Urban gradients: rent, density, and transportation costs[1]

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Preliminary and incomplete

Abstract

I use the monocentric city model to relate the rent gradient and the density gradient to a third gradient describing transportation costs. I estimate rent gradients for 734 cities worldwide using internationally comparable data on Airbnb objects. The average elasticity of rent to distance to the city center is -0.06. Rent gradients are less pronounced in cities that are smaller, situated by a large body of water, or located in upper-middle-income countries. Density gradients are more negative than rent gradients for most cities. Combining the two, I estimate the elasticity of transportation costs to distance to the city center to be around 0.3 on average, which implies a concave transportation cost function. This procedure relates closely to an approach Duranton and Puga (2022) use to determine their model's urban cost parameter. While I precisely match their 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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1 Introduction

The study of cities and the study of transportation costs are intertwined. The inherent advantage of cities is proximity. Being physically close to other people allows us to exchange knowledge and goods, sustain infrastructure, host events, and engage with one another. If moving across space would not be costly, cities might not exist. Within cities, people face a trade-off between being closer to advantageous locations and paying more for housing versus higher transportation costs with cheaper unit costs of housing. This trade-off is at the core of the monocentric city model, perhaps the most famous model in urban economics. However, how should we think about transportation costs? And how should we represent them in economic models?

A common simplifying assumption is to model them as being linear in the distance, implying that the monetary and non-pecuniary costs of traveling 10 km are twice as high as when traveling 5 km. In contrast, I argue that our cities feature decidedly concave transportation costs. I come to this conclusion by combining the monocentric city model with innovative data about short-term rental objects from Airbnb. The average elasticity of transportation costs with regard to distance is close to 0.3, while the linear case would suggest an elasticity of 1. 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 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 the 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. Estimating these two gradients for a worldwide cross-section of cities in a consistent way constitutes a large part of this paper.

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. 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. At the core of this project lies the novel idea of using rental data from Airbnb to compute rent gradients. With data on more than 3 million rental objects and a set of internationally standardized covariates, I can compute rent gradients for 734 cities worldwide.

I find an average rent gradient of -0.064, implying a 0.64% increase in prices for every 10% increase in distance. Comparing my estimates for different subsamples with the empirical literature that does exist (Gupta et al. (2022) for the United States, Combes et al. (2018) for France, Ding and Zhao (2014) and Li and Wan (2021) for Beijing), I find that they are 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 at 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, exhibiting positive transportation costs that are increasing in the distance. This is indeed the case for an overwhelming majority of cities, with an average density gradient of -0.356. Combining the two gradients yields an average transportation cost gradient of about 0.3.

This average value masks considerable heterogeneity. 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 estimate that Duranton and Puga (2022) get when performing a similar exercise for cities in the United States, although they disregard population density and focus solely on prices. This is one out of three methods they use to calibrate the urban cost parameter in their model, with the other two approaches also yielding an estimate of 0.07. 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, the elasticity of transportation costs to distance is about four times higher. In the context of their model, other world regions might experience urban costs that are considerably higher. However, also 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 Implications of the monocentric city model

The basis of this analysis is the monocentric city model, typically the first model discussed in a graduate course in urban economics. It was developed by Alonso (1964), Mills (1967), and Muth (1969), based on ideas that have been around at least since von Thünen (1826). The model assumes an exogenous employment center on a homogenous 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 flat 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 rents, $t(x)$ transportation costs, and $h(x)$ flat sizes. I use an extension of the baseline model that allows flats to differ in size while I keep the assumption that all buildings have the same height.[1] In this 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 house 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 dimension) 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.

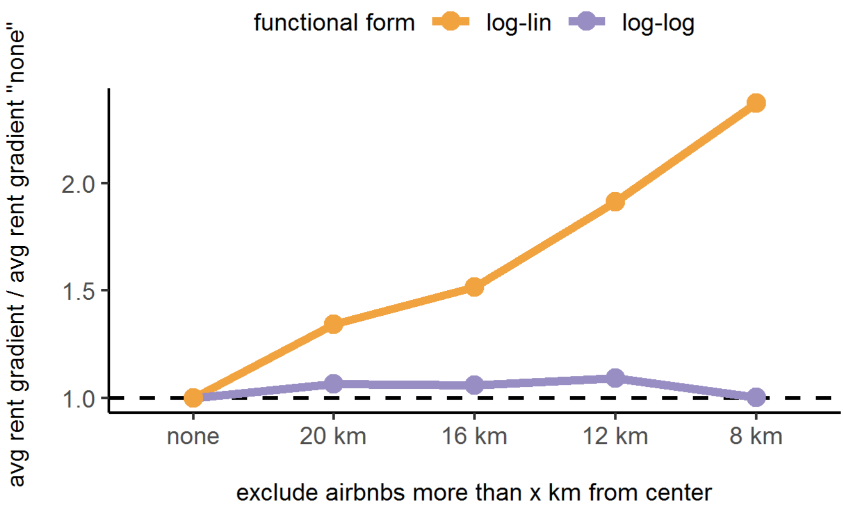
Leveraging my data, I find that the log-linear assumption is much more sensitive to the precise definition of cities. Figure 1 depicts this regularity for all cities with an Airbnb object further than 20 km from the city center. First, it recomputes the rent gradients using subsets of Airbnbs within 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. It then considers 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

[1] 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.

Figure 1: Funcitonal form and city definitions



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 A. Plugging 5 and 6 into Equation 3 and solving for $t'(x)$ yields

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

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

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

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 follow a similar gradient. Moreover, the transportation cost gradient θ equals the difference between the rent gradient b and the density gradient d.

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:[2]

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.[3]

Moreover, the transportation cost gradient θ holds information about the curvature of the transportation cost function. If $\theta = 1$, we live in a world of linear transportation costs, or $t(x) = \tau x$. This case is typically assumed in textbooks. If θ is between 0 and 1, transportation costs are concave. Several intuitive reasons would suggest this is the more likely case. Traffic is more congested in more central locations, speed limits are lower, and buses or metros stop more frequently. Moreover, there are fixed costs associated with getting to the next public transport stop or in the car. Longer trips to locations further outward (or from further outward) 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 predictions:

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

3 City definitions

It is not straightforward to determine where a city ends. Different countries have different rules to set their administrative units. Official city delineations are, therefore, hardly comparable. Fortunately, there have been attempts to find internationally consistent definitions of cities on

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

[3] Within this model, A and C are always positive because they are exponentials of regression intercepts (see Appendix A). 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 $\phi > 0$. In that case, $t'(x) > 0$ holds if and only if $b > d$, which is the same condition as above.

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 B provides more details.

I start with all city tags contained in the open collaboration database OpenStreetMap. I spatially join them to the Urban Centre Database of the Global Human Settlement Layer project (Florczyk et al., 2019).[4] I retain the city tags within an urban area with at least 300,000 inhabitants and at least 100 Airbnbs.[5] For cases in which several city tags are matched to an urban area, I include all cities with at least 40% as many inhabitants as the largest city in the urban area. This allows me, e.g., to keep Den Haag and Rotterdam as different cities without having to split the urban area 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. I then follow Akbar et al. (2021) in how I split the urban areas with more than one remaining tag.

OpenStreetMap uses crowd intelligence, letting users set and change geographic tags themselves. When it comes to city tags, users are asked to place them "at the center of the city, like the central square, a central administrative or religious building or a central road junction".[6] The coordinates of the tags are, therefore, a fitting choice for a transparent and globally consistent definition of city centers. Unfortunately, there are some cities for which visual inspection suggests 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. If they fail as well, I propose my own best guess. I provide robustness checks in which I take the coordinates from OpenStreetMap or the ones from Google Maps to define all city centers.

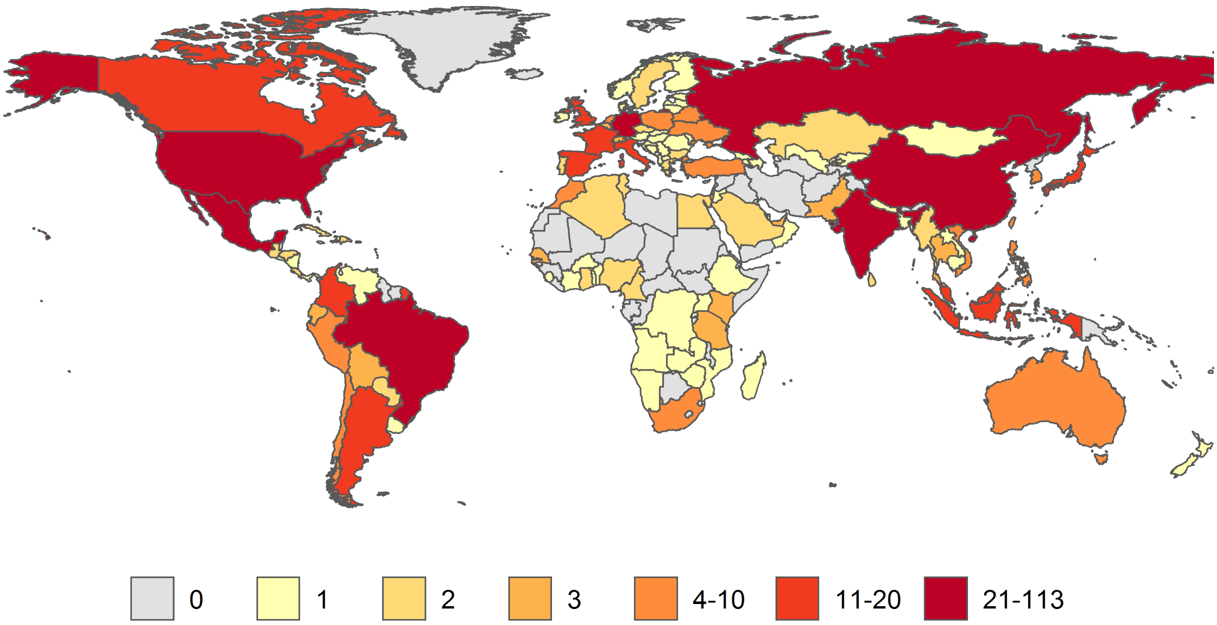
My final sample contains 734 cities worldwide. Figure 2 depicts their geographic distribution.

[4] 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 area 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.

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

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

Figure 2: 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).

4 Rent gradients

The data on Airbnbs come from AirDNA, a company specialized in "short-term rental data and analytics."[7] They contain close to all objects that were advertised on Airbnb at least once between 01.01.2018 and 25.03.2019.[8] By combining information about days for which objects are rented with information about the objects' prices for these days, AirDNA is able to estimate the prices actually paid by customers. For every object, I have information about the average daily price over the twelve months before the date on which an object was last scraped. After dropping objects that were never rented over the period in question, my dataset still contains more than 3 million objects within the cities defined in Section 3.[9]

Before exploring the relationship between the price of an object i and its distance to the city center, it is important to account for the fact that objects in a more central location might be fundamentally different from objects further outwards. Fortunately, Airbnb includes a number of variables that describe the advertised objects in an internationally standardized way, and I do have access to this information.[10] 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 to the city center.[11]

$$\ln(\text{price})_{ic} = \alpha + \gamma X_{ic} + u_{ic} \tag{10}$$

I mostly include the covariates X_i as nonparametric categories to allow for a flexible functional form. Figure A1 graphically depicts 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 objects with unrealistically high prices that are most likely misreported. Moreover, I normalize prices by subtracting their mean and dividing by their standard deviation. I do this to be able to compare rent gradients and density gradients. Without the normalization, the arbitrary choice of units would influence the comparison.

As expected, the number of bedrooms and the maximum number of guests allowed both increase prices monotonically. The same is true for the number of bathrooms, unless for the highest category.[12] Hosts can charge a substantially higher price if the guests have the entire apartment for themselves, while shared rooms are much cheaper than private rooms. Every additional amenity slightly increases the price, as do additional pictures of the object. Finally, guests are

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

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

[9] The raw dataset contains 9,419,495 observations. However, 2,354,445 of these objects were never reserved. I have to drop another 1,917 observations because their coordinates are missing. Afterwards, I can spatially join 3,093,755 objects 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.

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

[11] 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 an object.

[12] There are perhaps erroneous entries for very high numbers of bathrooms.

willing to pay extra for objects close to an ocean, sea, or big lake, with a higher premium for objects situated directly at the shore.[13] The large number of observations ensures that the effects are precisely measured. I then compute the predicted log price for each Airbnb object and the residual value

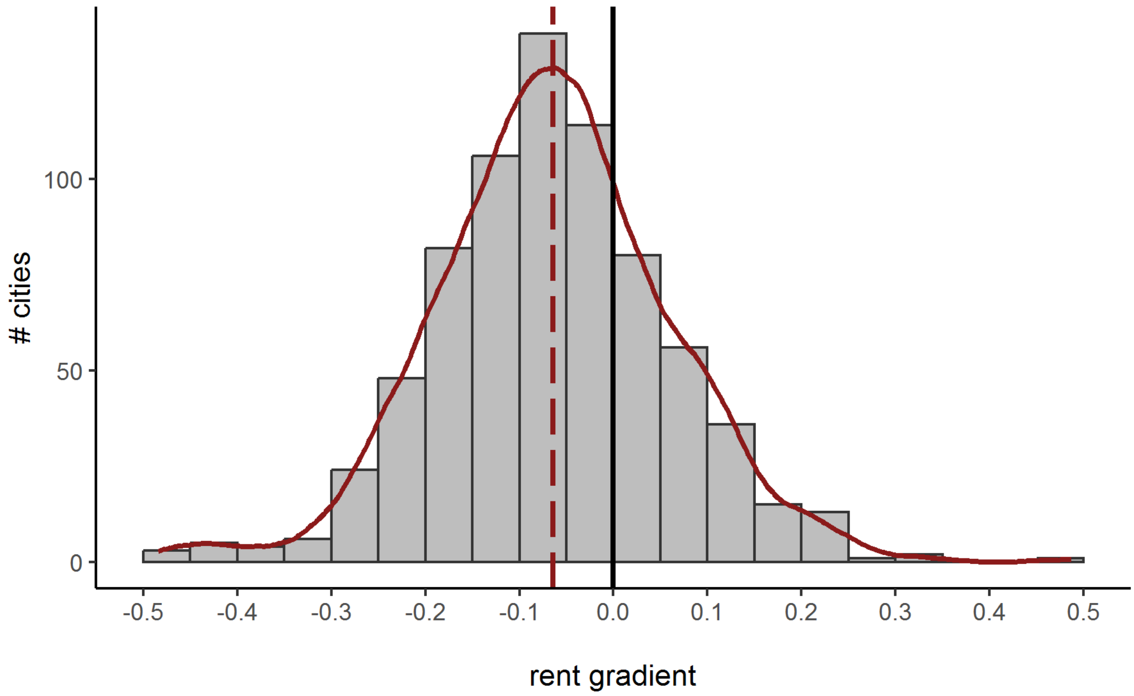
$$\ln(\text{price})^{\text{res}}_{ic} = \hat{u}_{ic} = \widehat{\ln(\text{price})}_{ic} - \ln(\text{price})_{ic} \tag{11}$$

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

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

Figure 3 depicts the spatial 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% increase in prices 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 and significantly negative rent gradients for 52%. On the other hand, I estimate positive rent gradients for 28% of cities and significantly positive rent gradients for 13%.

Figure 3: Distribution of rent gradients



Comparison with the literature

[13] The indicators for proximity to the beach are the only variables that are not directly taken from Airbnb. Instead, water distance can be inferred from the provided map. 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 an object 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).

How does this compare to the existing literature? Gupta et al. (2022) find a pre-pandemic rent gradient of -0.03 and a corresponding house price gradient of -0.10 for the 30 largest MSAs in the United States.[14] 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 0.01.[15] 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.

For this study, the Airbnb data seem to provide a decent approximation of long-term real estate objects. The distribution of rent gradients falls 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 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 objects myself and compare them with those obtained using short-term rental objects. 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 consistently choose their centers and borders. On the flip side, the availability of suitable data is an issue. There is publicly available data for France and the United States, so I use these two countries for the comparison.[16] However, this data is based on small administrative units (block groups for the United States, communes for France) rather than on individual objects.[17]

Figures 4 and 5 depict rent gradients estimated using long-term rental data on the x-axis and rent 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. One reason for this could be that the French long-term rental prices are constructed from hedonic regressions, considering object-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 these are also just

[14] 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.

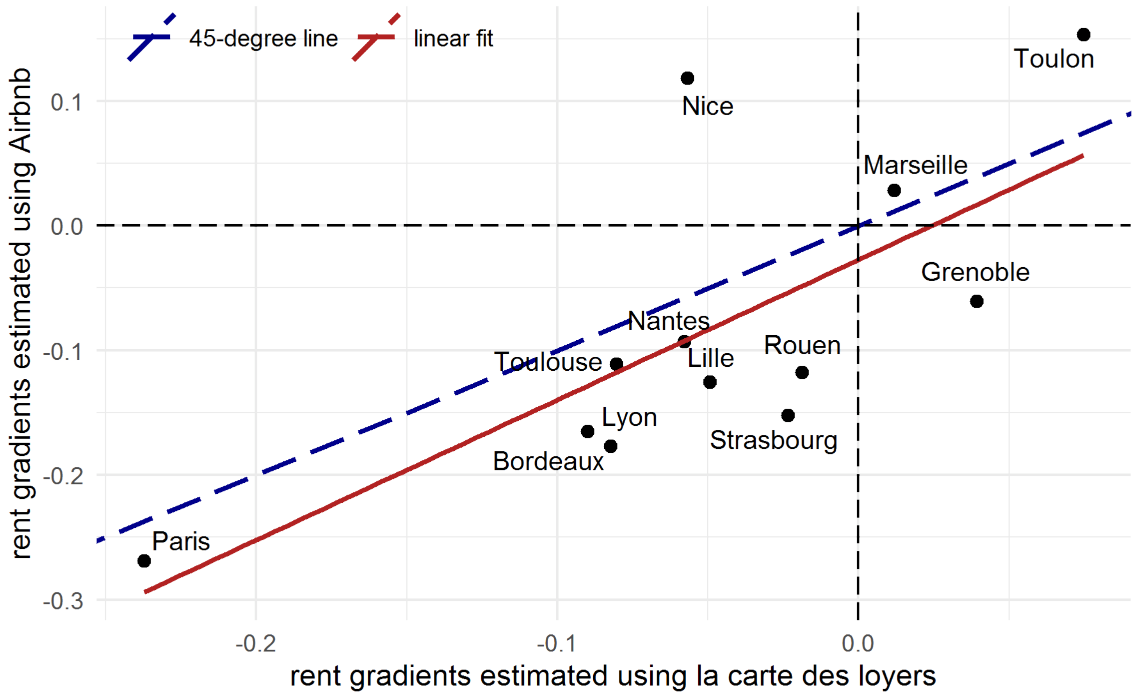
[15] I averaged the values over their seven specifications in Table 3, Panel A.

[16] The French data comes from the "carte des loyers", while the US data is based on the American Community Survey.

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

aggregate statistics on the block group level.[18] 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.

Figure 4: Comparison with long-term rental data: France



Regularities

Which type of cities exhibit more negative rent gradients? A first factor is the size of a city. Figure 6 regresses the rent gradient on the log of population size for 16 countries that host more than 10 cities. Indeed, 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 a more extensive set of 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. Interestingly, all four countries for which bigger cities are not associated with more negative rent gradients are situated in Latin America.

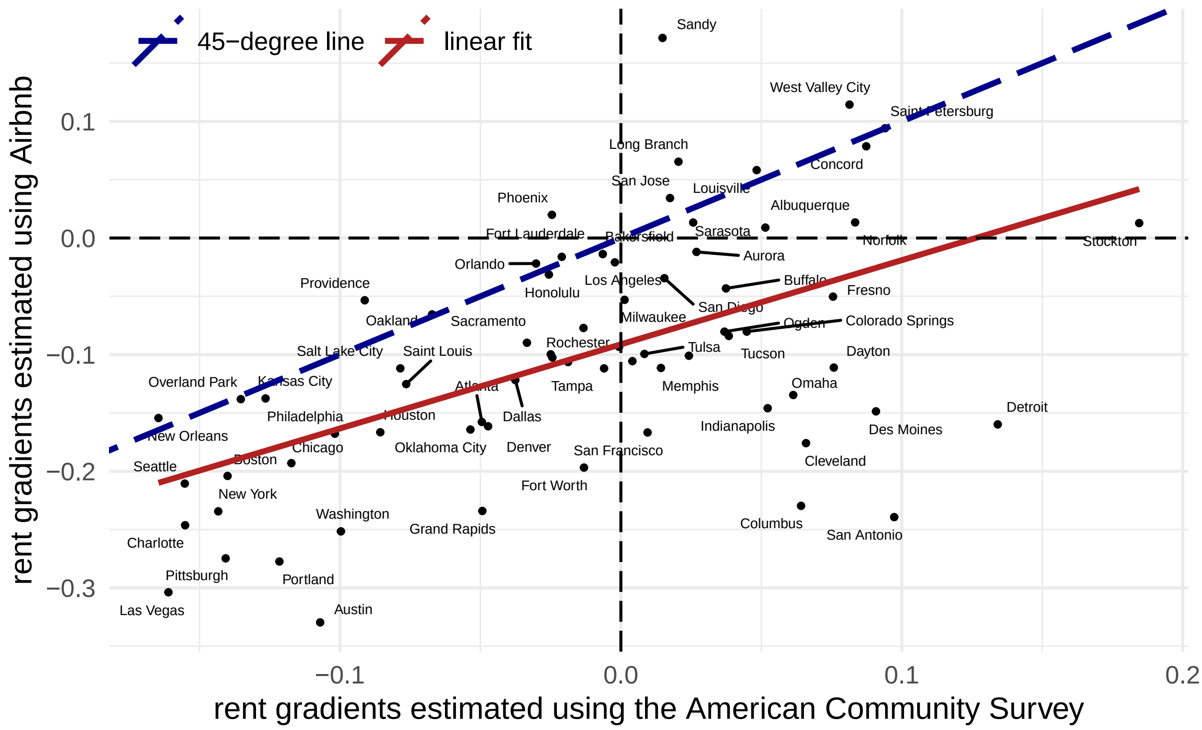
The next obvious suspect is differences by income level. Figure 7 explores this dimension. Its base are the income groups of the World Bank. However, I assign low-income and lower-middle-income countries into one group to get a sufficiently high number of observations.[19] For each group, I run a separate kernel density estimation.[20] There seems to be a non-linear relation

[18] 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 borders a large water body.

[19] 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.

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

Figure 5: Comparison with long-term rental data: United States



between rent gradients and income levels. 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 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 are 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. Figure 8 depicts this regularity. The average rent gradient for seaside cities is very close to zero (the point estimate is 0.0009). However, this group only consists of 75 cities. 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 higher valued by tourists than by permanent residents and as Airbnb objects might cluster particularly close to the seaside.

Robustness check

Figure A2 revisits the question of the optimal placement of the city center. It depicts 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 3. The orange curve takes

the group.

Figure 6: Rent gradients and city size

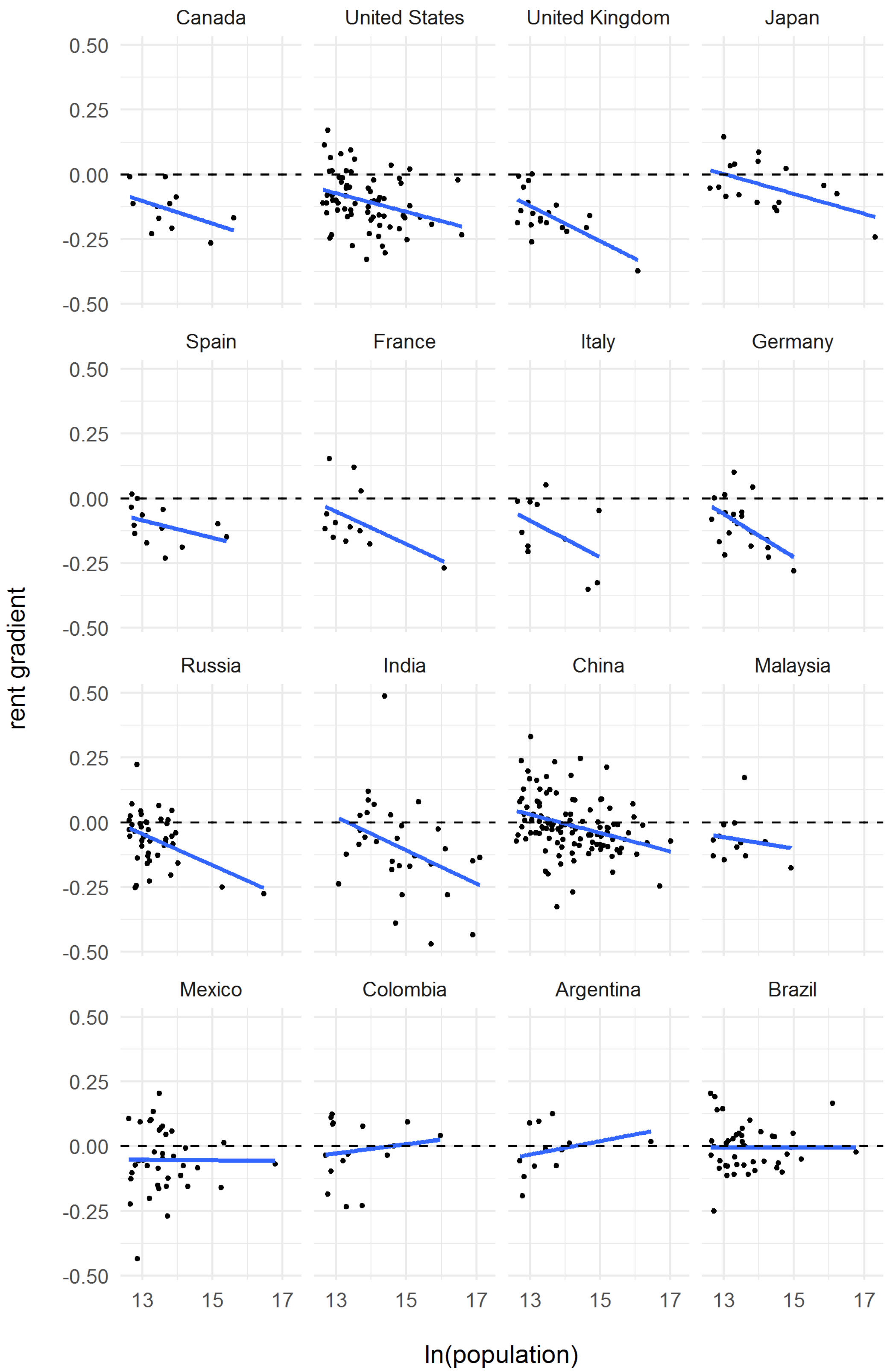
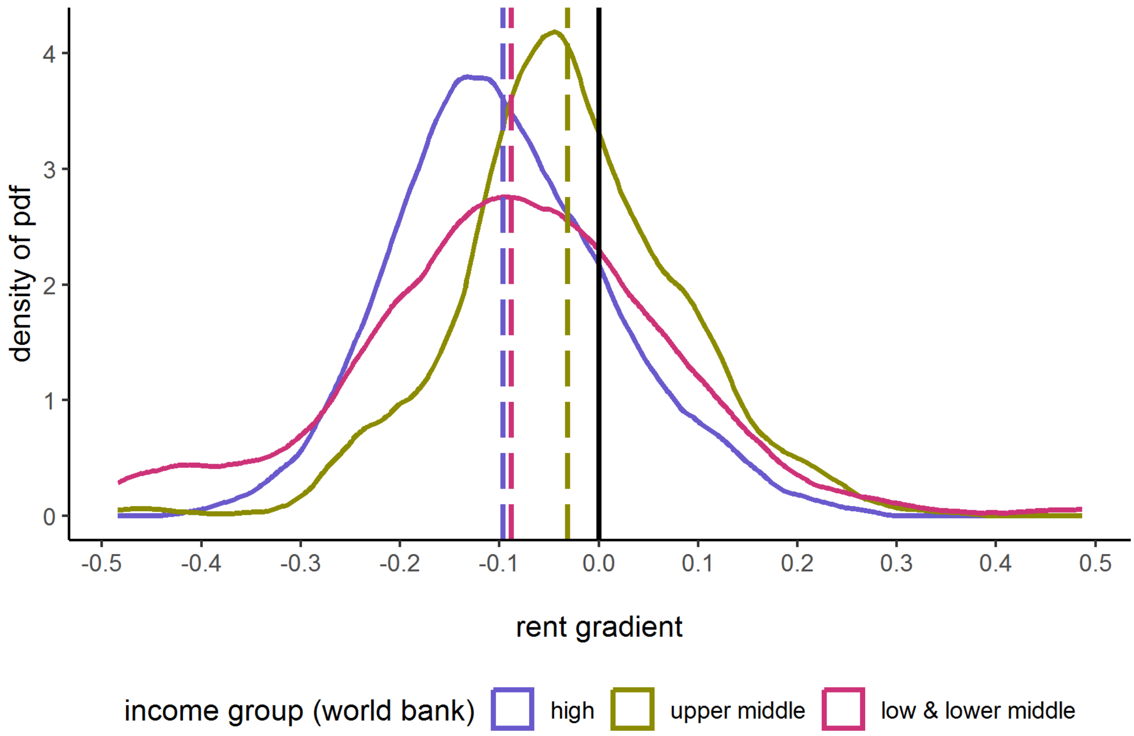


Figure 7: Rent gradients by income group



the city coordinates from OpenStreetMap for all cities, while the blue curve does the same with the city tags from Google Maps.[21] Choosing a different center source does not fundamentally alter the rent gradients' 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 biased the least towards zero.[22]

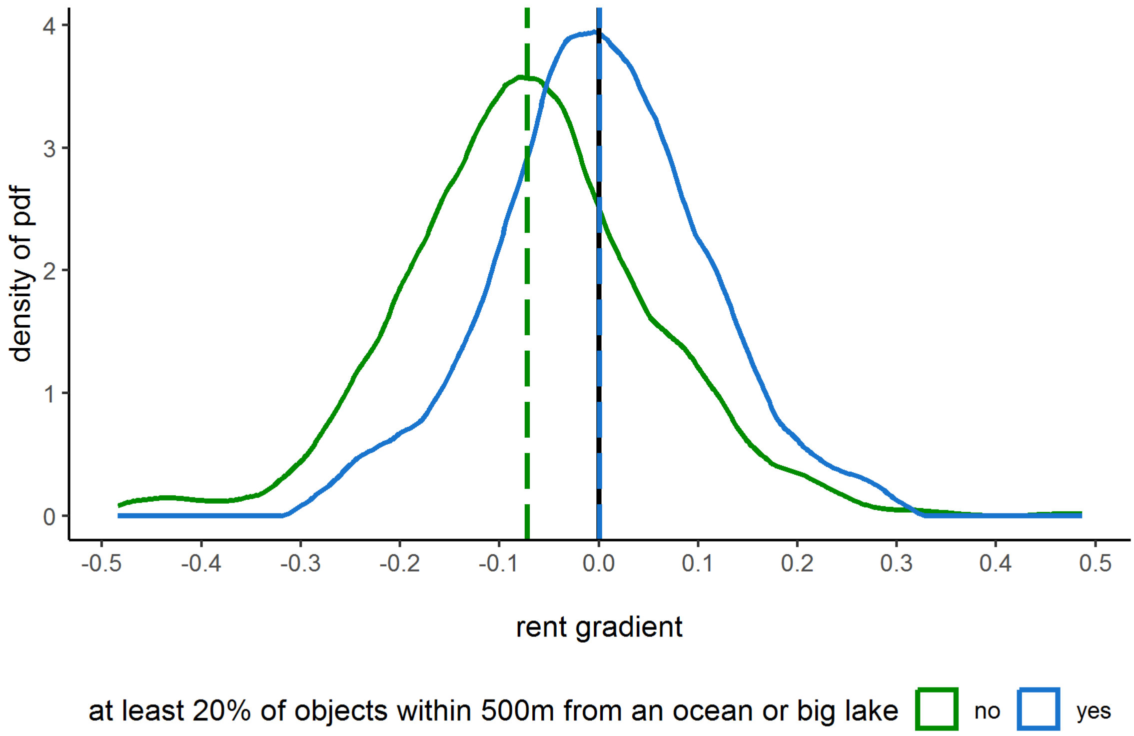
5 Density gradients

Data on population density comes from the Global Human Settlement Project described in Section 3 and Appendix B. 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. To estimate density gradients, I employ the version with the finer 100m

[21] 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.

[22] 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.

Figure 8: Rent gradients and proximity to the seaside



× 100m resolution.[23] I drop grid cells with a value below one inhabitant. These are mostly located in water bodies or other areas not suited or developed for housing.[24] The estimation of density gradients does not require a two-step procedure. Instead, I directly estimate

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

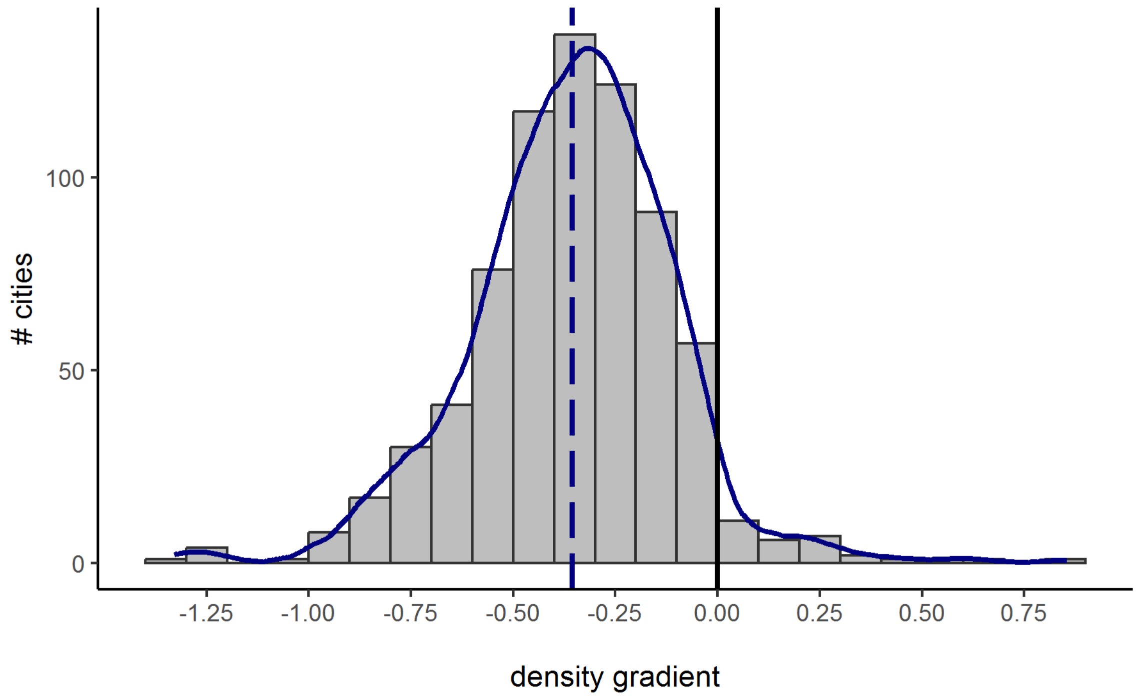
where FE_c are city fixed effects, and d_c denotes one density gradient per city. Analogous to the above, I normalize population density by subtracting its mean and then dividing by its standard deviation to make the estimated gradients comparable with the rent gradients and circumvent the arbitrary choice of units.

Figure 9 displays 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 proposition 2, I find density gradients to be negative in 96% of cities and significantly so in 93%. There exist positive gradients as well. This is true for 4.1% and significantly so for 3.5% of the cities in my sample. I can confirm the finding in the literature that South African cities have positive gradients, typically explained by discriminatory housing rules during apartheid. I estimate positive gradients for all 6 South African cities included in this study.

[23] For the delineation of cities I keep the 1km × 1km grid size on which the GHS urban center database is constructed.

[24] To see why this is necessary, consider the case of New York City. Manhatten is, without a doubt, very densely populated. Moreover, it 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 9: Distribution of density gradients



6 Transportation cost gradients

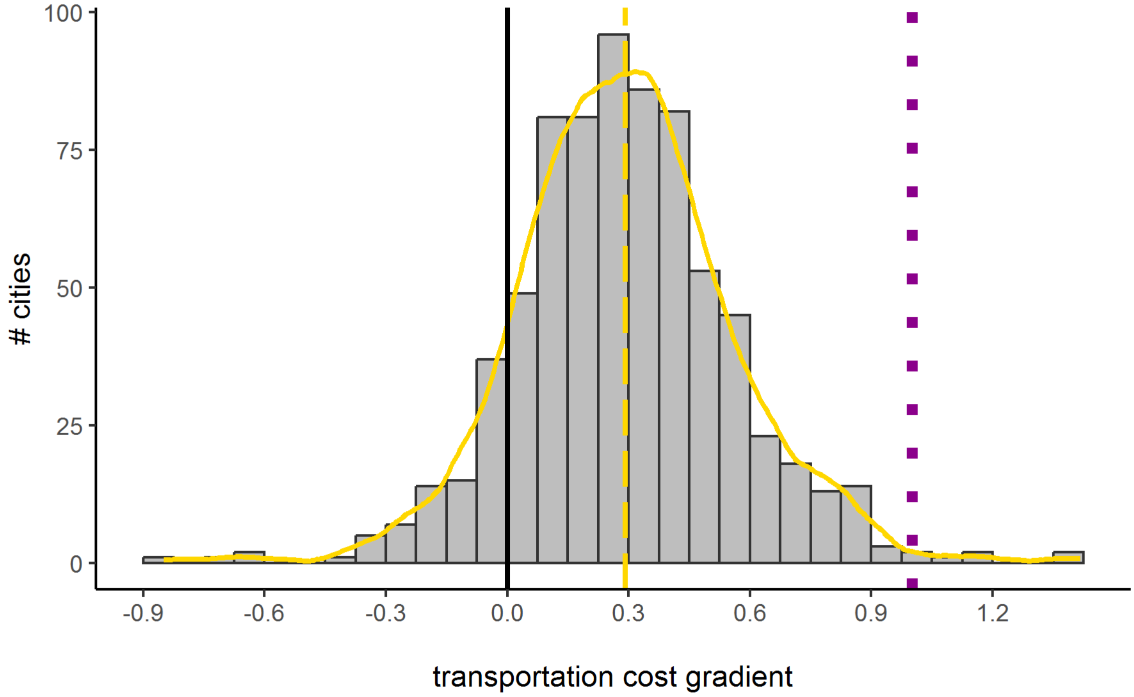
As derived in Section 2, the transportation cost gradient θ is equal to the difference between the rent gradient b and the density gradient d. In order to get transportation costs that are positive and increasing with distance, b needs to be larger (less negative) than d. Having estimated rent gradients and density gradients for all 734 cities in the sample, I can now assess this third proposition. Out of all 734 cities, I obtain a positive θ in 89% of the cases. Only for 11% of the cities, the density gradient is larger (less negative) than the rent gradient. This includes cities for which I have estimated a positive b and/or d, which makes them not compatible with the theoretical predictions of the monocentric city model in the first place. The subset with negative values for both b and d contains 513 cities. However, within this subset, I obtain a positive θ for 89% of the entries as well.

Figure A3 depicts the distribution of θ. Figure 10 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 linear case often assumed in textbooks. 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

Figure 10: Distribution of transportation cost gradients



costs decrease in distance is very different across cities. Table 1 depicts the average θ by country or region.[25]

There might be a relationship between the average θ and the importance of public transport vs. individual transport modes (work in progress). This conjecture is supported by the differences between cities within the United States presented in Table A1.[26]

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

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

with θ being the elasticity of transportation costs to living further towards the outskirts of a city. This equation can, in principle, be taken to the data, even if it is not easy to find good data on transportation costs, in particular, if the choice of the transport mode is relevant, as suggested above. Nevertheless, while they focus on car travel, the work by Akbar et al. (2021), who measure transportation costs in urban India using Google Maps, could be an exciting starting point.

[25] All countries with at least 10 cities in the sample are included as such. For all other countries, I assign them to geographical regions following the definition of the World Bank.

[26] The US has particularly many negative θ, consistent with the low average θ. However, it also exhibits the lowest θ when focusing on the subset of cities with negative rent and density gradients.

Table 1: Average 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

Crucially, the θ estimated in this paper is closely related to the parameter of urban costs that is a key input in the model of Duranton and Puga (2022).[27] In their model, they interpret it as the "elasticity of urban costs with respect to city population" (p.3). They provide three distinct empirical ways to estimate it. One of these ways is closely related to the methodology deployed in this paper. The most notable difference is that I allow for different flat 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 θ for all United States cities included in my sample precisely matches this value.[28] This is reassuring concerning the validity of the Airbnb data for questions beyond the short-term rental market itself.

Moreover, it suggests that the estimates in this paper can yield interesting insights about the urban cost parameter estimated by Duranton and Puga (2022). According to my analysis, the United States is on the absolute lowest 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 (2022) also show a similar pattern when applied to other countries. Furthermore, even within the US, their pooled

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

[28] 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.

estimate masks a distribution of patterns, and urban costs might be quite different for different cities.

Abstracting from their formal model, a more literal interpretation of θ also holds interesting insights. An exponent of 0.07 suggests that marginal transportation costs are decreasing extremely quickly with distance. Living far outside the most densely populated areas comes with limited additional private transport costs (due to externalities this might not be true for social costs). An exponent of 0.30 implies that living at more remote locations increases private transport costs by much more, which has implications for urban planning and, eventually, for real estate prices.

While quite 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 metropolises worldwide.

8 Conclusion

I use novel data on over 3 million short-term rental objects from Airbnb to estimate rent gradients in a sample of 734 cities worldwide. The resulting estimates are in the ballpark of the few existing studies computing gradients using house prices or long-term rents. Rent gradients are negative for most cities, with an average elasticity of -0.064 between price and distance. However, there is a a substantial number of cities for which 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 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. Its average is 0.29, which implies concave transportation costs. For almost all cities, I can reject the textbook case of linear transportation costs (elasticity of 1).

The transportation costs gradient maps to a key parameter in the model of Duranton and Puga (2022) representing urban costs. 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 the one for the United States. Moreover, there is also considerable heterogeneity among cities within the US. I suspect that the importance of public transport can explain part of this heterogeneity (work in progress).

While quite 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 metropolises worldwide.

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A Derivations of the monocentric city model

Start with the Alonso-Muth condition:

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

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

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

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

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

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

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

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

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

It follows that

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

Following the same logic, log-log density implies

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

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

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

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

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

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

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

Integrating with regard to x gives

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

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

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

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

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

B City definitions in more detail

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.[29] I downloaded all entries with a place = city tag using Overpass turbo.[30] 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.[31] Their definition of urban areas mainly builds on two factors: i) build-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 build 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 center candidates 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,[32] using the English version whenever possible, but turning 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 are either representing subcenters that appear to be a lot smaller than an another city in the same urban area, or they are in close distance 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[33] 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 objects. As I am eventually interested in the distance from Airbnb objects to the city center, this is consistent with the center coordinates from Google Maps.

[29] `https://openstreetmap.org` I last accessed this and all other websites in this section on 12.01.2023.
[30] `https://overpass-turbo.eu`, downloaded on 25.06.2021.
[31] `https://ghsl.jrc.ec.europa.eu/ghs_stat_ucdb2015mt_r2019a.php`, downloaded on 30.01.2019.
[32] `https://wikipedia.org`.
[33] `https://google.com/maps`.

However, the coordinates provided by OpenStreetMap appear to be based on the 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 separate city tags that are in the same urban area but not so close to each other that it is unlikely that they constitute two different cities. To do so, 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, i.e. sets of neighbors that are directly or indirectly (a neighbors 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 $\times$ 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

$$\frac{\text{dist}(X, A)}{\text{dist}(X, B)} = \left(\frac{\text{Pop A}}{\text{Pop B}}\right)^{\frac{0.57}{2}} \tag{B.1}$$

   where dist(X, A) denotes the distance of a grid point X to the center of city A. 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).[34] 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 objects. My final sample contains 734 cities worldwide.

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

C Additional regressions results

Figure A1: Estimates of hedonic regression

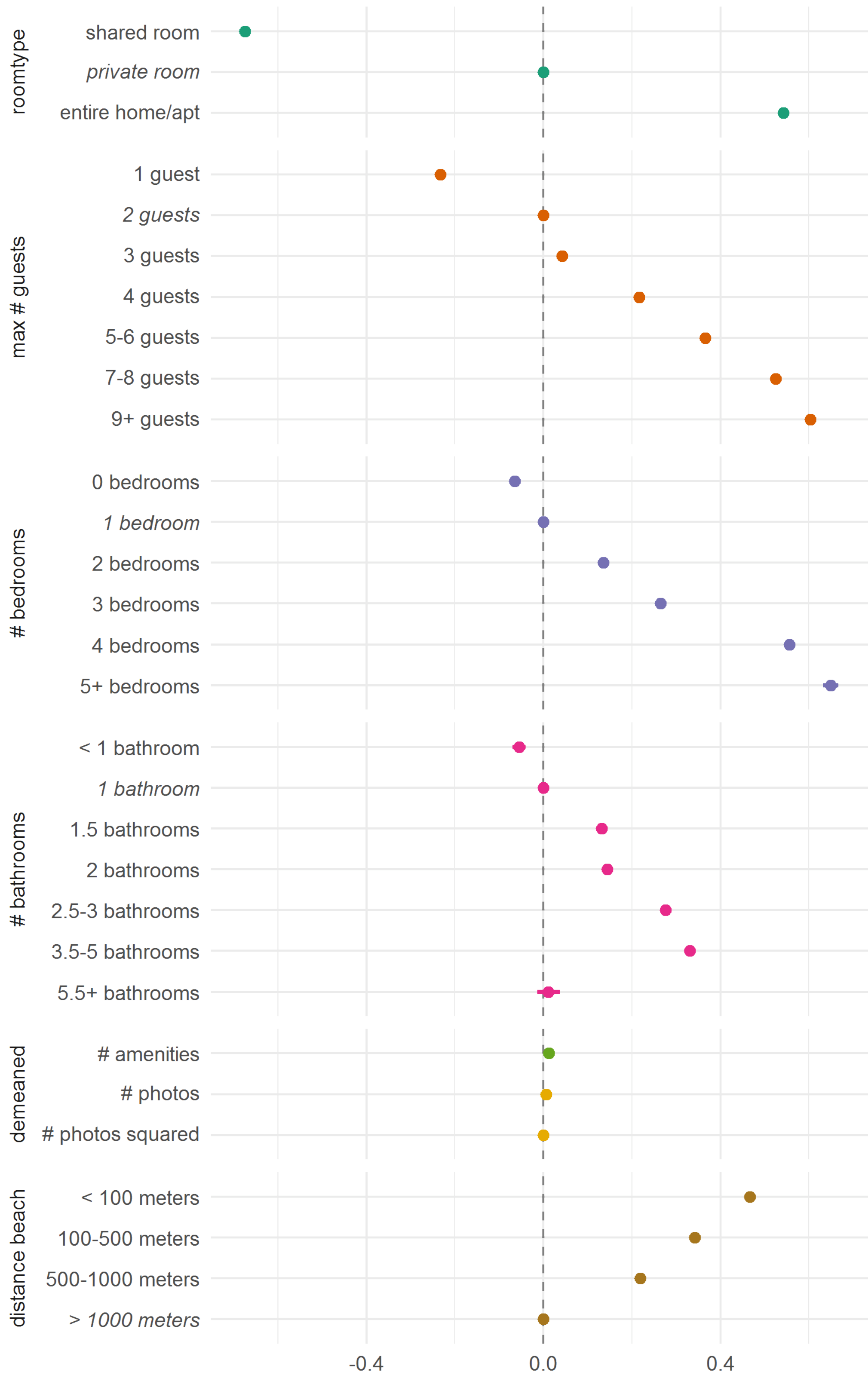

Figure A2: Rent gradients by source of the city center

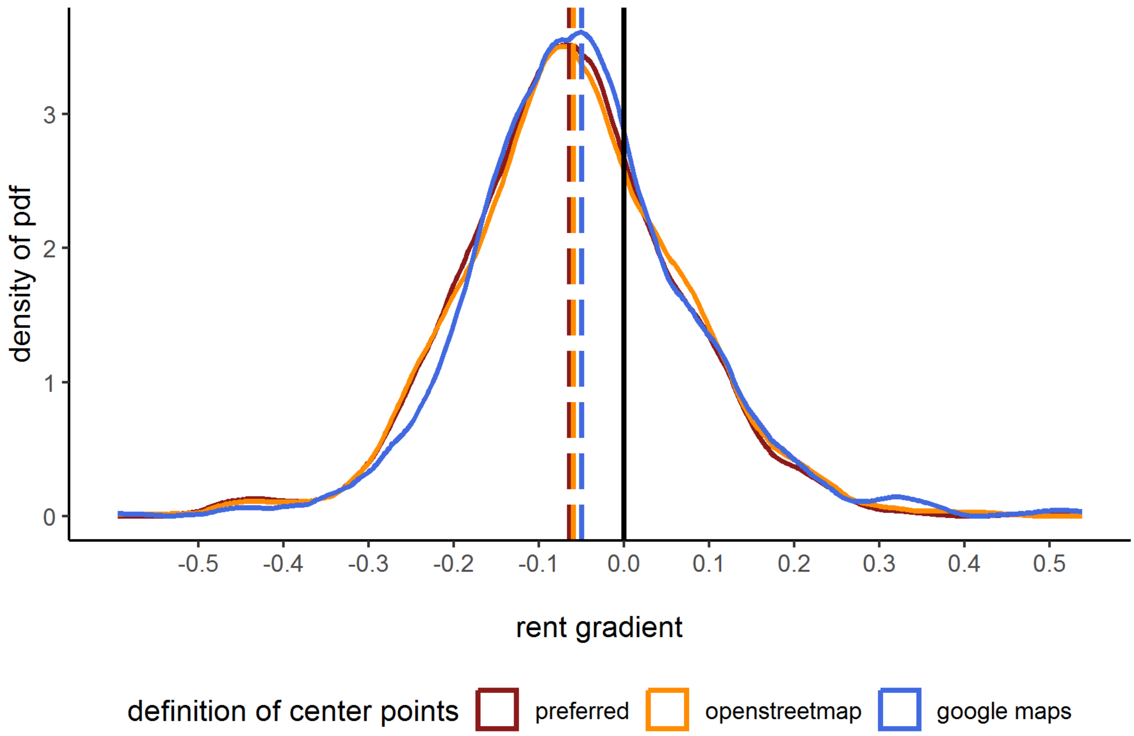

Figure A3: Distribution of transportation costs gradients for cities with $b < 0$ and $d < 0$

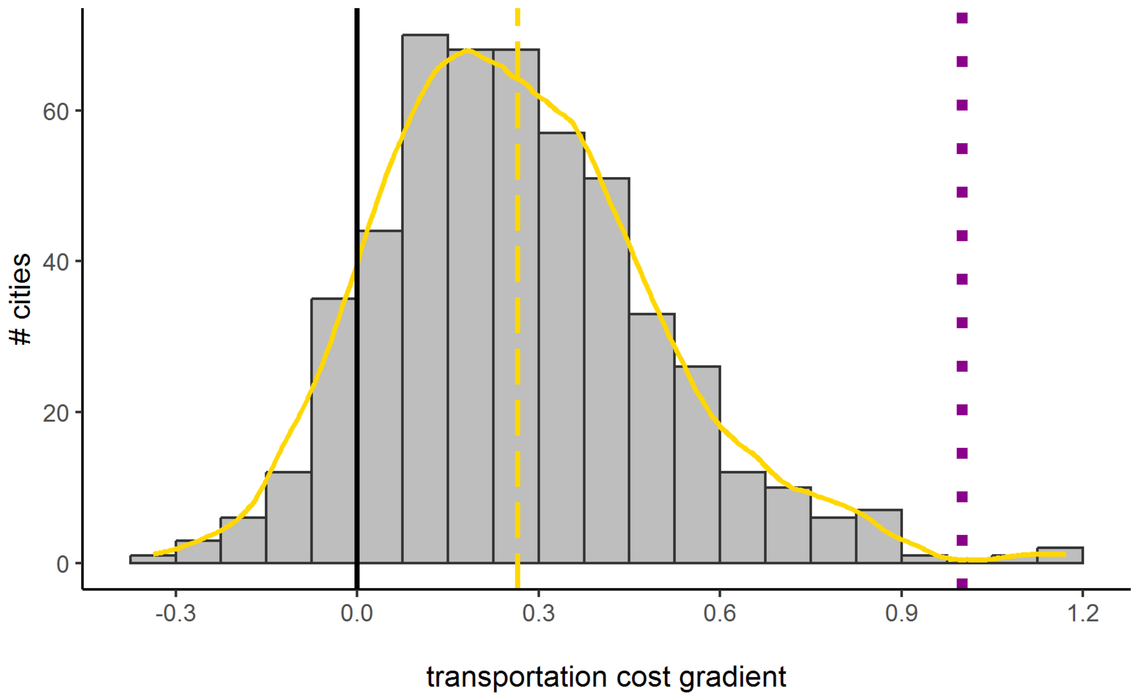

Table A1: Ranking of US cities by transportation cost gradient

	θ		θ		θ
Milwaukee	0.56	Concord	0.12	Memphis	-0.03
New York	0.47	Detroit	0.10	Albuquerque	-0.04
Boston	0.45	Honolulu	0.09	Washington	-0.04
Chicago	0.43	Sandy	0.08	Kansas City	-0.05
Providence	0.43	Fresno	0.08	Salt Lake City	-0.05
Rochester	0.34	Cincinnati	0.08	Indianapolis	-0.06
West Valley City	0.30	Miami	0.08	Tulsa	-0.07
Buffalo	0.27	Long Branch	0.07	Jacksonville	-0.08
Philadelphia	0.27	Tucson	0.07	Sacramento	-0.08
Louisville	0.25	Dayton	0.06	Dallas	-0.09
Los Angeles	0.25	Seattle	0.05	Atlanta	-0.10
Baltimore	0.24	Denver	0.05	San Antonio	-0.10
Minneapolis	0.22	Aurora	0.04	Portland	-0.11
Sarasota	0.20	Bakersfield	0.04	Forth Worth	-0.13
San Diego	0.19	Pittsburgh	0.04	New Orleans	-0.14
Saint Petersburg	0.17	Orlando	0.04	Columbus	-0.15
Cleveland	0.19	Houston	0.03	Charlotte	-0.17
Hialeah	0.16	Stockton	0.01	Overland Park	-0.18
San Francisco	0.16	Ogden	0.00	Colorado Springs	-0.20
Norfolk	0.15	Saint Louis	0.00	Oklahoma City	-0.21
Phoenix	0.15	Oakland	-0.01	Austin	-0.25
Grand Rapids	0.14	Omaha	-0.02	Las Vegas	-0.30
San Jose	0.14	Tampa	-0.02		
Fort Lauderdale	0.14	Des Moines	-0.02		