two predictions that I assess empirically below. Intuition would suggest that a reasonable transportation cost function fulfills the following minimal requirements:[10]

1. Transportation is costly, or $t(x) > 0$ for all $x > 0$.
2. Traveling longer distances is more costly than traveling shorter distances, or $t'(x) > 0$.

As long as the predictions of the monocentric city model and therefore $b < 0$ and $d < 0$ hold, both conditions are fulfilled if $b > d$. In other words, the density gradient d needs to be steeper (more negative) than the rent gradient b. This is another prediction that I will test.[11]

Moreover, the transportation cost gradient θ holds information about the curvature of the transportation cost function. If $\theta = 1$, transportation costs are linear, or $t(x) = \tau x$. This is the typical assumption in the baseline version of the monocetric city model (Brueckner, 1987; Duranton and Puga, 2015).[12] If θ is between 0 and 1, transportation costs are concave. Several intuitive reasons would suggest this to be a plausible case. Traffic is more congested in more central locations, speed limits are lower, and buses, trains, or subways stop more frequently. Moreover, there are fixed costs associated with getting to the next public transport stop or into the car. Longer trips to locations further away (or from further away) often contain parts where traffic goes faster and the marginal costs to cover an additional kilometer decrease. If $\theta > 1$, transport costs are convex. This could, for example, be the case if more central locations are well connected but the infrastructure becomes very bad once one travels further away from the city center. In summary, I assess the following hypotheses:

- *Hypothesis 1*: Rent gradients are negative.
- *Hypothesis 2*: Density gradients are negative.
- *Hypothesis 3*: Density gradients are steeper (more negative) than rent gradients.
- *Hypothesis 4a*: Transportation costs are linear.
- *Hypothesis 4b*: Transportation costs are concave.
- *Hypothesis 4c*: Transportation costs are convex.

For each prediction, I am interested in estimating whether it holds globally and in which cities it holds to what extent.

4 Rent gradients

Before exploring the relationship between the price of a property i and its distance to the city center, it is important to account for the fact that properties in a more central location might

[10] Moreover, a person not traveling should not bear any transport costs, or $t(0) = 0$. This condition is fulfilled by construction (see Appendix B).

[11] Within this model, A and C are always positive because they are exponentials of regression intercepts (see Appendix B). When equation 8 is applied strictly, $t'(x) > 0$ is always true (as long as $b < 0$), as $b - d$ cancels. However, due to the exponentials, the constant ϕ is highly sensitive to the precise estimates. An alternative is to impose the less restrictive condition of positive transportation costs, i.e. $\phi > 0$. In that case, $t'(x) > 0$ holds if and only if $b > d$, which is the same condition as above.

[12] Linear transportation costs are a frequent assumption in all kinds of spatial models. Sometimes they are referred to as iceberg trade costs, albeit this term often refers to travels between cities.

be fundamentally different from properties further in the suburbs. Fortunately, Airbnb includes a number of variables that describe the advertised properties in an internationally standardized way.[13] In a first step, I, therefore, run the following hedonic regression of average daily rental prices on different covariates to get a measure of prices net of observable characteristics other than the distance from the city center[14]

$$\ln(\text{price})_{ic} = \alpha + \boldsymbol{\gamma}\mathbf{X}_{ic} + u_{ic} \ . \tag{10}$$

I mostly include the covariates X_i as nonparametric categories to allow for a flexible functional form. Figure A5 shows the variables I control for and their respective effects on the average daily rental price. Prices are winsorized to the 0.01 and 0.99 percentiles within each country to exclude properties with unrealistically high or low prices that risk being misreported.[15] Moreover, I normalize prices by subtracting their mean in the 734 city sample and dividing by their standard deviation. I do the same to population density below, bringing the two measures on equivalent scales. Without the normalization, the arbitrary choice of units (prices in USD or 100 USD, people per m^2 or per km^2) would influence the comparison.

As expected, the number of bedrooms and the maximum number of allowed guests both increase prices monotonically. The same is true for the number of bathrooms, exept for the highest category.[16] Hosts can charge a substantially higher price if the guests have the entire apartment for themselves, while shared rooms are cheaper than private rooms. Every additional amenity slightly increases the price, as do additional pictures of the property. Finally, prices are higher for properties close to an ocean, sea, or big lake, with a higher premium for properties situated directly at the shore.[17] The large number of observations ensures that the effects are precisely measured. I then compute the predicted log price for each Airbnb property and the residual value

$$\ln(\text{price})^{\text{res}}_{ic} = \hat{u}_{ic} = \widehat{\ln(\text{price})}_{ic} - \ln(\text{price})_{ic} \ . \tag{11}$$

As a second step, I regress these residual prices on city fixed effects and the log distance from the city center. I allow the effect of distance to vary for each city. This gives me 734 different rent gradients b_c:

$$\ln(\text{price})^{\text{res}}_{ic} = a + b_c \ln(\text{distance})_{ic} + \text{FE}_c + \varepsilon_{ic} \ . \tag{12}$$

[13] There is, of course, heterogeneity that is not described in the profile of an Airbnb property. However, I would argue that when potential renters make their decision, it is not easy for them to access information about a property unless it is provided on the platform. Nevertheless, some omitted variable bias remains, as there is information in pictures and descriptions from which I abstract in this study.

[14] One notable absence is floor area, which Airbnb does not collect. However, the number of bedrooms, the number of bathrooms, and the maximal number of guests give a good impression of the size of a property.

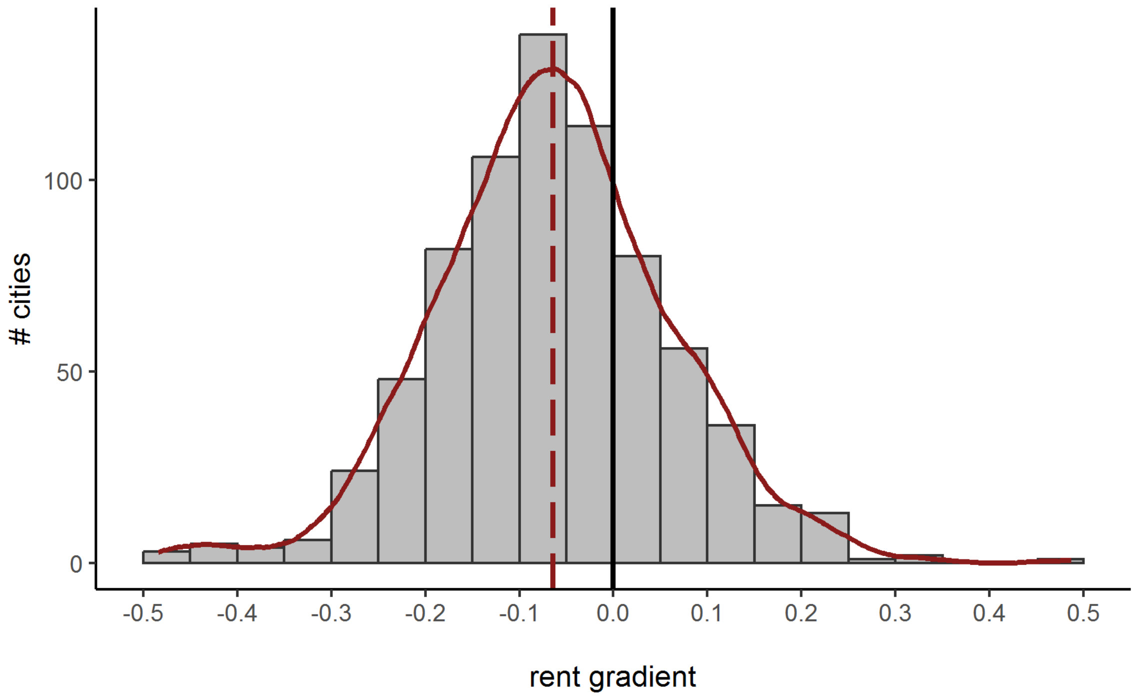
[15] In some cases, these high prices might also be a consequence of money laundering. Reports on money laundering on Airbnb are provided, for example, by Bell (2021) and Fazzini (2019).

[16] There are entries with an unrealistically high number of bathrooms that is probably erroneous in most cases.

[17] The indicators for proximity to the beach are the only variables that are not directly taken from Airbnb. Instead, guests can infer this distance from a map that is provided with the properties. Moreover, the hosts seem to have a clear incentive to mention a location close to a beach in the description or their photos. To construct these indicators, I measure the air-line distance from a property to the closest ocean, sea, or big lake (at least 80km^2). To determine the location of waters, I use ESRI's "World Water Bodies" layer (`https://arcgis.com/home/item.html?id=e750071279bf450cbd510454a80f2e63`, downloaded on 10.10.2023) and the HydroLAKES data from `https://hydrosheds.org/products/hydrolakes` (downloaded on 10.01.2023).

Figure 3 shows the distribution of these gradients, both as a histogram and using a kernel density function. I estimate an average rent gradient of -0.064, implying a 0.64% decrease in price for every 10% increase in distance. The median rent gradient is -0.067, while the 25% and the 75% quartiles are -0.145 and 0.011, respectively. I find negative rent gradients for 72% of cities in my sample and statistically significantly negative rent gradients at the 5% level for 52% of cities. On the other hand, I estimate positive rent gradients for 28% of cities and statistically significantly positive rent gradients (also at the 5% level) for 13% of cities.

Figure 3: Distribution of rent gradients



Note: This figure depicts the distribution of rent gradients for all 734 cities in my sample. I estimate these gradients using internationally consistent data from Airbnb. In particular, I regress log prices on city fixed effects, and the log distance to the city center interacted with an indicator for every city. The dashed line depicts the average rent gradient, while the solid line shows the corresponding Epanechnikov kernel density estimate. This estimation is the second stage of a two-stage procedure. The first stage is a hedonic regression in which I regress winsorized (0.01, 0.99) and standardized (subtract the mean and divide by the standard deviation) prices on different object characteristics.

Comparison with the literature

How do these estimates compare to the existing literature? Gupta et al. (2022) find a rent gradient of -0.03 and a corresponding house price gradient of -0.10 for the 30 largest MSAs in the United States.[18] The average gradient for the 70 US cities in my sample is also -0.10. Combes et al. (2018) estimate house price gradients for 277 urban areas in France. They find a median price gradient of -0.03, with the 25% quartile being -0.07 and the 75% quartile being

[18] These estimates refer to the situation before the pandemic. They find that the gradients became considerably flatter during the pandemic (0.00 / -0.09 in December 2020). This finding is confirmed by Li and Wan (2021). Their estimate of the rent gradient in Beijing flattened from -0.17 to -0.12 in June 2020 (before somewhat decreasing again). Future studies will show whether this is a pure pandemic effect that fully reverts eventually or whether this induced a more structural change.

0.01.[19] Looking at the 12 French cities included in my sample, the respective values that I find are -0.11 (median), -0.16 (25%) and -0.04 (75%). However, they find that gradients are more negative in larger urban areas, an empirical fact that I confirm below. Given that my sample only includes the very largest cities in France, this could reasonably explain my more negative estimates. Li and Wan (2021) report a pre-pandemic rent gradient of -0.17 for Beijing, with my corresponding estimate being -0.25. For Beijing, there exists also an estimate from Ding and Zhao (2014), based on housing prices between 1999 and 2003. However, they estimate a log-linear specification. Their estimates range between -0.03 and -0.07. If I apply a log-linear specification myself, I obtain an estimate of -0.03 for Beijing. Liotta et al. (2022) also apply a log-linear specification of rents on transportation costs in a robustness check.[20] They find an average estimate of -0.014 for their 192 cities, while the average log-linear estimate across the 734 cities in my sample is -0.017.

The distribution of rent gradients I find falls well within the ballpark of the existing estimates. If anything, my estimations show more negative gradients than the studies using long-term rental data while being more in line with those using house price data. This is not surprising, as long-term rents are often more tightly regulated than house prices and nightly Airbnb rates.

Comparison with long-term rental data

I can also compute rent gradients based on long-term rental properties myself and compare them with those obtained using Airbnb short-term rental properties. An advantage of this approach is that I can compare each city's gradients instead of having to rely on aggregate statistics like in the comparisons with the literature. Moreover, I can control the set of cities and define their centers and borders in a consistent manner. There are publicly available data for France and the United States, so I use these two countries for the comparison.[21] These data are based on small administrative units (block groups for the United States, communes for France) rather than on individual properties.[22]

Figure 4 shows rent gradients estimated using long-term rental data on the x-axis and corresponding gradients estimated using data on Airbnbs on the y-axis. There is a strong positive correlation between the two, although more so for France than for the US.[23] One reason for this difference could be that the French long-term rental prices are constructed from hedonic regressions, considering property-specific characteristics. The American Community Survey, on the other hand, only provides raw median rents by block group. I control for a set of covariates, but

[19] I averaged the values over their seven specifications in Table 3, Panel A.

[20] They use income net of transportation costs as the variable of interest in their main specifications, which makes it harder to compare the estimates.

[21] The French data come from *la carte des loyers*, while the US data are based on the American Community Survey. They can be found on `https://www.data.gouv.fr/fr/datasets/carte-des-loyers-indicateurs-de-loyers-dannonce-par-commune-en-2022/` (downloaded on 17.02.2023) and on `https://www.nhgis.org/` (downloaded on 16.12.2021), respectively.

[22] For the three big cities of Lyon, Marseille, and Paris, the French data contain information at the level of arrondissements.

[23] Regressing gradients obtained using Airbnb properties on gradients obtained using long-term rentals yields an coefficient of 1.12 for France, with a standard error of 0.35. For the United States, the corresponding coefficient is 0.72, with a standard error of 0.13. The underlying correlations are 0.71 (France) and 0.55 (United States), respectively.

these are also just aggregate statistics on the block group level.[24] Moreover, the US has a larger degree of local autonomy concerning taxes and public services that could influence long-term gradients beyond pure geographical considerations.

Heterogeneity

Which cities exhibit steeper rent gradients? A first factor is the size of the city. Figure 5 shows regressions of the rent gradients on the log of population size for 16 countries that are represented by more than 10 cities in my sample. I confirm the finding of Combes et al. (2018) that more populous French cities are associated with more negative gradients. Moreover, this regularity extends to other countries. It is particularly strong for European cities but also for Canada and India. While somewhat weaker, more populous cities also feature more negative gradients in the United States, China, Japan, and Malaysia. An explanation might be that location in smaller cities is less crucial, as many places are accessible within reasonable distance. This might change for larger cities, where housing location is likely to be more correlated with the part of the city in which people spend their leisure or do their shopping. Interestingly, all four countries for which bigger cities are not associated with more negative rent gradients are situated in Latin America.

I also explore heterogeneity by income level. Panel A of Figure 6 shows results for this dimension. Its base are the income groups of the World Bank.[25] I combine low-income and lower-middle-income countries into one level to get a sufficiently high number of observations.[26] For each income level, I run a separate kernel density estimation.[27] There seems to be a non-linear relation between rent gradients and income. While high-income countries have the steepest rent gradients (with an average value of -0.10), low & lower-middle-income countries exhibit similarly negative gradients (average of -0.09). Upper middle-income countries, however, have, on average, substantially flatter gradients, with an average of -0.03. The reasons for the more negative gradients will most likely differ between high income and low & middle income countries. Transportation tends to be slow in economically poorer countries (Berg et al., 2017). Car ownership is lower (Cervero, 2013) and formal public transport less expanded, while informal transport infrastructure is more common (Kumar, 2011). If the costs of commuting longer distances are higher, this might explain why people are willing to pay a higher premium to live at more central locations. In high-income countries, on the other hand, central cities might offer amenities that are nice, but not indispensable. Once people reach a certain income level, they might be willing to pay a premium to live next to these amenities.

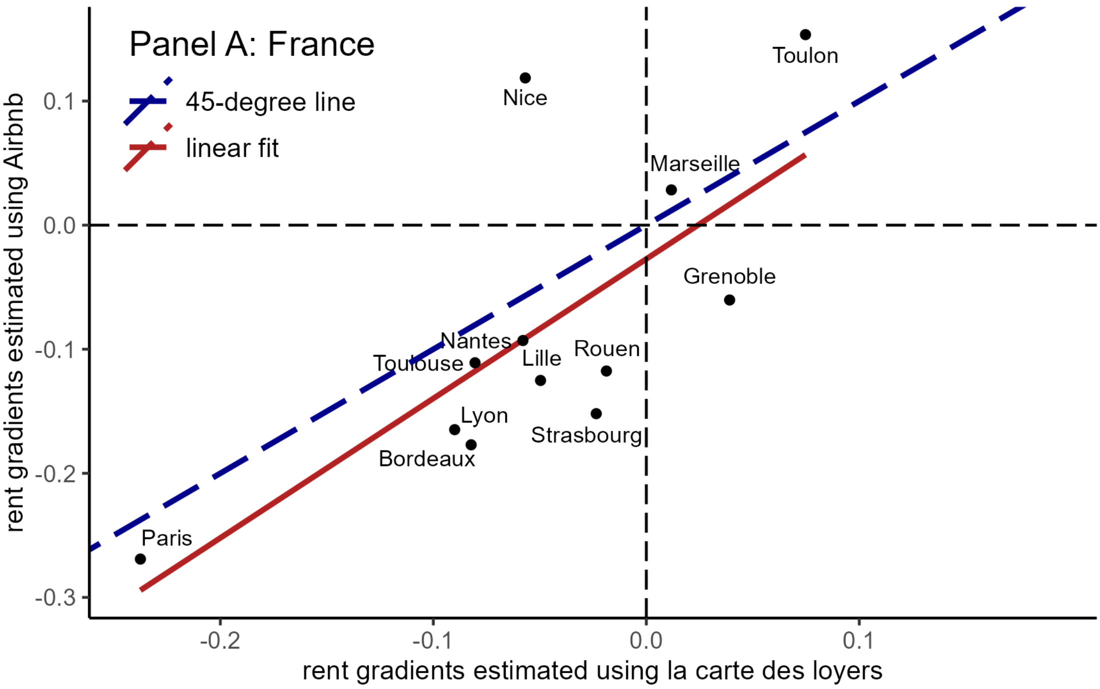
[24] I control for the fractions of apartments that meet certain characteristics in the following categories: Number of bedrooms, number of units in the building, the year the building was built, the year the tenant moved in, presence of plumbing, presence of a kitchen and whether meals are provided, and energy source used. Moreover, I control for whether a block group is in immediate proximity to a large water body.

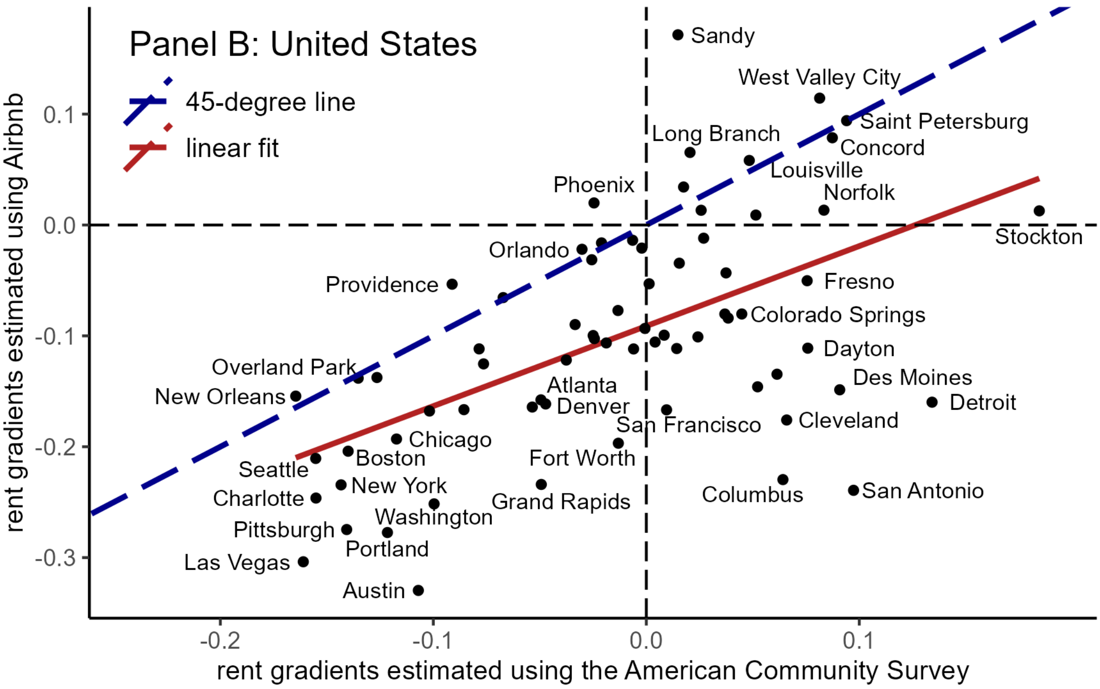
[25] In downloaded the income groups on 18.08.2022 from `https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups`.

[26] Low & lower middle income is still the smallest group with 135 cities, 11 of which are classified as low income by the World Bank. 336 cities are in the upper middle income category, while 262 cities are in the high income category. I drop Caracas for this graph, as the World Bank does not classify Venezuela due to issues with data availability.

[27] The area under each curve sums to one and is thus of equal size, independent of the number of observations within the group.

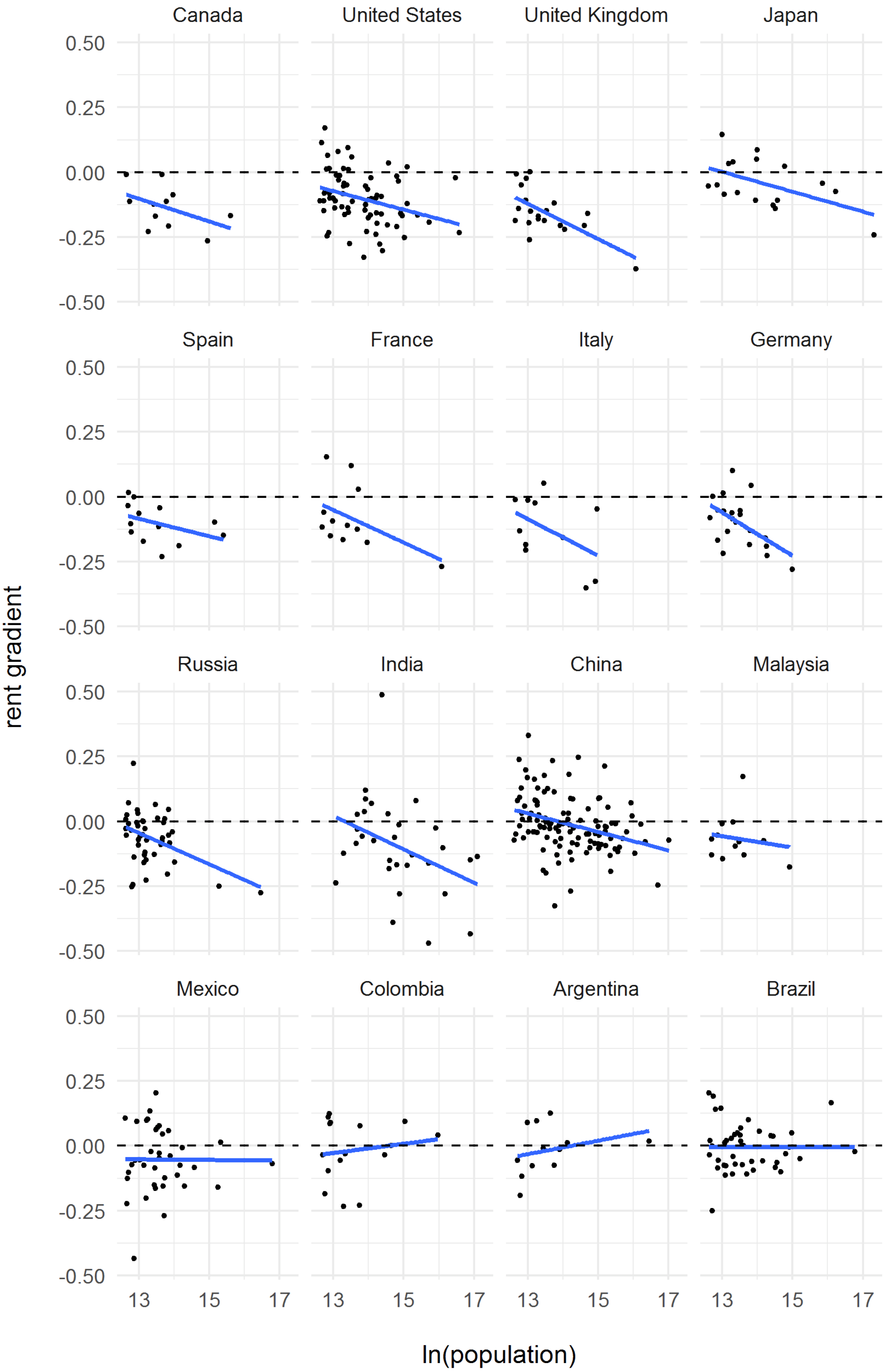
Figure 4: Comparisons with gradients estimated from long-term rental data





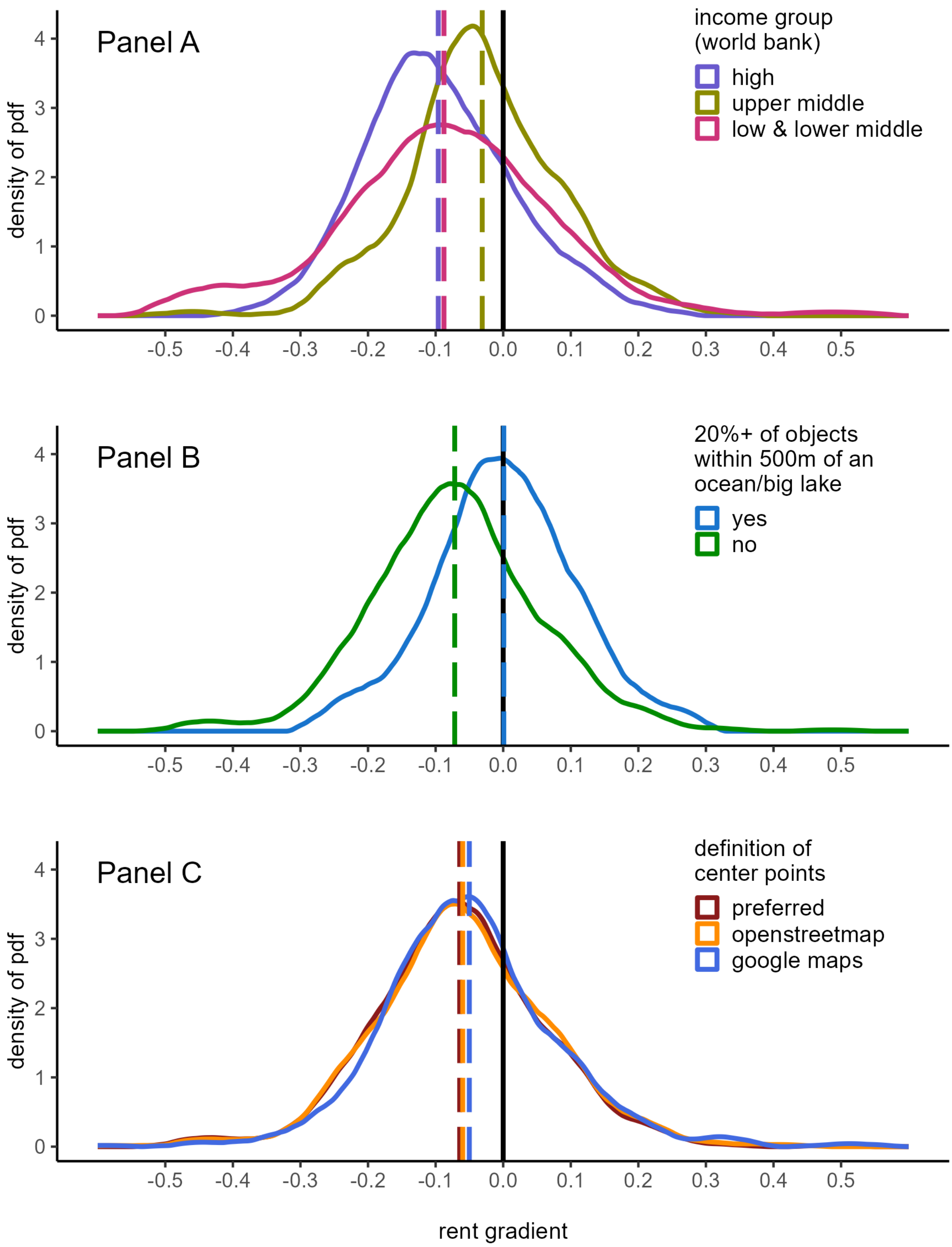
Note: Both panels show rent gradients estimated with Airbnb data on the y-axis. Panel A depicts long-term rent gradients for France on the x-axis. These gradients are estimated using hedonic prices on the commune level provided by *la carte des loyers*. The x-axis of Panel B shows long-term rent gradients for the United States. They are estimated using median rents per blockgroup from the American Community Survey (2015-2019). Unlike for France, these are raw rental prices. I therefore control for various building-characteristics at the blockgroup level. Each black point represents a city. The red line depicts the linear fit, while the blue line represents the 45-degree line.

Figure 5: Rent gradients and city size



Note: The figure shows estimated rent gradients (y-axis) against the population size of cities on a log scale (x-axis). Each dot represents a city, while the blue lines show the linear fits. The comparison is shown for the 16 countries with the highest number of cities in my sample.

Figure 6: Regularities



Note: Analogously to Figure 3, this figure shows distributions of rent gradients. Panel A classifies cities by their countries' income group, according to the World Bank definition. Panel B compares the subset of cities in which at least 20% of Airbnb properties are within 500m of an ocean or big lake versus those cities for which this is not the case. Panel C recomputes rent gradients using different definitions of the city center. Dashed lines represent the average rent gradients, while solid lines show the corresponding Epanechnikov kernel density estimates. All of the latter sum to one, facilitating visual comparisons between categories with different numbers of cities.

The most striking regularity concerns cities close to an ocean, sea, or big lake (at least 80 km^2). I measure this by requiring that at least 20% of Airbnbs be within 500m of the shore. I choose this relatively restrictive cutoff because I suspect that it is not the sheer presence of a large water body in proximity to a city that makes a difference, but rather whether beaches and ports play an important role in the life of its inhabitants. In a way, the seaside can act as an elongated secondary center that absorbs parts of the economic, cultural, and leisure-based activities that would otherwise be concentrated in the city center. Panel B of Figure 6 shows this analysis. The average rent gradient for seaside cities is very close to zero (the point estimate is 0.0009). Note that the first-stage hedonic regression controls for whether an individual property is in close proximity to the beach. This implies that the effect across cities is not just driven by more costly properties directly at the seaside. However, there are only 75 coastal cities in the sample, according to the definition above. Moreover, if one expects Airbnb prices to be a bad proxy for other types of real estate prices, despite the evidence presented above, this would probably be the most vulnerable sub-analysis, as access to beaches might be valued more highly by tourists than by permanent residents, and Airbnb properties might be clustered particularly close to the seaside. Nevertheless, the difference is sizeable and supported by the fact that Liotta et al. (2022) also report a weaker relationship between rents and transportation costs for coastal cities.[28]

Robustness check

Panel C of Figure 6 revisits the question of the optimal placement of the city center. It shows three different kernel density functions that differ in the source of the center coordinates. The red curve represents my preferred center definitions described in Section 2. The orange curve takes the city coordinates from OpenStreetMap for all cities, while the blue curve does the same with the city tags from Google Maps.[29] Choosing a different center source does not fundamentally alter the rent gradient distribution. In particular, taking all centers from OpenStreetMap results in a similar distribution as my preferred center choices. The respective average values are -0.064, -0.060, and -0.050. The fact that my preferred specification results in the most negative gradients is consistent with it having the least measurement error and therefore being the least biased towards zero.[30]

[28] In their case, they do not consider transportation costs per se, but income net of transportation costs.

[29] To pin down the center locations proposed by Google Maps, I searched for the route to travel to a given city and chose the endpoint. These are also the places on top of which Google Maps depict the city names.

[30] In that regard, the fact that using Google Maps returns an average estimate that is closest to zero is also in line with my expectations. Together with a research assistant, I evaluated the center candidates from OpenStreetMap and Google Maps on a scale from 1 (suitable choice for the center) to 3 (absolutely not suitable choice for the center). Whenever the center from OpenStreetMap is classified as a 1, it is locked as my preferred center choice. If it is classified as a 2 or a 3 and the center inferred from Google Maps is classified as a 1, I take the latter as my preferred center. We only manually defined an alternative when both sources were classified as unsuitable for the center. Center candidates from OpenStreetMap are classified as 1 in 76% and 3 in only 4% of cases. In comparison, the candidates from Google Maps are classified as 1 in 59% of cities and 3 in 14%. According to our assessment, the centers inferred from Google Maps are, therefore, less accurate (at least, this was the case at the time of the analysis). This is consistent with a larger bias towards zero.

5 Density gradients

Data on population density are taken from the Global Human Settlement Project described in Section 2 and Appendix A. I use the GHS-POP file (Schiavina et al., 2019) that is computed by combining population data from administrative sources and machine-learning-based detection of artificial structures. I employ the version with the 250m $\times$ 250m resolution.[31] Figures A1b (Paris), A2b (Den Haag and Rotterdam), and A3b (Rosario) show population counts on this resolution for exemplary cities. I drop grid cells with a value of one inhabitant or less. These are mostly located in water bodies or other areas not suited or developed for housing.[32] Moreover, I again normalize population density by subtracting its mean and dividing by its standard deviation to bring it on the same scales as rents and make the estimated gradients as comparable as possible. I then estimate

$$\ln(\text{population density})_{ic} = c + d_c \ln(\text{distance})_{ic} + \text{FE}_c + \varepsilon_{ic} \ , \tag{13}$$

where FE_c are city fixed effects, and d_c denotes one density gradient per city.

Figure 7 shows the distribution of density gradients in the sample. I estimate an average density gradient of -0.356. If the distance to the city center increases by 10%, density decreases by 3.56% on average. The median, 25% quartile, and 75% quartile are -0.344, -0.494, and -0.203, respectively. Concerning hypothesis 2, I find density gradients to be negative in 96% of the cities in my sample and statistically significantly negative at the 5% level in 93% of cities.

There exist positive gradients as well. This is true for 4.1% and statistically significantly so for 3.5% of the cities in my sample (also at the 5% level). I can confirm the finding in the literature that South African cities have positive gradients, explained by discriminatory housing rules during apartheid (Selod and Zenou, 2001). I estimate positive gradients for all six South African cities included in this study.

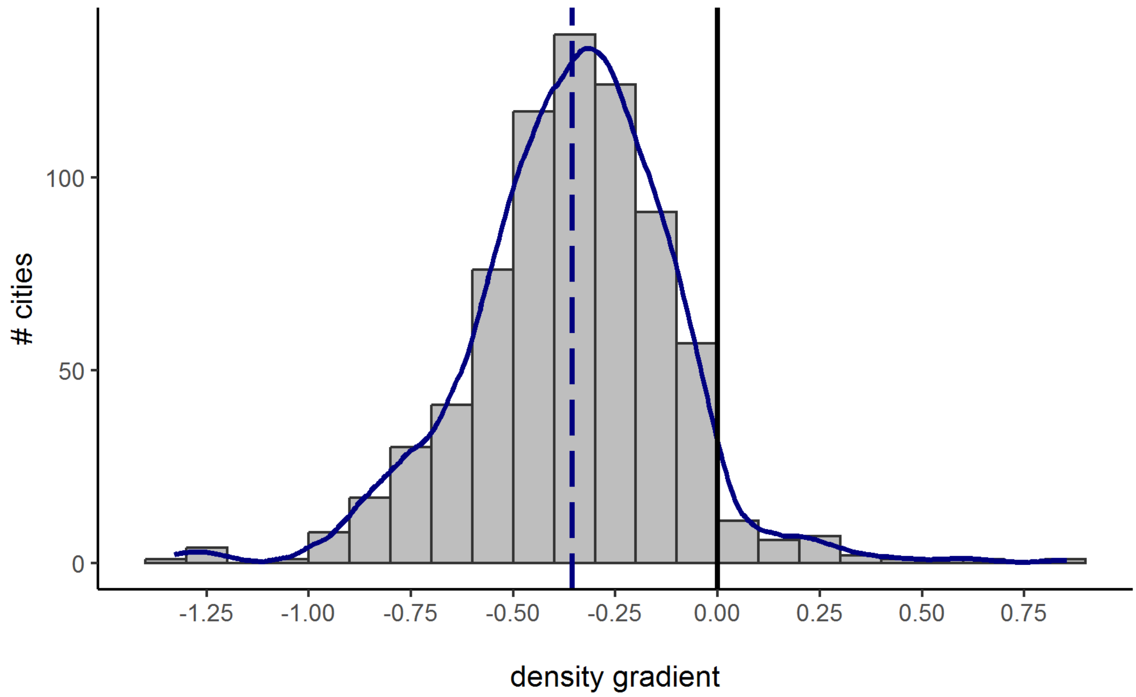
6 Transportation cost gradients

As derived in Section 3, under certain functional-form assumptions, the transportation cost gradient θ is equal to the difference between the rent gradient b and the density gradient d. In order to obtain transportation costs that are positive and increasing with distance, d needs to be more negative (steeper if $d < 0$ and $b < 0$) than b. Having estimated rent gradients and density gradients for all 734 cities, I can now assess hypothesis 3. I obtain a positive $\hat{\theta}$ in 89% of the cases. Only for 11% of the cities is the density gradient larger (less negative) than the rent gradient. This includes cities for which I have estimated a positive $\hat{b}$ and/or $\hat{d}$, which makes them incompatible with the theoretical predictions of the monocentric city model in the first place. The subset with negative values for both $\hat{b}$ and $\hat{d}$ contains 513 cities. However, within this subset, I also obtain a positive $\hat{\theta}$ for 89% of cities.

[31] For the delineation of cities I keep the 1km $\times$ 1km grid size on which the GHS urban center database is constructed.

[32] To see why this is necessary, consider the case of New York City. Manhatten is, without a doubt, very densely populated. It also hosts the city center. However, it is surrounded by water. Including the pixels located in the water would lead to a severe underestimation of the density of the areas around the city center.

Figure 7: Distribution of density gradients



Note: This figure shows the distribution of density gradients for all 734 cities in my sample. In particular, I regress log population counts on city fixed effects, and the log distance to the city center interacted with an indicator for every city (shown here). The dashed line depicts the average density gradient, while the solid line shows the corresponding Epanechnikov kernel density estimate. The underlying data come from the Global Human Settlement (GHS) project. They disaggregate administrative population counts to 250m $\times$ 250m cells using the fraction of built-up area in a cell. I standardize the data by subtracting their sample mean and dividing it by their standard deviation to facilitate the comparison with the rent gradients.

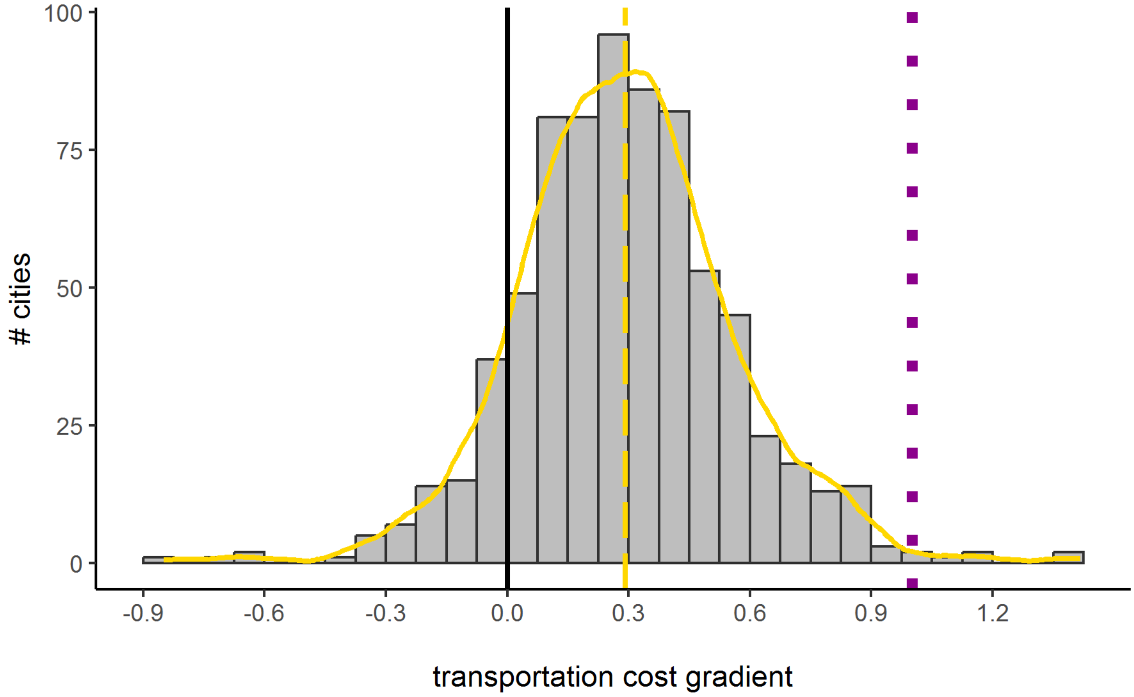
Figure 8 shows the distribution of $\hat{\theta}$. Figure A6 provides an equivalent representation for the subset of cities for which I estimate negative rent and density gradients. The results are qualitatively similar. I estimate a mean transportation cost gradient of 0.29. The median, the 25%, and the 75% quartile are 0.28, 0.13, and 0.44, respectively.

The dotted line represents a transportation cost gradient of 1. This is the usual assumption in baseline versions of the monocentric city model model. However, based on my estimation, I reject linear transportation costs for the overwhelming majority of cities. Instead, it suggests that we should think about transportation costs as a concave function in distance.

While I estimate the transportation cost function to be concave for most cities, there is substantial heterogeneity concerning the curvature. In other words, how fast marginal transportation costs decrease in distance is very different across cities. Table 1 depicts the average $\hat{\theta}$ by country or region.[33] There appear to be some general trends: the US, Canada, and the United Kingdom are all on the lower end of the spectrum, while Latin American countries, as well as France, Italy, and Spain exhibit steeper transportation cost gradients.

[33] All countries with at least 10 cities in the sample are included as such. All other countries are assigned to geographical regions following the definition of the World Bank, downloaded on 2022-08-18 from `https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups`.

Figure 8: Distribution of transportation cost gradients



Note: This figure depicts the distribution of transportation cost gradients for my 734 sample cities. As theoretically suggested by the monocentric city model with log-log relations, these gradients are inferred from the difference between rent and density gradients. The dashed line depicts the average inferred transportation cost gradient, while the solid line shows the corresponding Epanechnikov kernel density estimate. The dotted line indicates an elasticity of transportation costs of one, equivalent to linear transportation costs.

Figure A7 translates these elasticities of transportation costs with regards to distance to transportation cost functions. It includes all countries with more than 10 cities in the sample. For each of these countries, I compute the average of the estimated $\hat{\theta}$ and use it to calibrate the transportation cost function $t(x) = \phi x^{\theta}$. I set ϕ to one for all countries. Hence, the figure does not imply that France has higher inferred transportation costs than the US for any given distance. Instead, the curves can be interpreted as transportation costs by distance relative to the transportation costs for a one kilometer trip. Thus, the figure suggests that the transportation costs of the first kilometer of transportation account for a larger part of transportation costs in the United States than in France. Possible explanations for this include higher fixed costs from getting to the bus stop and waiting for the bus, or a high level of congestion at central locations, combined with free-flowing traffic further away from the center.

7 Discussion

By combining the rent gradient b and the density gradient d, I provide an estimate for the transportation cost gradient θ. If I write equation 9 in logs, I obtain

$$ln(t(x)) = \Phi + \theta ln(x) \ , \qquad \text{where } \Phi = ln(\phi) \ , \tag{14}$$

Table 1: Average inferred transportation cost gradients by country / region

	average $\hat{\theta}$	# cities
United States	0.07	70
Sub-Saharan Africa	0.12	37
Canada	0.13	11
United Kingdom	0.14	20
Malaysia	0.16	12
Germany	0.17	21
Russia	0.24	44
Mexico	0.25	38
Brazil	0.25	44
Europe & Central Asia	0.31	74
India	0.33	31
Japan	0.33	17
Latin America & Caribbean	0.35	40
East Asia & Pacific	0.35	50
Middle East & North Africa	0.35	30
South Asia	0.36	7
Argentina	0.36	12
Spain	0.36	13
Colombia	0.40	16
Italy	0.41	11
Indonesia	0.45	11
China	0.45	113
France	0.47	12

with θ being the elasticity of transportation costs to living further away from the city center. This equation can, in principle, be directly estimated, even if it is not easy to find good data on transportation costs, in particular, if the choice of the transport mode is relevant.

Crucially, the $\hat{\theta}$ estimated in this paper is closely related to the parameter of urban costs that is an input in the model of Duranton and Puga (2022).[34] In their model, they interpret the parameter as the "elasticity of urban costs with respect to city population" (p. 3). They provide three distinct empirical ways to estimate this elasticity. One of these ways is closely related to the methodology deployed in this paper. The most notable difference is that I allow for different housing unit sizes at different locations within a city, which leads me to include data on density in the estimation. Their work focuses on the United States, and all their estimation strategies lead them to a parameter of 0.07. My average $\hat{\theta}$ for all United States cities included in my sample precisely matches this value.[35] This is reassuring concerning the validity of the Airbnb data for questions beyond the short-term rental market itself.

However, according to my analysis, the United States' $\hat{\theta}$ is at the low end of the spectrum. The global average urban cost estimator might be closer to 0.29 or about four times as large. Future research is needed to assess whether the other empirical strategies used by Duranton and Puga

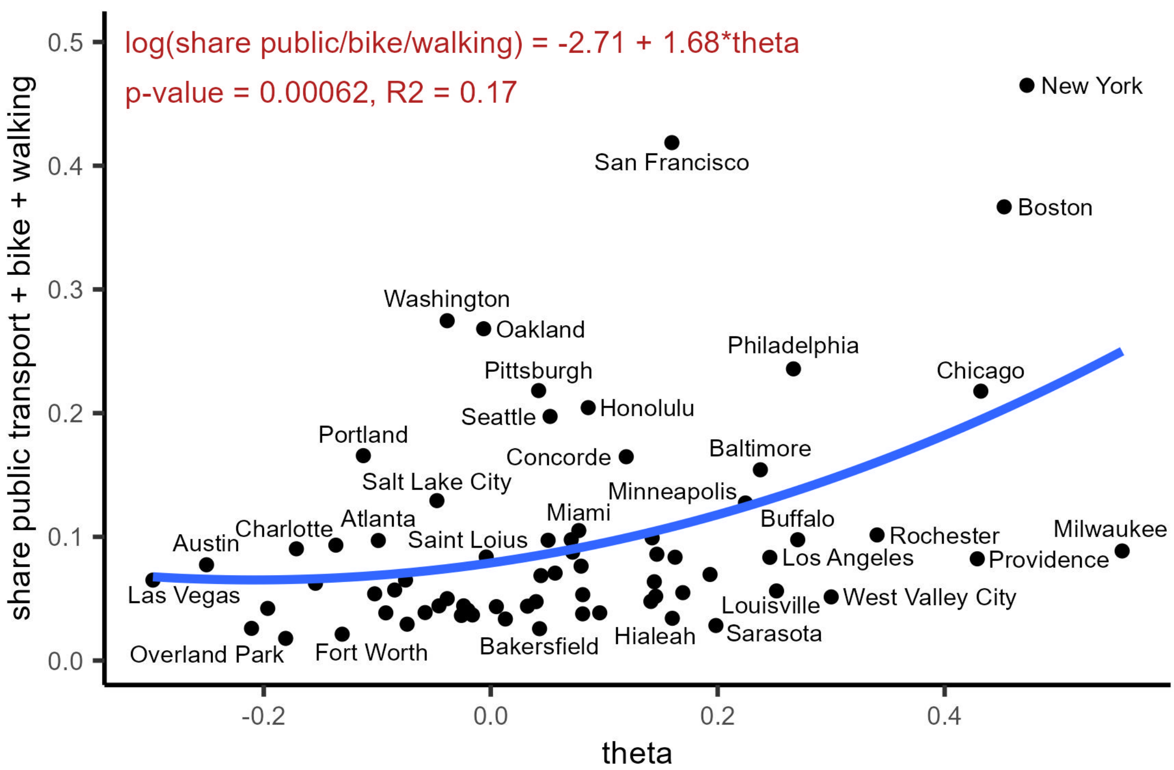
[34] The corresponding parameter in their model is denoted γ.

[35] They provide just one estimate from a pooled regression of the entire country. Given my estimates, I consider it plausible that their data and methodology would also lead them to negative values for certain cities if they would allow their parameter to vary by city.

(2022) also show a similar pattern when applied to other countries. Furthermore, even within the US, their pooled estimate masks a distribution of patterns, and urban costs might vary considerably for different cities.

Figure 9 depicts this heterogeneity among cities within the United States.[36] It also suggests that the prevalent transportation modes in a city matter for the elasticity of transportation costs. Using data from the American Community Survey, I compute the share of commutes done by foot, bike, or public transport. Without claiming causality, this share appears to be correlated with $\hat{\theta}$. This relation makes intuitive sense. When looking at trips by bike or walking, a linear transportation cost function suddenly seems not too unrealistic anymore, as we are limited by our physical capacities. Moreover, public transport networks are often quite dense and well-served in more central parts of cities, while it becomes more cumbersome to travel by public transport in the suburbs, as stops are further apart and connections are less frequent. On the other hand, these are places where traveling by car is very convenient due to lower congestion levels.

Figure 9: US heterogeneity and transport modes



Note: For the 70 US cities in my sample, this figure shows the relation between the transportation cost gradient and the share of people commuting by public transport, bike, or walking. The x-axis shows the inferred transportation cost gradients $\hat{\theta}$ that are computed from the difference between rent and density gradients. The y-axis shows the share of people using public transport, bikes, or walking for their commute to work. The corresponding data come from the American Community Survey (2015-2019). When computing that share, people working from home were disregarded from the calculation of the total, as were answers referring to unspecified "other means".

[36] The US has particularly many negative $\hat{\theta}$, consistent with the low average $\hat{\theta}$. However, it also exhibits the lowest $\hat{\theta}$ when focusing on the subset of cities with negative rent and density gradients.

Abstracting from the formal model of Duranton and Puga (2022), a more literal interpretation of θ also holds interesting insights. An exponent of 0.07 suggests that marginal transportation costs decrease extremely quickly with distance. Living far beyond the most densely populated areas comes with very limited additional private transport costs. An exponent of 0.30 implies that living in more remote locations increases private transport costs by much more. This can have implications for urban planning. Imagine there is a consensus to densify cities, in order to counteract negative social externalities from a more dispersed population. If the private costs of travelling additional distance are lower, measures will have to be stronger and affect more people, in order to achieve the same effect.

8 Conclusion

I use novel data on over 3 million short-term rental properties from Airbnb to estimate rent gradients in a sample of 734 cities worldwide. The resulting estimates are similar to those of the few existing studies computing gradients using house prices or long-term rents in a few select countries. I find rent gradients to be negative for most cities, with an average elasticity of -0.064 between price and distance. However, there are a substantial number of cities for which estimated rent gradients are flat or even positive. These are, in particular, cities that are smaller, situated at the shore of a large water body, or located in upper-middle-income countries. I also estimate density gradients for the same set of cities. Density gradients are steeper/more negative than rent gradients in almost 90% of cities, with an average elasticity of -0.36.

My results suggest that computing these gradients using a log-log specification is less sensitive to the precise city definitions than the alternative log-linear specification that is also much used in the literature. I show that imposing log-log gradients to a standard version of the monocentric city model implies a third gradient of transportation costs as a function of the distance to the city center. This gradient equals the difference between the rent and the density gradient. I estimate it to be 0.29 on average, which implies concave transportation costs. For almost all cities, I can reject the assumption of linear transportation costs (elasticity of 1).

The transportation cost gradient maps to the urban cost parameter in the model of Duranton and Puga (2022). They focus on the United States, and I closely match their estimate using the US cities in my sample. However, my research suggests that the United States is an outlier on the global scale, with the worldwide average transportation cost gradient being about four times as large as that of the United States. Moreover, there is also considerable heterogeneity among cities within the US. In particular, cities with a higher share of commutes by foot, bike, or public transport tend to have transportation costs that are more heavily influenced by distance.

A promising path for future work will be to directly estimate the transportation cost gradient empricially and to compare it with the transportation cost gradient that can be inferred from the monocentric city model and the rent and density gradients. The work by Akbar et al. (2021), who measure car travel transportation costs in urban India using Google Maps, could be an exciting starting point. The increase in data availability might also make it possible to take other modes of transportation into account. It would be interesting to observe whether directly estimated transportation cost gradients can be squared with the assumptions and predictions of the monocentric city model.

While highly stylized, the monocentric city model remains relevant to this day. It helps us to understand the interdependence of transportation costs, population density, and real estate prices. This paper shows that a number of its key predictions still hold for most large cities worldwide.

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A City definitions and delineations

This appendix describes the choices I make when defining the cities that form the basis of the analysis in a more detailed way.

1. I start with all city tags from OpenStreetMap.[37] I downloaded all entries with a place = city tag using Overpass turbo.[38] At the time of the download, OpenStreetMap contained 10,394 city tags worldwide.

2. The Global Human Settlement Layer project of the European Commission provides the Urban Centre Database UCDB R2019A.[39] Their definition of urban areas mainly builds on two factors: i) built-up area, evaluated from (daylight) satellite data using machine learning techniques and ii) administrative population data. 1km $\times$ 1km grid cells with an estimated population of at least 1,500 or a built-up area of at least 50 % form the basis of their 13,135 urban areas. According to their estimation, 1,799 of the urban areas were inhabited by at least 300,000 people in 2015. Additionally, I filter out urban areas for which I do not have data on at least 100 Airbnbs, including data on prices charged for at least one night over the study period. This further lowers the number of urban areas to 721.

3. I spatially join the city tags to the urban areas. After this step, there are 2010 tags within 707 urban areas remaining. For these tags, I look at the population count that is linked to them in OpenStreetMap. Whenever this information is not available (451 cases), I try to add it from Wikipedia,[40] using the English version whenever possible, but resorting to other languages if the English version has no population count. In 11 cases this still does not yield a result. However, all of these tags either represent subcenters that appear to be a lot smaller than another city in the same urban area, or they are in close proximity to another tag that represents essentially the same city. I identify the highest population count among all city tags in an urban area and remove the tags that have a population count of less than 40% from that maximum. After this step, 852 cities remain.

4. For all of these cities, the accuracy of the center coordinates proposed by 1) OpenStreetMap and 2) Google Maps[41] was visually assessed. For 76% of cities the coordinates from OpenStreetMap provide a very accurate location. In another 8% of cities I resort to the coordinates proposed by Google Maps instead. For the remaining 16% of cities, I provide an own best guess. For Chinese cities, the maps displayed by Google Maps are not superimposable to satellite images because of government regulations. Instead they are shifted in a non-monotonic way (Fuentes, 2019). Airbnb uses Google Maps to display the location of their properties. As I am eventually interested in the distance of Airbnb properties from the city center, this is consistent with the center coordinates from Google Maps. However, the coordinates provided by OpenStreetMap appear to be based on the

[37] `https://openstreetmap.org` I last accessed this and all other websites in this section on 12.01.2023.
[38] `https://overpass-turbo.eu`, downloaded on 25.06.2021.
[39] `https://ghsl.jrc.ec.europa.eu/ghs_stat_ucdb2015mt_r2019a.php`, downloaded on 30.01.2019.
[40] `https://wikipedia.org`.
[41] `https://google.com/maps`.

actual satellite images. I therefore artificially “falsify” their center coordinates by shifting them in a way that makes them consistent with Google Maps.

5. Once the city centers are determined, I split urban centers with multiple city tags. However, there are cases in which multiple tags are so close that it is unlikely that they constitute two separate cites, in which case I keep them as one city. To filter out these cases, I measure the distances between all tags in an urban area. If they are less than 7 kilometers apart I classify them as neighbors. I then use network analysis to find components, that is, sets of neighbors that are directly or indirectly (a neighbor's neighbor) connected to each other, but not to any other city tag. Within each component I only keep the tag with the largest population. The number of urban areas is still unchanged at 707 after this step and so is their extent. However, the number of cities deacreases to 800.

6. In cases in which an urban area is located in one single country, I use the rule described by Akbar et al. (2021) (Appendix A, point 7) to split urban areas that host multiple cities. Keeping the 1km × 1km grid structure of the GHSL, I compute the distances of each grid cell centroid to the different city centers. To split two cities A and B, border points X are assigned such that

$$\frac{\text{dist}(X, A)}{\text{dist}(X, B)} = \left(\frac{\text{Pop A}}{\text{Pop B}}\right)^{\frac{0.57}{2}} \tag{15}$$

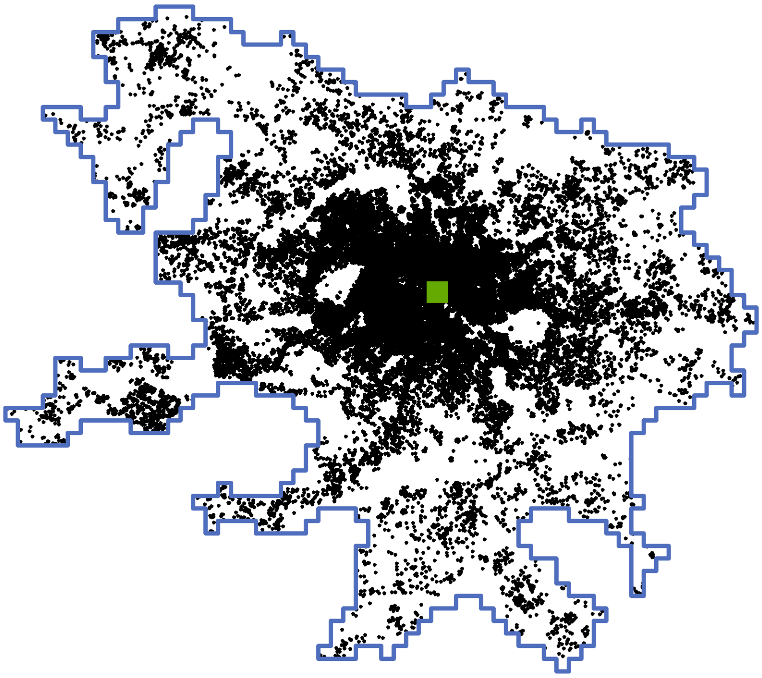
where $\text{dist}(X, A)$ denotes the distance of a grid point X to the center of city A and dist (X, B) denotes the distance of the grid point the the center of city B. In some cases, this creates little enclaves; city parts that are not connected to the rest of the city. If the enclaves have only one city they share a border with (defined as sharing at least one edge of one grid cell) they are reassigned to that city. This already solves most cases. The procedure is then repeated until all enclaves are reassigned. Urban areas that span across a national border are split at the border. In this case, enclaves that do not contain a city tag are disregarded.

7. In a final step, I recount the number of Airbnbs in each newly defined city. I also recompute the number of inhabitants, based on the GHS-POP file from the Global Human Settlement Layer project (Schiavina et al., 2019).[42] Consistent with the rule used above, I discard cities with less than 300,000 inhabitants or for which I have information on less than 100 Airbnb properties. My final sample contains 734 cities worldwide.

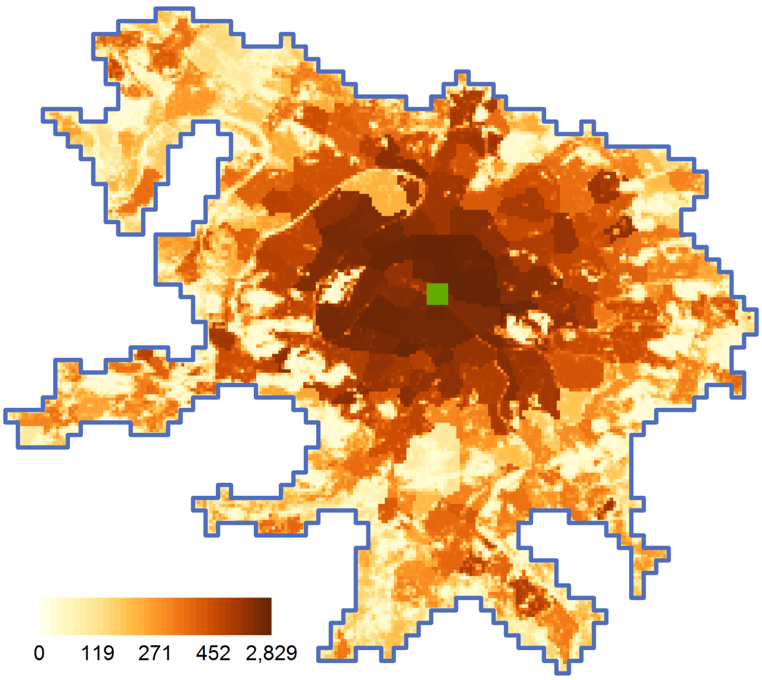
[42] `https://ghsl.jrc.ec.europa.eu/download.php?ds=pop`, downloaded on 06.08.2021.

Figure A1: Example of city definition: Paris

(a) Distribution of Airbnb properties



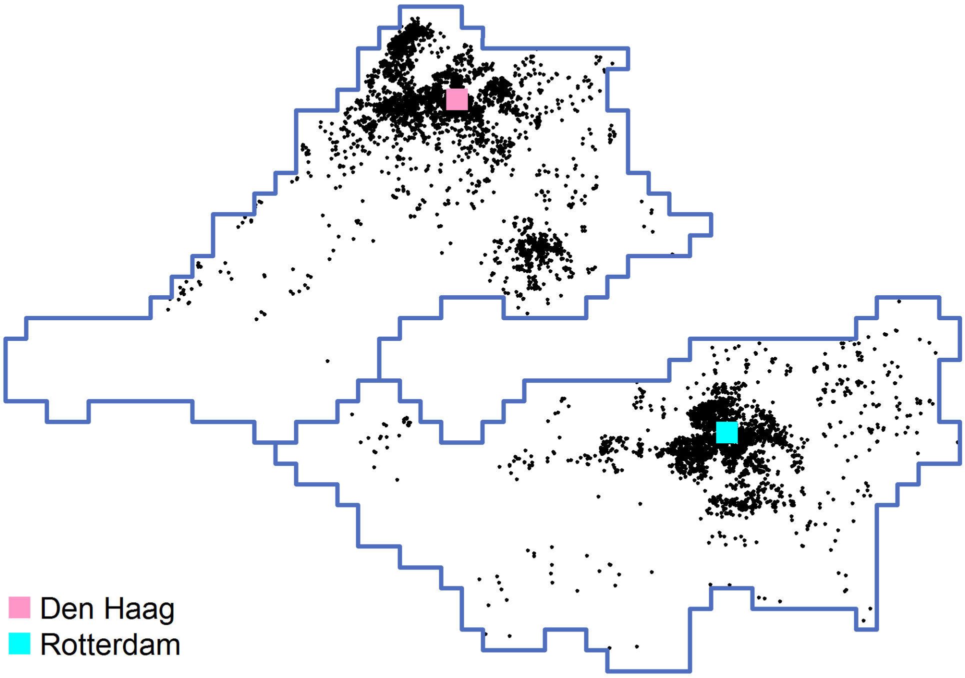
(b) Population count in 250 × 250 meter grid cells



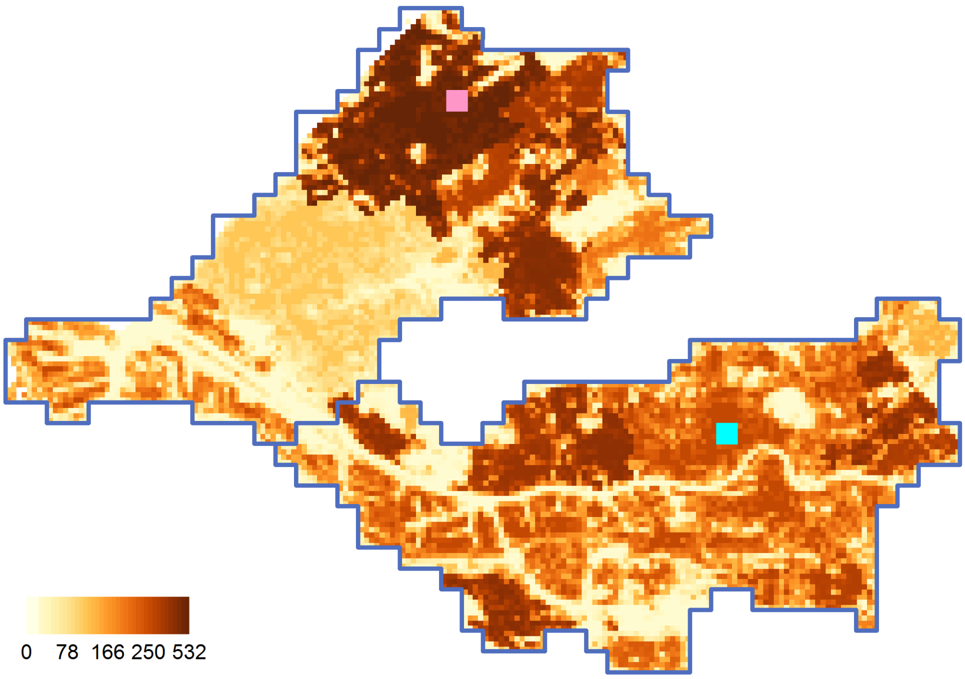
Note: The blue polygons show the delineation I use for Paris. The boundaries are taken from Florczyk et al. (2019). The green squares show my preferred city center definition. The coordinates are taken from OpenStreetMap and coincide with the Google Maps city center. The black dots in Subfigure (a) show the distribution of the 106,684 Airbnb properties in the city that were active during the study period. The raster in Subfigure (b) shows population counts in 250 meter × 250 meter grid cells, taken from Schiavina et al. (2019).

Figure A2: Example of city definition: Den Haag and Rotterdam

(a) Distribution of Airbnb properties



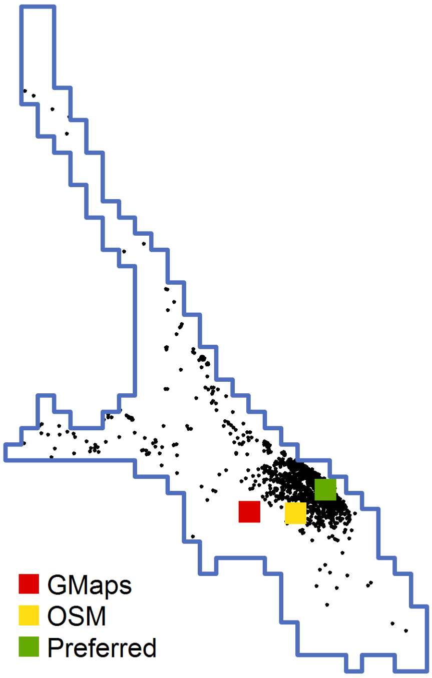
(b) Population count in 250 × 250 meter grid cells



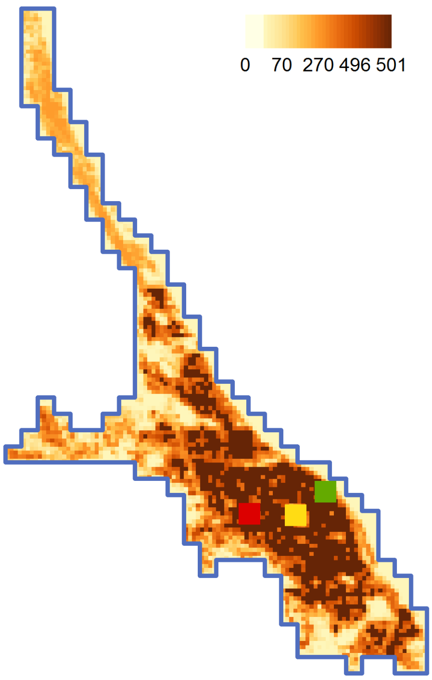
Note: The blue polygons show the delineation I use for Den Haag and Rotterdam. I split the boundaries of a combined urban center from Florczyk et al. (2019) by using the procedure described in Point 6 above. The pink and light blue squares show my preferred city center definitions for Rotterdam and Den Haag respectively. The coordinates are taken from OpenStreetMap. They coincide with the Google Maps city center for Rotterdam, but not for Den Haag. The black dots in Subfigure (a) show the distribution of the 3,282 Airbnb properties in Den Haag and the 2,638 Airbnb properties in Rotterdam that were active during the study period. The raster in Subfigure (b) shows population counts in 250 meter × 250 meter grid cells, taken from Schiavina et al. (2019).

Figure A3: Example of city definition: Rosario

(a) Distribution of Airbnb properties

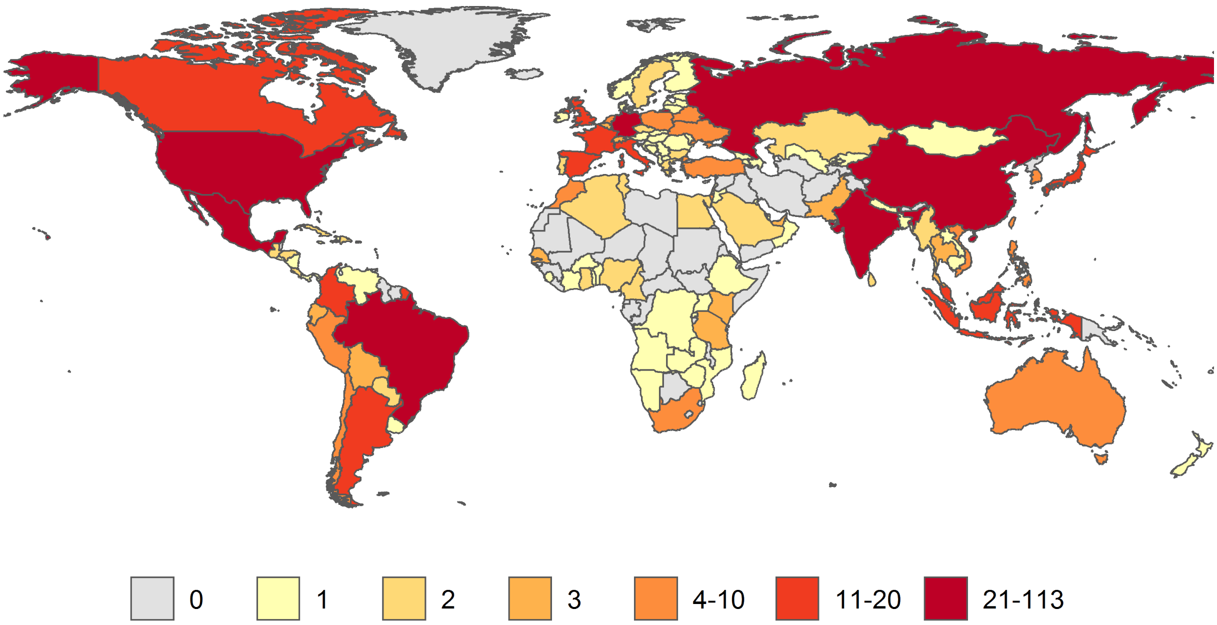


(b) Population count in 250 × 250 meter grid cells



Note: The blue polygons show the delineation I use for Rosario. The boundaries are taken from Florczyk et al. (2019). The green squares show my preferred city center definition, the yellow squares show the definition according to OpenStreetMap, and the red squares show the definition according to Google Maps. The black dots in Subfigure (a) show the distribution of the 1,307 Airbnb properties in the city that were active during the study period. The raster in Subfigure (b) shows population counts in 250 meter × 250 meter grid cells, taken from Schiavina et al. (2019).

Figure A4: Number of cities included in the sample



Note: This figure shows the geographic distribution of the 734 cities in the sample. To be included, a city must have at least 300,000 inhabitants and at least 100 Airbnbs that have been rented at least once over the sample period. The exact counts that are not visible from the map are: China (113 cities), United States (70), Brazil, Russia (both 44), Mexico (38), India (31), Germany (21), United Kingdom (20), Japan (17), Colombia (16), Spain (13), Argentina, France, Malaysia (all 12), Canada, Indonesia, Italy (all 11), Morocco, Philippines, Poland, South Korea (all 9), Peru, Taiwan, Ukraine, Vietnam (all 8), Australia, Belarus, South Africa, Turkey (all 6), Chile, Netherlands (both 5), and Isreal (4).

B Derivations of the implied transportation cost gradient

Start with the Alonso-Muth condition (from Alonso (1964) and Muth (1969); for the derivation of the condition see Duranton and Puga, 2015):

$$R'(x) = -\frac{t'(x)}{h(x)} , \tag{B.1}$$

where x denotes distance from the city center, $R(x)$ describes rents, $t(x)$ transportation costs, and $h(x)$ housing unit sizes. Assume that we are in a world where all buildings have the same height, while housing units can differ in size. In that case

$$D(x) = \frac{1}{h(x)} , \tag{B.2}$$

$$R'(x) = -t'(x)D(x) . \tag{B.3}$$

Estimating rents with regard to distance as log-log implicitly assumes the following functional form for $R(x)$

$$\ln\big(R(x)\big) = a + b\ln(x) , \tag{B.4}$$

$$\ln\big(R(x)\big) = a + \ln(x^b) , \tag{B.5}$$

$$\ln\big(R(x)\big) = \ln(Ax^b) , \tag{B.6}$$

$$R(x) = Ax^b , \qquad \text{where } A = \mathrm{e}^a . \tag{B.7}$$

It follows that

$$R'(x) = bAx^{b-1} . \tag{B.8}$$

If we assume that density is also best represented as log-log in distance, this implies

$$\ln\big(D(x)\big) = c + d\ln(x) , \tag{B.9}$$

$$\ln\big(D(x)\big) = c + \ln(x^d) , \tag{B.10}$$

$$\ln\big(D(x)\big) = \ln(Cx^d) , \tag{B.11}$$

$$D(x) = Cx^d , \qquad \text{where } C = \mathrm{e}^c . \tag{B.12}$$

Plugging B.8 and B.12 into B.3 yields

$$bAx^{b-1} = -t'(x)Cx^d , \tag{B.13}$$

$$t'(x) = -\frac{bA}{C}x^{b-d-1} . \tag{B.14}$$

Integrating with regard to x yields

$$t(x) = \int -\frac{bA}{C} x^{b-d-1} dx \ , \tag{B.15}$$

$$t(x) = -\frac{bA}{C} \int x^{b-d-1} dx \ , \tag{B.16}$$

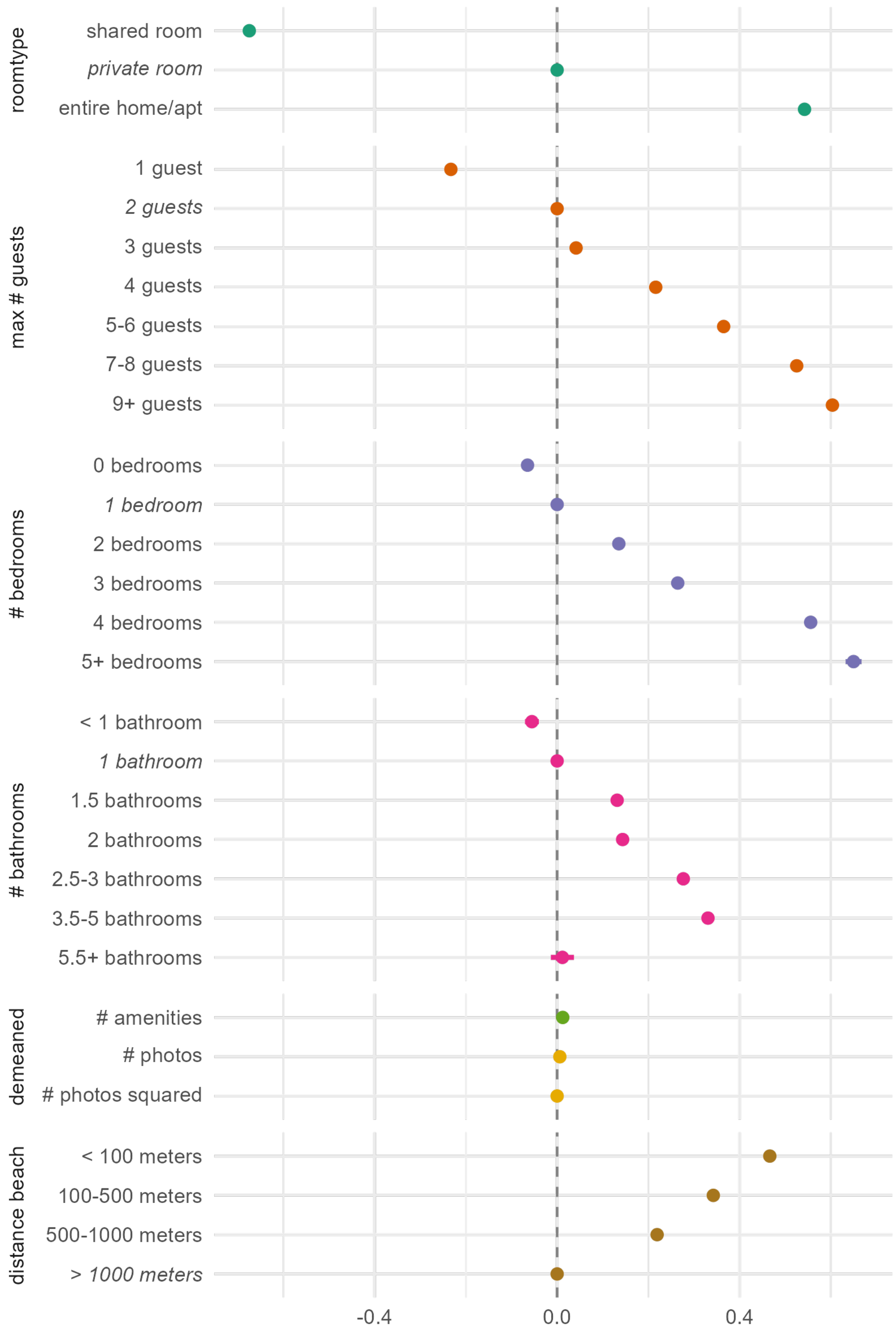
$$t(x) = -\frac{bA}{C(b-d)} x^{b-d} + \text{constant} \ . \tag{B.17}$$

As we want $t(0) = 0$, the constant drops out and we are left with

$$t(x) = -\frac{bA}{C(b-d)} x^{b-d} \ . \tag{B.18}$$

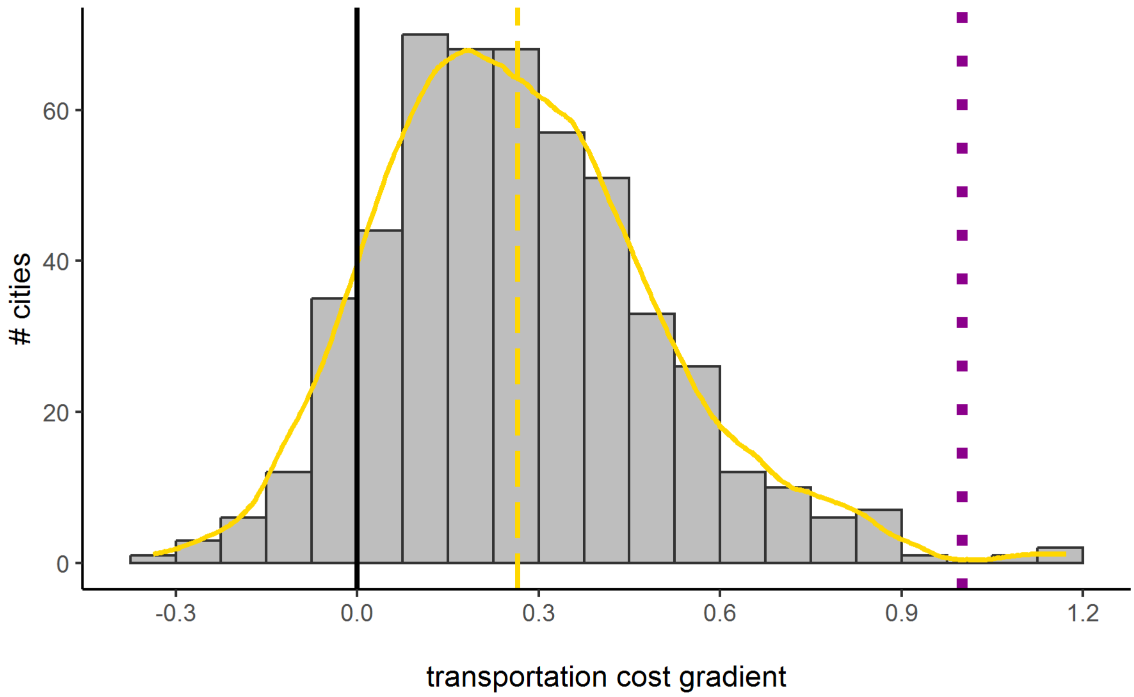
C Additional regression results

Figure A5: Estimates of rental object-level hedonic regression



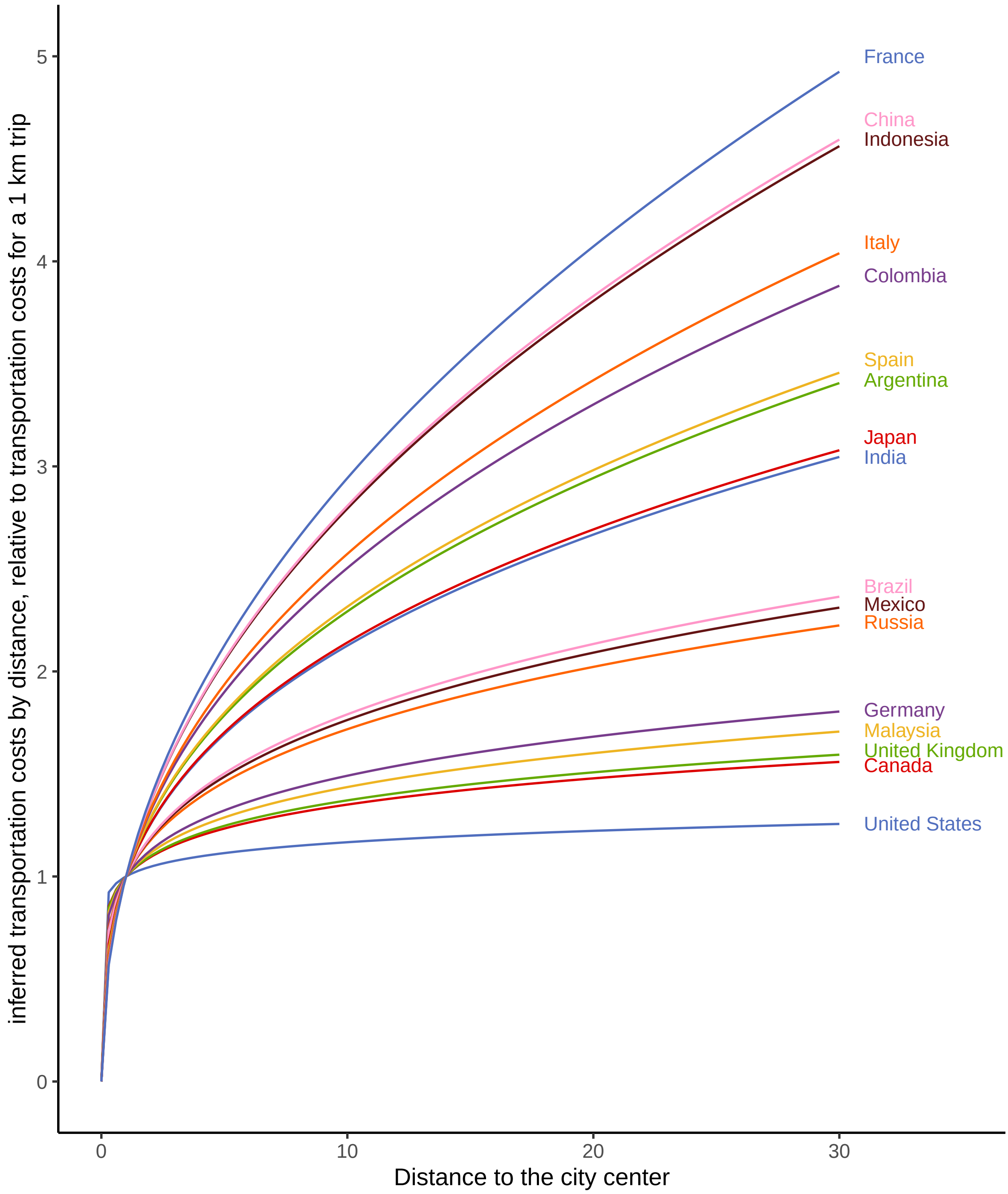
Note: This figure depicts the estimates of the first-stage hedonic regression of prices on property characteristics. The baseline categories are denoted in italic. Given the large number of 3,068,152 observations, most coefficients are so precisely estimated that the heteroscedasticy robust 99% confidence intervals are not visible.

Figure A6: Distribution of transportation cost gradients for cities with $b < 0$ and $d < 0$



Note: Analogously to Figure 8, this figure shows the distribution of transportation cost gradients for all 734 cities in my sample. However, it only includes cities for which I estimate negative rent and density gradients, as predicted by the monocentric city model. The dashed line depicts the average transportation cost gradient, while the solid line shows the corresponding Epanechnikov kernel density estimate. The dotted line indicates an elasticity of transportation costs of one; equivalent to linear transportation costs.

Figure A7: Inferred transportation cost by distance,
relative to transportation costs for a 1 km trip



Note: This paper infers a transportation cost function $t(x) = \phi x^{\theta}$. In a monocentric city model setting in which rent and density are both assumed to follow a log-log relation with distance, θ is shown to be equal to the difference between the rent and the density gradient. I estimate both gradients and infer $\hat{\theta}$ for 734 cities worldwide. This figure depicts transportation cost functions for all countries with more than 10 cities in the sample. θ is set to the average $\hat{\theta}$ for each country, while ϕ is set to one. Importantly, the figure does not imply that France has higher transportation costs as the United States, as France might potentially have a much lower ϕ. Instead, the curves can be interpreted as the inferred transportation costs by distance, relative to the transportation costs for a 1 km trip. Thus, the figure suggets that the transportation costs of the first kilometer of transportation close to the city center account for a larger part of transportation costs in the United States than in France.