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Comparing Housing Rents in Cities Around the World: Can an Airbnb Big-Mac Index Help?

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Paper prepared for the 38th IARIW General Conference
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Session 4B-2, Inequality and Housing: Measuring Housing Affordability Challenges II

Time: Wednesday, August 28, 2024 [16:00-17:30 GMT]

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Evaluation of Natural Capital (Renewable and Non-Renewable) and its Contribution to the GDP And TFP Growth of Selected Developing Countries

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Comparing Housing Rents in Cities Around the World: Can Airbnb Help?

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Abstract:
Housing rents are one of the most important and difficult elements of spatial cost of living comparisons. Difficulties arise from the lack of sufficiently detailed and harmonized data, especially at the international level. The emergence of Airbnb has created a valuable new source of internationally harmonized, micro-level rental data that can help circumvent these difficulties. In this paper, we combine hedonic regression and multilateral price index methods to construct an Airbnb spatial rent index for 60 cities across Europe, the Americas, Asia, Africa, and Australia. We then use this index to investigate five main issues: (i) How Airbnb rents differ across cities; (ii) The relationship between Airbnb and long-term rents; (iii) How Airbnb rent indices can be used to improve long-term rent indices; (iv) Exploring the key role that rents play in determining spatial price differences across cities; (v) Showing how spatial differences in housing affordability across cities depend crucially on the extent to which the rents are quality adjusted. (JEL. C21; C43; L85; R31; R52; Z32)

Keywords: Spatial hedonic rent index; City-level comparison; Airbnb rent premium; Housing affordability; Cost of living

This paper has been presented at the International Comparisons Conference in Groningen (May 15-16, 2023), the ESCoE annual conference in London (May 18-20, 2023), the International Statistical Institute Conference in Ottawa (July 16-20, 2023), the CEPA workshop at University of Queensland (November 22-24, 2023), the Economic Measurement Workshop at Hitotsubashi University (January 18, 2024) and at departmental seminars at University of Sydney (October 11, 2023) and University of New South Wales (December 13, 2023). We thank participants at these conferences/seminars for their comments.

1 Introduction

> "The cost of shelter is the single most important component of interarea differences in the cost-of-living." (Moulton, 1995)

Spatial cost-of-living comparisons are needed to measure poverty rates, real incomes, price levels, and the relative size of economies. Housing rents are one of the most important but most difficult elements of such comparisons. The difficulty stems from the lack of sufficiently detailed and internationally comparable housing data. Micro-level rental datasets typically include few property characteristics, which also tend to differ across countries (and sometimes even within countries). Furthermore, depending on the country, rents may or may not include taxes, strata, heating, subsidies and maintenance costs. Freely available harmonized micro-level Airbnb data can help overcome these difficulties.

In this paper, we address a number of issues related to international city-level comparisons of housing rents. First, we construct spatial Airbnb rent indices for 60 cities across Europe, the Americas, Asia, Africa, and Australia. We find, for example, that quality-adjusted Airbnb rents in the most expensive city – San Francisco – are 55 percent higher than in London and five times higher than in Mexico City. Also, Airbnb rents increase at an average rate of $69 per week for every $10 000 increase in per-capita income.

Second, we compare short-term Airbnb rents with long-term rents obtained from a crowd-sourcing website (Numbeo) and from the International Service for Remuneration and Pensions (ISRP). This comparison reveals that the Airbnb rent premium (the percentage difference between short- and long-term rents) is higher in cities with lower income levels. This result is much more pronounced for Numbeo than for ISRP long-term rents. We consider some possible explanations for this finding.

Third, we show how our Airbnb rent index can be used to optimally combine the Numbeo and ISRP long-term rent indices. This strategy is based on an errors-in-variables approach proposed by Pinkovskiy and Sala-i-Martin (2016, 2020).

Fourth, with this combined long-term spatial rent index, we demonstrate the pivotal role rents play in determining the price level. We find that a 1% increase in rents in a city raises its overall price level by about 0.65% relative to other cities. It follows that omitting rents in cross-city international cost-of-living comparisons – as, for example, in the Economist-Intelligence Unit city-level comparison (Nakamura et al., 2021) – could lead to significant mismeasurement of spatial cost-of-living differences.

Fifth, our results shed new light on the topic of housing affordability. A standard metric for comparing housing affordability is the rent/income ratio. We find that housing affordability based on raw rent/income ratios is broadly stable across our international sample of cities. This finding is consistent with the within-country results of Davis and Ortalo-Magné (2011) for the US, and with the common assumption in the academic literature of a unit elasticity of substitution between consumption of goods and housing. However, in a spatial context, a comparison of rent/income ratios depends crucially on the extent to which rent differences are quality adjusted. This is a point that has not received enough attention in the literature. When we use quality-adjusted rents, we find that housing affordability is clearly worse in poorer cities. This is consistent with the higher prevalence of informal housing and slums in poorer cities which Brueckner and Lall (2015) interpret as a symptom of the lack of affordability.

Our final contribution is methodological. To construct our Airbnb spatial rent index, we combine hedonic regression, applied at a bilateral level between pairs of countries, with a multilateral method from the price index literature. Our multilateral hedonic method avoids the problem of representativeness bias that arises from estimating the hedonic model directly over the full sample of cities.

Our results are relevant to a number of literatures. First, the International Comparisons Program (ICP) calculates purchasing power parity (PPP) exchange rates for almost every country in the world (World Bank, 2020).[1] Pinkovskiy and Sala-i-Martin (2020) describe the

[1]These PPP exchange rates are used to measure poverty and inequality, monitor progress toward the United Nations Sustainable Development Goals, determine the relative size of economies, construct the Penn World Table, and in cross-country growth regressions. See Feenstra, Inklaar, and Timmer (2015) on the Penn World Table; Deaton (2010), Milanovic (2012), and Majumder, Ray, Santra (2018) on poverty and inequality; Hamadeh et al. (2022) on the Sustainable Development Goals; Ravallion (2018) on the size of economies; and

ICP's development of PPP exchange rates as "one of the defining achievements of economic measurement." However, large international differences in housing quality and the lack of harmonized international data sets make rent comparisons one of the most challenging components of ICP comparisons (Heston, 2020). Additionally, ICP rent comparisons are made only at the national level, whereas in many economic applications, city-level comparisons would be preferable.

Empirical comparisons of housing costs at the city level are relevant to several subfields of urban economics. Interest in the economies and diseconomies of agglomeration dates back at least to Marshall (1920). According to the so-called fundamental trade-off of urban economics, city size increases until the benefits of agglomeration are offset by associated congestion costs (Glaeser and Gottlieb, 2009; Desmet and Rossi-Hansberg, 2013; Fujita and Thisse, 2013; Combes, Duranton and Gobillon, 2019). While other factors, such as traffic and pollution are relevant, high rents (real and imputed) are probably the most important factor limiting city size. Therefore, reliable empirical rent comparisons across an international sample of cities are needed to calibrate city size distribution models in a multinational setting.

Housing rents also help us resolve the apparent contradiction between the increasing returns arising from agglomeration externalities and the observed steady long-run growth path of economies. As a major component of the congestion costs associated with agglomeration, housing rents hence play a key role in determining and limiting not only the size of cities, but even the long-run rate of economic growth (Rossi-Hansberg and Wright, 2007). Lucas (1988) puts it this way:

> [T]he 'force' we need to postulate to account for the central role of cities in economic life is of exactly the same character as the 'external human capital' I have postulated as a force to account for certain features of aggregative development. If so, then land rents should provide an indirect measure of this force. (Lucas, 1988, pages 38-39)

The relationship between rents and incomes across cities is another key issue in urban eco-

Barro (1991) and Johnson and Papageorgiou (2020) on cross-country growth regressions.

nomics. Urban models that include housing and non-housing consumption in the utility function often assume a Cobb-Douglas functional form (Eeckhout, 2004; Michaels, Rauch, and Redding, 2012; Guerreiri, Hartle, and Hurst, 2013; Berger et al., 2018). Cobb-Douglas utility functions imply that the share of housing expenditures does not vary across cities. The empirical literature essentially confirms this prediction for within-country comparisons (Davis and Ortalo-Magné, 2011). However, much less is known about how the rent/income ratio varies across cities internationally. We contribute to this literature by extending the empirical evidence to an international sample of cities. We also show how the results of such comparisons depend crucially on the extent to which rents are quality adjusted across cities.

Finally, our paper relates to the literature on spatial hedonic methods. This literature is not as well developed as the literature on temporal hedonic methods, although recently progress has been made on within-country comparisons. For example, the Bureau of Economic Analysis (BEA) computes spatial house price and rent indices for all Metropolitan Statistical Areas (MSAs) in the United States using the multilateral hedonic city dummy method. However, this method may be subject to representativeness bias, as the estimated characteristic shadow prices may better represent the actual characteristic prices in some cities than in others. Therefore, we prefer the bilateral hedonic city dummy method GEKS, where GEKS is the method used by the ICP to transitivize bilateral indices (World Bank, 2020).[2]

The remainder of the paper is organized as follows. Section 2 consists of a literature review. Section 3 presents our methodology for estimating hedonic rent indices for the Airbnb dataset. Section 4 introduces the two long-run rental datasets and explains the error-in-variables approach for combining our long-term rent indices using weights derived from the Airbnb rent indices. Our main results and applications are presented in Section 5, followed by the conclusion in Section 6.

[2]Hedonic methods have previously been combined with GEKS in the scanner data literature to construct temporal price indices (Ivancic, Diewert, and Fox, 2011; De Haan and Krsinich, 2014; Melser 2018; Diewert and Fox, 2022). The situation here is somewhat different, as the main rationale in the scanner data literature for using multilateral methods is to prevent temporal drift in the price index.

2 Literature Review

The literature on international housing cost comparisons consists of three main strands. The first deals with housing cost comparisons as part of broader international price comparisons, the second with cost-of-living comparisons between international cities conducted by large private firms, and the third with academic studies of differences in rents and housing affordability across cities. We discuss each of these strands below.

The World Bank, the United Nations, the OECD, and Eurostat all conduct international price comparisons to calculate PPP exchange rates between countries. Although actual or imputed housing rents are only one component of these comparisons, they are a particularly important one because of their large expenditure share. The methodology used by these international organizations to compare rental costs is well documented. For example, Eurostat and the OECD conduct an annual rent survey among National Statistical Offices, which identifies a fixed number of rent strata (or cells) for which member countries should provide information (see OECD/Eurostat, 2012). For each such stratum (cell), each country is asked to provide an average rent per square meter and the average square meter size for properties of that type (e.g., a 1-2 bedroom apartment with central heating). All participating countries use the same list of cells, so it is relatively easy to calculate an overall rent index from this dataset. These cells are then weighted according to their relative expenditure shares.

The comparison of rents in the World Bank's ICP calculations is more complicated due to the greater heterogeneity at the global level. For this reason, the ICP is divided into 6 regions (Africa, Asia-Pacific, Eurostat-OECD, CIS, Latin America, and West Asia) (World Bank, 2020). Separate comparisons are made for each region, and these regional comparisons are then linked to obtain the overall global comparison. In some regions, rent surveys are not considered sufficiently reliable, requiring an indirect approach that calculates a housing price index by dividing total housing expenditure by a quality-adjusted quantitative measure of the housing stock (Heston, 2020). While these international rent comparisons follow a clear and well-documented structure, it is not always clear how reliable and internationally consistent the source data provided by individual countries are.

Once calculated, these PPP exchange rates are used in many contexts. For example, the ICP's PPP exchange rates are used in the World Bank's World Development Indicators, the IMF's World Economic Outlook, the Penn World Table (see Feenstra, Inklaar, and Timmer 2015), and the United Nations Human Development Index (HDI) (World Bank, 2020). The ICP methodology is described in World Bank (2020). In addition, these PPP exchange rates are used by the World Health Organization (WHO) and the United Nations Educational, Scientific, and Cultural Organization (UNESCO) to measure regional and global poverty levels and to compare spending on health and education, respectively, across countries (Rao, 2013). The IMF uses PPP exchange rates to calculate its Special Drawing Rights (SDRs), which determine member countries' budget contributions and voting rights (Silver, 2010). UN PPP exchange rates are used to adjust the salaries of UN staff worldwide.[3] In the European Union, PPP exchange rates are used to determine the budget contributions of member countries (OECD/Eurostat, 2012).

We now turn to the second type of international housing cost comparison, which focuses on international rent comparisons at the city level. These comparisons are typically conducted by large private companies with the expat community in mind. For example, Deutsche Bank (2019) uses data from the online crowd-sourcing platform Expatistan to compare rents in 55 cities around the world.[4] We use data from Numbeo, another international crowd-sourcing platform, which lists rents and prices for about 400 cities worldwide.[5] Deloitte (2019) compares transaction prices per square meter in 48 European cities, using data collected by individual Deloitte offices in selected countries. The Economist Intelligence Unit (EIU) conducts a biennial global survey of the cost of living, including residential rents, and produces the EIU Cost of Living Index, which covers more than 130 cities worldwide.[6]

These comparisons typically focus on properties of a particular type (e.g. 2-bedroom apart-

[3] https://icsc.un.org/Home/PostAdjustment).

[4] https://www.expatistan.com

[5] https://www.numbeo.com

[6] The EIU index is derived from survey data, and users must pay a fee to access the results. Although the EIU collects rental data, it is not included in the EIU Cost of Living Index. See the following website for further details: https://www.eiu.com/n/campaigns/worldwide-cost-of-living-2023/.

ments in the city center) and then calculate the average price for that type in a city. The methodology used to construct spatial rent indices is usually not made publicly available. As a consequence, it is often unclear what types of properties are considered, how the averages are formed (i.e., whether they are median, arithmetic mean, geometric mean, or other values), and in what form the data are available (i.e., whether they are asking rents, actual rents, or estimates by real estate agents).

The third part of the literature on rent comparisons concerns academic studies. Most of these academic studies focus on rent differences between cities in the same country. For example, several papers compare rents in US cities, often as part of broader cost-of-living comparisons. The American Community Survey estimates median rent and median gross household income for 355 metropolitan areas (Edmiston, 2016). This makes it possible to compare average housing affordability across cities. Edmiston finds large differences in affordability across cities, with affordability improving over time in some cities and decreasing in others. Other city-based comparisons include rent as a component, such as the American Chamber of Commerce Research Association (ACCRA) index (see https://resources.acce.org/benchmarking) or the study by Aten (2006). Looking specifically at rent differences across cities has yielded some important economic insights. For example, a study by Moretti (2013) suggests that the wage gap between skilled and unskilled workers has not widened as much as previously thought, once the higher rents in cities with a higher concentration of skilled workers are taken into account. There are very few academic studies that focus specifically on comparing housing costs at the city level. One example is Kallergis et al. (2018), although they focus on prices rather than rents.

Regarding Airbnb, several studies have made comparisons across multiple cities. However, these studies generally do not focus on actually comparing Airbnb rental costs. For example, Wang and Nicolau (2017) use data from 33 cities to determine which features are most valued by guests. Jiao and Bai (2020) use data from 40 cities to examine which neighborhoods Airbnb properties tend to be located in. Yang and Mao (2019) use data from 28 cities to identify the factors that most influence the supply of Airbnb rentals. We did not find a single paper that focuses specifically on comparing how Airbnb rents differ across cities.

3 Airbnb Rents Across Cities

In this section we construct Airbnb spatial rent indices for our sample of 60 cities using hedonic regression methods.

3.1 The Airbnb dataset

We use Airbnb rental listings from the *Inside Airbnb* website created by Murray Cox.[7] Our focus is on weekly apartment rentals in 60 cities worldwide in 2019, the most recent year without Covid-19 distortions.[8] We remove Airbnb listings that have never received a review and may therefore not be active. If properties appear multiple times in the dataset, we randomly select one of the listings. We also exclude studio apartments and those with more than four bedrooms or three bathrooms which increases consistency with the long-term Numbeo and ISRP rental data that consist of one- to three-bedroom apartments. In addition, we remove the top and bottom 1 percent of the weekly rent distribution to exclude atypical properties and data entry errors. Finally, we eliminate all properties that are not located within 30 km of the city center. After these steps, our dataset consists of 407 773 rental observations for the year 2019 across 60 cities.[9]

Hosts often include a cleaning fee in their Airbnb listings. However, the split between the rent and cleaning fee is purely notional, as renters must pay the total amount - rent plus cleaning fee - regardless of how these costs are classified. Thus, we focus on the total amount paid by the customer (the sum of the rent and the cleaning fee), but subtract the three percent fee that Airbnb charges hosts on the sum of the rent and the cleaning fee. fee.[10]

[7] `http://insideairbnb.com`

[8] We concentrate on whole-apartment rentals in our analysis.

[9] More details on the Airbnb dataset are provided in Table A1 in Appendix A.

[10] Inclusion of this fee, however, would not bias our spatial Airbnb rent indices, as the rate is the same across cities.

3.2 Hedonic rent indices

3.2.1 The multilateral city-dummy method

As a first step, we convert all rents to US dollars using market exchange rates (MER) (World Bank, 2022). A simple starting point is to compare median rents. However, this is not ideal as it confounds actual rent differences with differences in the quality of the median properties across cities. Hedonic methods provide a way to compute quality-adjusted spatial rent indices. A hedonic model regresses the price (here rent) of a property on its observed characteristics. The hedonic equation itself is a reduced form resulting from the interaction of supply and demand (Rosen, 1974). There are a number of methods for constructing quality-adjusted price indices from the estimated hedonic model.

In the following sections, we consider two hedonic methods for calculating quality-adjusted spatial rent indices for cities: the multilateral city dummy method and the GEKS city dummy method. Calculating two sets of hedonic indices provides a robustness check. The multilateral city dummy hedonic model estimates a semi-log hedonic model for the entire dataset. The log rent of a property is regressed on the observed physical characteristics.[11] A dummy variable is included for each city in the dataset. This method is a spatial variant of the time dummy method (see Melser, 2005 and Diewert, 2007).

$$\ln(r_n) = \sum_{c=1}^{C} \beta_c x_{cn} + \sum_{k=1}^{K} \delta_k d_{kn} + u_n, \tag{1}$$

where r_n is the daily Airbnb rent for property n.[12] The characteristics in the hedonic model (e.g., number of bedrooms or number of bathrooms) are indexed by $c = 1, \ldots, C$. The cities in the comparison are indexed by $k = 1, \ldots, K$. The level of characteristic c for property n is given by x_{cn}, while d_{kn} is a dummy variable. The parameters to be estimated are the characteristic shadow prices, β_c and the shadow prices on the city dummies, δ_k. The term u_n

[11] See Diewert (2003) and Malpezzi (2008) for a discussion of some of the advantages of the semi-log functional form.

[12] We focus on daily rather than weekly rents since daily rents are available for more properties. When comparing Airbnb with long-term rents in section 4 and section 5, we convert the daily Airbnb rents to weekly using the average scaling factor derived from properties that provide both daily and weekly rents.

is a random error.

We obtain the rent index for city k relative to the base city (here San Francisco) by exponentiating its estimated city shadow price:

$$R_k = \exp(\hat{\delta}_k).$$

The rent indices are invariant to the choice of base city up to a constant of proportionality.

3.2.2 The GEKS city-dummy method

One potential concern with the multilateral city dummy method is that it relies on a single vector of shadow prices $\hat{\beta}_c$ to compute the price indices of all cities. This can lead to a representativity problem, as this vector of shadow prices is inevitably more representative of some cities than of others. For this reason, we also consider a second hedonic method that constructs the multilateral comparison from bilateral city dummy comparisons between pairs of cities. In the bilateral version, the hedonic model is estimated as follows:

$$\ln(r_n) = \sum_{c=1}^{C} \beta_c x_{cn} + \delta d_n + u_n \tag{2}$$

where now there is only one city dummy variable, d_n. For example, in a comparison between London and Geneva with London as the base, the city dummy equals 1 for property n if it is in Geneva, and 0 if it is in London. The rent index for Geneva with London normalized to 1 is obtained by exponentiating the estimated shadow price on the city dummy:

$$R_{Gen} = \exp(\hat{\delta}). \tag{3}$$

The question now is how to link these bilateral comparisons. The star city dummy method does this by selecting a base city and performing bilateral comparisons between it and each of the other cities in the comparison. The underlying structure of this system is a star-shaped comparison with the base city at the center of the star. One problem with this star-city-dummy method is that the resulting indices are not invariant to the choice of base city. This problem is part of a more general problem, namely that the bilateral city-dummy indices are not transitive (i.e., $P_{jk} \times P_{kl} \neq P_{kl}$). We can solve the intransitivity problem by discarding all but $K - 1$ of the possible bilateral comparisons (where the set of cities are still connected).

The star-city dummy method is one such solution.

However, a better solution is the GEKS method used by the ICP to transitivize bilateral Fisher price indices (World Bank, 2020). When the bilateral city dummy method is combined with GEKS, the results are base-city invariant method, transitive and unaffected by representativity biases (see Diewert, 1999, for a more detailed discussion of the properties of GEKS).[13]

$$\frac{R_k}{R_1} = \left[\prod_{j=1}^{K}\left(\frac{R_{jk}}{R_{j1}}\right)\right]^{1/K}, \tag{4}$$

where R_{jk} denotes a bilateral city-dummy rent index between cities j and k with j as the base. The overall GEKS base in (4) is city 1, although choosing a different base would only rescale all the GEKS rent indices by the same factor. In essence, the GEKS method makes K separate bilateral city-dummy star comparisons, each placing a different city at the star's center. GEKS then takes the geometric mean of these K star comparisons. The resulting method, therefore, treats all cities symmetrically.

A further problem with spatial hedonic comparisons is that the number of observations can vary widely from one city to another. If not handled carefully, such differences in the number of properties can bias the results. To ensure that each city receives equal weight in each hedonic model, we rescale the observations in each city to equal that of the city with the most observations. We do this rescaling using random sampling with replacement. For example, since Paris has 2.4 times as many properties as Geneva, in a bilateral city-dummy comparison, the Geneva dataset is scaled up by a factor of 2.4 before estimating the hedonic model. In the multilateral city-dummy comparison, London has the most data (12.8 times more observations than Geneva and 5.6 times more than Paris). Therefore, before estimating the multilateral city dummy model, we rescale both the Geneva and Paris datasets to match the number of observations in the London dataset.

Another issue concerns the treatment of location in the hedonic models. We construct inner, middle and outer rings for each city. These rings could be defined on an absolute scale,

[13] As was noted above, temporal versions of GEKS are also combined with hedonic methods in the scanner data literature (Ivancic, Diewert and Fox, 2011; De Haan and Krsinich, 2014; Melser, 2018; Diewert and Fox, 2022).

measured in kilometers, or on a relative scale (e.g., by construction for each city, one-third of the properties are placed in each ring). The problem with an absolute scale is that in a large city, a much larger proportion of properties will be in the outer ring. If this city also tends to be expensive (e.g. London), this can have a perverse effect on the location dummy variables, especially in a bilateral city-dummy comparison. In particular, the outer ring may end up with the highest estimated shadow price due to the fact that it has the highest proportion of London properties (which are on average more expensive). For this reason, we prefer a relative approach. The inner, middle, and outer rings of each city are constructed so that exactly one-third of the properties are in each ring. This structure ensures that the location dummy variables better capture the location price gradient as one moves away from the city center.

3.3 Estimated spatial Airbnb rent indices

The functional form of the hedonic models is semi-log. The characteristics included are as follows:

Dependent variable: Log weekly rent

Explanatory variables: Constant; Dummy for city; Dummy for number of bedrooms; Dummy for number of bathrooms; Dummy for quarter of year; Dummy for professional landlord; Dummy for superhost; Dummy for inner, middle and outer ring of city; Washing machine (yes, no), dryer (yes, no), dishwasher (yes, no); Wifi (yes, no); Laptop friendly workspace (yes, no); Gym (yes, no); Bathtub (yes, no); Paid parking off premises (yes, no); Patio or balcony (yes, no).

It is important to note that our objective here is to construct quality-adjusted Airbnb rent indices, not to explain how and why Airbnb rents differ across cities. For example, the inclusion of per capita GDP and some measure of tourism intensity in the hedonic model would increase the adjusted R-squared. However, per capita GDP and tourism intensity are not themselves quality characteristics of Airbnb properties. Therefore, they should not be included in the hedonic model if the objective is quality adjustment rather than explaining Airbnb rents.[14]

The results are shown in Table A2 in Appendix A. The R^2 of the multilateral city-dummy hedonic model is 0.57. All estimated coefficients are highly significant and the coefficients on the characteristics all have the expected signs.

The hedonic and median spatial rent indices for 2019 are shown in Figure 1. The base is Washington DC.[15] The results for the multilateral city dummy and the GEKS city dummy are very similar, suggesting that the hedonic results are quite robust to the choice of method. In contrast, the median results differ substantially in some cases. In particular, the median rental prices for Mexico City, Valencia, Malaga, Girona, Rio de Janeiro and Barcelona are all higher than their hedonic quality-adjusted counterparts. When the median rental price is higher, it indicates that the median Airbnb rental in that city is of higher quality (based on the observable characteristics - such as the number of bedrooms and bathrooms). Conversely, the median rental price in Oslo, Brussels, Antwerp, Bordeaux, Lyon, Geneva, Copenhagen, Berlin, Stockholm, Milan, Paris, Munich, and Amsterdam are all lower than their hedonic quality-adjusted counterparts, indicating lower quality median properties.

[14] The same argument applies to data on hotel room availability.

[15] We chose Washington DC as the base as it is one of only two US cities in all the datasets considered here - the other being New York. We prefer Washington DC because its coverage is more homogeneous across the datasets.

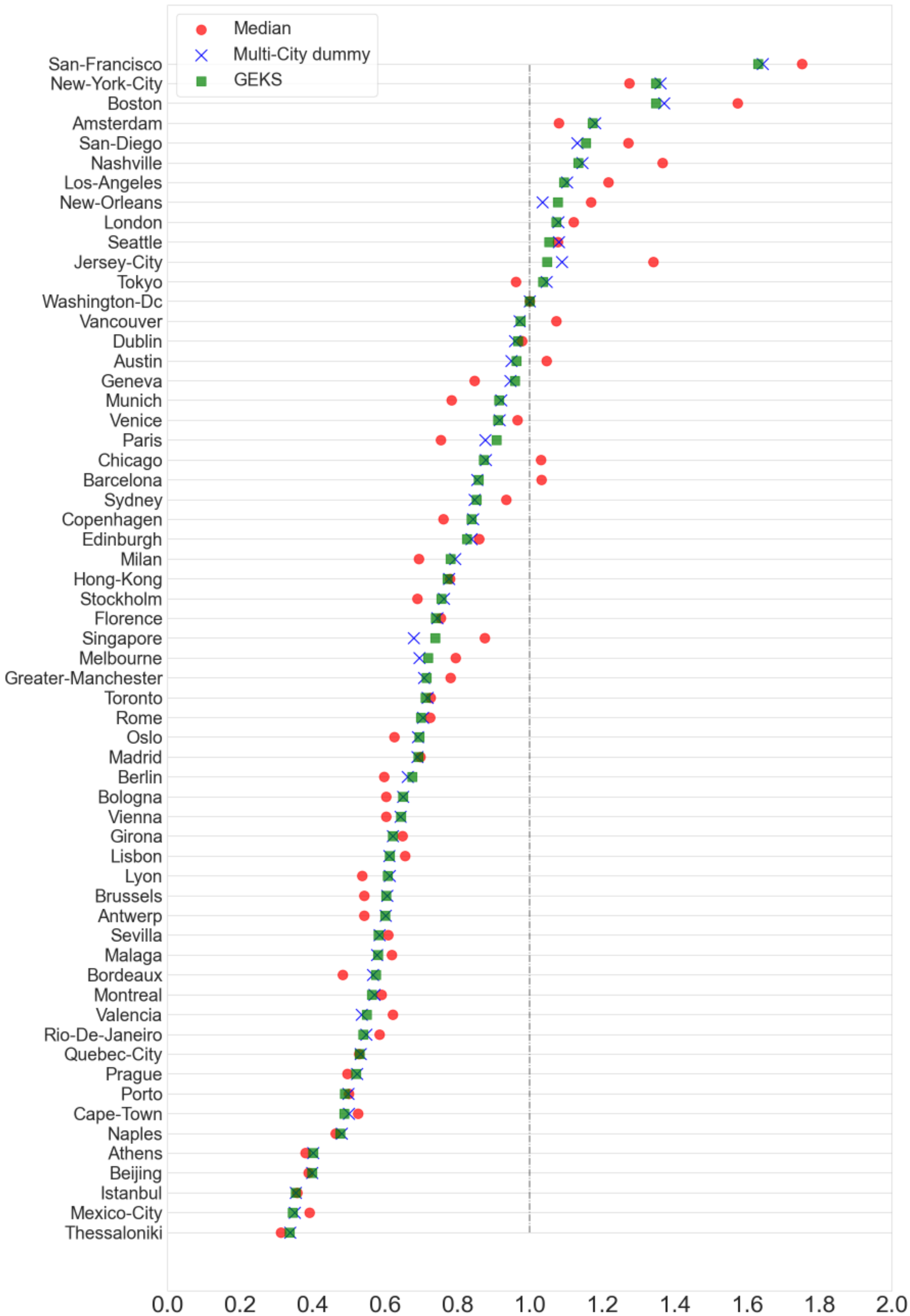


Figure 1: Airbnb Rent Indices (washington DC = 1)

Note: Figure 1 shows for 60 cities the spatial rent index based on median price, hedonic multi-city, and GEKS city dummy methods, in all cases with Washington DC = 1.

Focusing on our preferred GEKS-city-dummy results in Figure 1, we find, for example, that quality-adjusted Airbnb rents in the most expensive city – San Francisco – are about 55 percent higher than in London and five times higher than in Mexico City (see also Table A3 in Appendix A). Also, the rental price rises at an accelerating rate as one moves from the cheaper end of the distribution towards the more expensive end.

4 Combining Rent Indices

In this section we show how Airbnb rent indices can be used to optimally combine long-term rents from Numbeo and the International Service for Remuneration and Pensions (ISRP). The approach used is based on an errors-in-variables method proposed by Pinkovskiy and Sala-i-Martin (2016, 2020).

4.1 Long-Term Rental Data Across Cities

4.1.1 The Numbeo dataset

Numbeo is a crowd-sourced international database of housing and other quality-of-life indicators.[16] Numbeo provides median rents for the 60 cities in our Airbnb dataset for the following categories:

Apartment (1 bedroom) in City Center; Apartment (1 bedroom) Outside of Center; Apartment (3 bedrooms) in City Center; Apartment (3 bedrooms) Outside of Center.

Here we compute the average weekly Numbeo rent for each city k as the geometric mean of these four medians:[17]

$$Numbeo_k = (Numbeo_{k1}^{in} \times Numbeo_{k3}^{in} \times Numbeo_{k1}^{out} \times Numbeo_{k3}^{out})^{1/4}, \tag{5}$$

where $Numbeo_{k1}^{in}$ denotes the median rent for 1-bedroom apartments in the city center in city k, $Numbeo_{k3}^{in}$ is the median rent for 3-bedroom apartments in the city center, $Numbeo_{k1}^{out}$

[16] https://www.numbeo.com/cost-of-living/

[17] The Numbeo rents are reported on a monthly basis. We convert them to weekly rents by multiplying by $365/(7 \times 12)$.

is the median rent for 1-bedroom apartments outside the city center, and $Numbeo_{k3}^{out}$ is the median rent for 3-bedroom apartments outside the city center. Numbeo rents are provided in domestic currency. We convert them into US dollars using market exchange rates from the World Bank (2022).

4.1.2 The International Service for Remuneration and Pensions (ISRP) dataset

Each year the International Service for Remuneration and Pensions (ISRP) together with Eurostat publishes a report that compares rents across a sample of cities. The rent estimates are obtained from surveys of real estate agents. The ISRP report describes its focus as follows:

> Real estate agents are asked to provide the monthly rent for various types of accommodation, excluding charges and utilities, for an unfurnished property. The quality of the accommodation should be good to very good, but not luxurious. (International Service for Remuneration and Pensions, 2020, page 2)

The types of properties covered are 1-bedroom apartments, 2-bedroom apartments, 3-bedroom apartments, non-detached houses and detached houses. The report goes on to describe the neighborhood selection process as follows:

> [The selected neighborhoods] are residential areas of good quality, favoured by expatriates and professional people such as international civil servants, university staff, doctors, managers, etc., who pay their rent themselves (i.e. not paid by their employers). (International Service for Remuneration and Pensions, 2020, page 3)

The 2020 report provides rents for 23 of the cities in our Airbnb sample for the year 2019. The 23 Airbnb cities included in the ISRP report are Vienna, Brussels, Prague, Copenhagen, Paris, Lyon, Berlin, Munich, Athens, Dublin, Rome, Lisbon, Madrid, Stockholm, London, Oslo, Geneva, Montreal, Mexico City, Washington DC, New York, Tokyo, and Singapore.

Here we compute the average weekly ISRP rent for each city k as the geometric mean of three averages:[18]

$$ISRP_k = (ISRP_{k1} \times ISRP_{k2} \times ISRP_{k3})^{1/3}, \tag{6}$$

where $ISRP_{k1}$ denotes the average rent for 1-bedroom apartments in city k, $ISRP_{k2}$ is the average rent for 2-bedroom apartments, and $ISRP_{k3}$ is the average rent for 3-bedroom apartments. Again, ISRP rents are provided in domestic currency. We convert them into US dollars using market exchange rates from the World Bank (2022).

4.2 Optimal linear combinations of spatial rent indices

Pinkovskiy and Sala-i-Martin (2016, 2020) propose an error-in-variables method for optimally combining different per capita income series using nighttime satellite illumination intensity as a benchmark. Their 2016 paper uses satellite data to optimally combine per capita income data from two sources - National Accounts and household surveys (both initially converted to US dollars using PPPs). Their 2020 paper again relies on satellite data as a benchmark to determine the optimal per capita income series from PPP and MER-converted series. The objective is to find the linear combination of the available per capita income series that predicts actual income with the lowest mean squared error.

Here, we employ the Pinkovskiy and Sala-i-Martin method to combine the long-term Numbeo and ISRP rent indices into a composite index for the 23 cities in the ISRP dataset that are also in our Airbnb dataset. We use the short-term Airbnb rent index to determine the optimal weights for combining the long-term rent indices.

Let $R_k^* = \ln Rent_k^*$ denote the true underlying long-term rent in city k, while the Airbnb, Numbeo, and ISRP series are denoted by $A_k = \ln Airbnb_k$, $N_k = \ln Numbeo_k$, and $S_k = \ln ISRP_k$. We assume that the Airbnb, Numbeo, and ISRP indices are related to the true underlying rent as follows (ignoring constants and controls):

$$A_k = \beta_A R_k^* + \varepsilon_{Ak}, \tag{7}$$

[18]The ISRP rents are again reported on a monthly basis. We convert them to weekly rents by multiplying by $365/(7 \times 12)$. Also, the ISRP report (International Service for Remuneration and Pensions (2020) does not say whether these averages are medians, arithmetic means or geometric means.

$$N_k = \beta_N R_k^* + \varepsilon_{Nk}, \quad (8)$$

$$S_k = \beta_S R_k^* + \varepsilon_{Sk}. \quad (9)$$

In this setting, Pinkovskiy and Sala-i-Martin make three further assumptions. Translated into our context, the first assumption is that

$$(A1) \qquad Cov(R_k^*, A_k) > 0.$$

For this assumption to be plausible, the Airbnb rent indices should be positively correlated with each of the observed long-term rent indices.

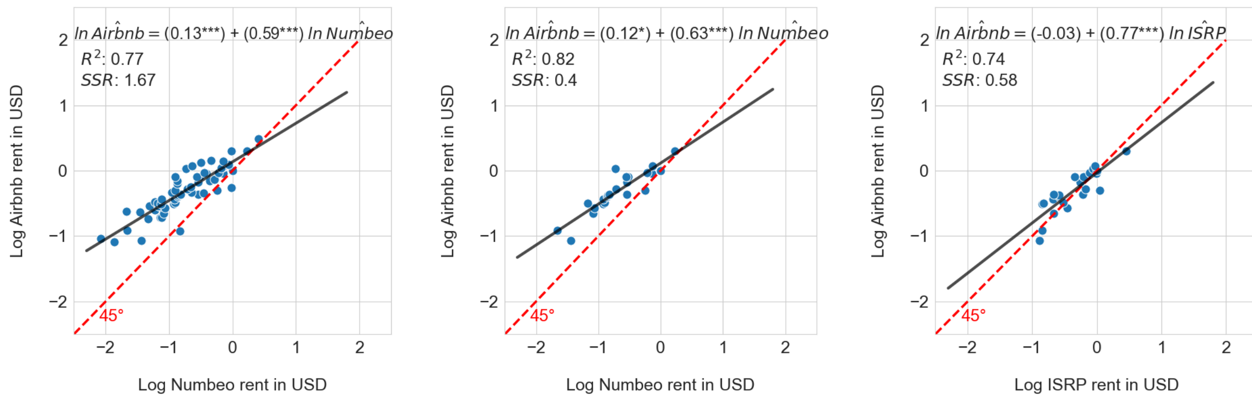
The correlation between Airbnb and Numbeo rents is 0.865, while the correlation between Airbnb and ISRP it is 0.619. The positive correlations and the largely linear relationship between Airbnb rent indices and each of the two long-term rent indices can be seen in Figure 2. These positive correlations are to be expected given that all three series measure rents.[19]

The second assumption is that the conditional expectation of each of the log measures (i.e., Airbnb, Numbeo, and ISRP rents) is linear in the log of the true underlying rent.

$$(A2) \qquad E(\varepsilon_{A_k}|R_k^*) = 0, \quad E(\varepsilon_{N_k}|R_k^*) = 0, \quad E(\varepsilon_{S_k}|R_k^*) = 0.$$

The scatter plots in Figure 2 provide support for this assumption. The plots show that the relationship is largely linear when two of the three observed series are plotted against each other in logarithmic form. Since they are all linear with respect to each other, this suggests that they are also linear with respect to the true underlying rent.

[19]The correlation between our three rent series is much higher than the correlation between the three measures of per capita GDP used by Pinkovskiy and Sala-i-Martin (2016) (i.e., survey-based GDP, national accounts GDP, and Nightlight satellite data).



(a) Airbnb against Numbeo Rent (60 cities) (b) Airbnb against Numbeo Rent (23 cities) (c) Airbnb against ISRP Rent (23 cities)

Figure 2: Scatter Plots of Airbnb against Long-Term Rents for 60 Cities

Note: In all three panels and on both axes, the log price in Washington DC is normalized to 0.

The third assumption is that

$$(A3) \qquad E(\varepsilon_{Nk}\varepsilon_{Ak}|R_k^*) = E(\varepsilon_{Sk}\varepsilon_{Ak}|R_k^*) = 0.$$

This assumption states that the Airbnb dataset errors are independent of the errors in the Numbeo and ISRP datasets at any given underlying rent level. Again, this assumption is plausible given that all three datasets were independently constructed.

The optimal weights are derived by regressing the Airbnb rent indices on the Numbeo and ISRP rent indices. We estimate the model with and without control variables. The controls we use are per capita GDP and Airbnb Tourist Density, which is defined as the number of annual visitors to a city divided by the number of available Airbnb rental properties (see Appendix B for sources and further details). In section 5 it is shown that the relationship between Airbnb and long-term rents (at least for Numbeo) depends on per capita GDP. It is plausible that the tourism intensity of a city relative to the supply of Airbnb properties will also affect the relationship between Airbnb and long-term rents. The inclusion of these controls helps to ensure that A3 is satisfied.

Model 1a: Long-term rent (without control variables)

$$\ln Airbnb = \beta_0 + \beta_1 \ln Numbeo + \beta_2 \ln ISRP + \varepsilon.$$

Model 1b: Long-term rent (with controls)

$$\ln Airbnb = \beta_0 + \beta_1 \ln Numbeo + \beta_2 \ln ISRP + \beta_3 \ln PC\_GDP + \beta_4 \ln Airbnb\_Tourism\_Intensity + \varepsilon. \tag{10}$$

The optimal weights for combining the Numbeo and ISRP rent indices are derived from the OLS estimates of β_1 and β_2 in (10). They are $\hat{\beta}_1/(\hat{\beta}_1 + \hat{\beta}_2)$ for Numbeo and $\hat{\beta}_2/(\hat{\beta}_1 + \hat{\beta}_2)$ for ISRP, respectively. It follows that the optimal combined index is constructed as follows:

$$\ln Rent = \left(\frac{\hat{\beta}_1}{\hat{\beta}_1 + \hat{\beta}_2}\right) \ln Numbeo + \left(\frac{\hat{\beta}_2}{\hat{\beta}_1 + \hat{\beta}_2}\right) \ln ISRP. \tag{11}$$

Combined Long-Term Rent index			
Dependent variable is log Airbnb rent			
	No controls		
	(1)	(2)	(3)
Log Numbeo rent		0.627***	0.486**
		(0.064)	(0.152)
Log ISRP rent	0.77***		0.200
	(0.099)		(0.196)
R^2	0.74	0.82	0.83
	incl. p.c. GDP and Airbnb Tourism Intensity		
	(1)	(2)	(3)
Log Numbeo rent		0.559***	0.333
		(0.110)	(0.197)
Log ISRP rent	0.562***		0.277
	(0.116)		(0.201)
R^2	0.83	0.83	0.85

Table 1: Regression results for combined long-term rent index

Note: Our preferred results are from the model including controls in column (3). Asterisks represent significance as follows: * p-value <= 0.05; ** p-value <= 0.01, *** p-value <= 0.001.

From Table 1, our preferred estimates are $\hat{\beta}_1 = 0.333$ and $\hat{\beta}_2 = 0.277$ from the model including per capita GDP as a controls in column (3). Form these estimates we obtain the following weights:

$$\ln Rent = 0.546 \ln Numbeo + 0.454 \ln ISRP. \tag{12}$$

Hence the errors-in-variables approach gives slightly more weight to Numbeo, which is consistent with the higher correlation coefficient between Numbeo and Airbnb rent indices (0.865) than between ISRP and Airbnb rent indices (0.619).

The Airbnb, Numbeo, ISRP and Combined Long-Term rent indices are compared in Figure 3 and in Table A3 in Appendix A.

5 Main Findings and Applications

This section covers four main topics. The first is the relationship between our Airbnb rent indices and per capita GDP. Second, we explore how Airbnb rents compare to long-term rents. Third, we examine how much of the variation in price levels across cities can be explained by rents. Finally, we consider the implications of our rent indices for housing affordability.

5.1 Main findings for Airbnb rents

As can be seen from Figure 1, the multilateral city dummy and the GEKS city dummy methods produce very similar results. We focus on the GEKS city dummy method because it allows the characteristic shadow prices in the hedonic model to vary across cities. Figure 4 shows how the spatial Airbnb rent indices vary with a city's per capita GDP (sources for city-level per capita GDP are discussed in Appendix B). The relationship between Airbnb rent and per capita GDP appears to be approximately linear.

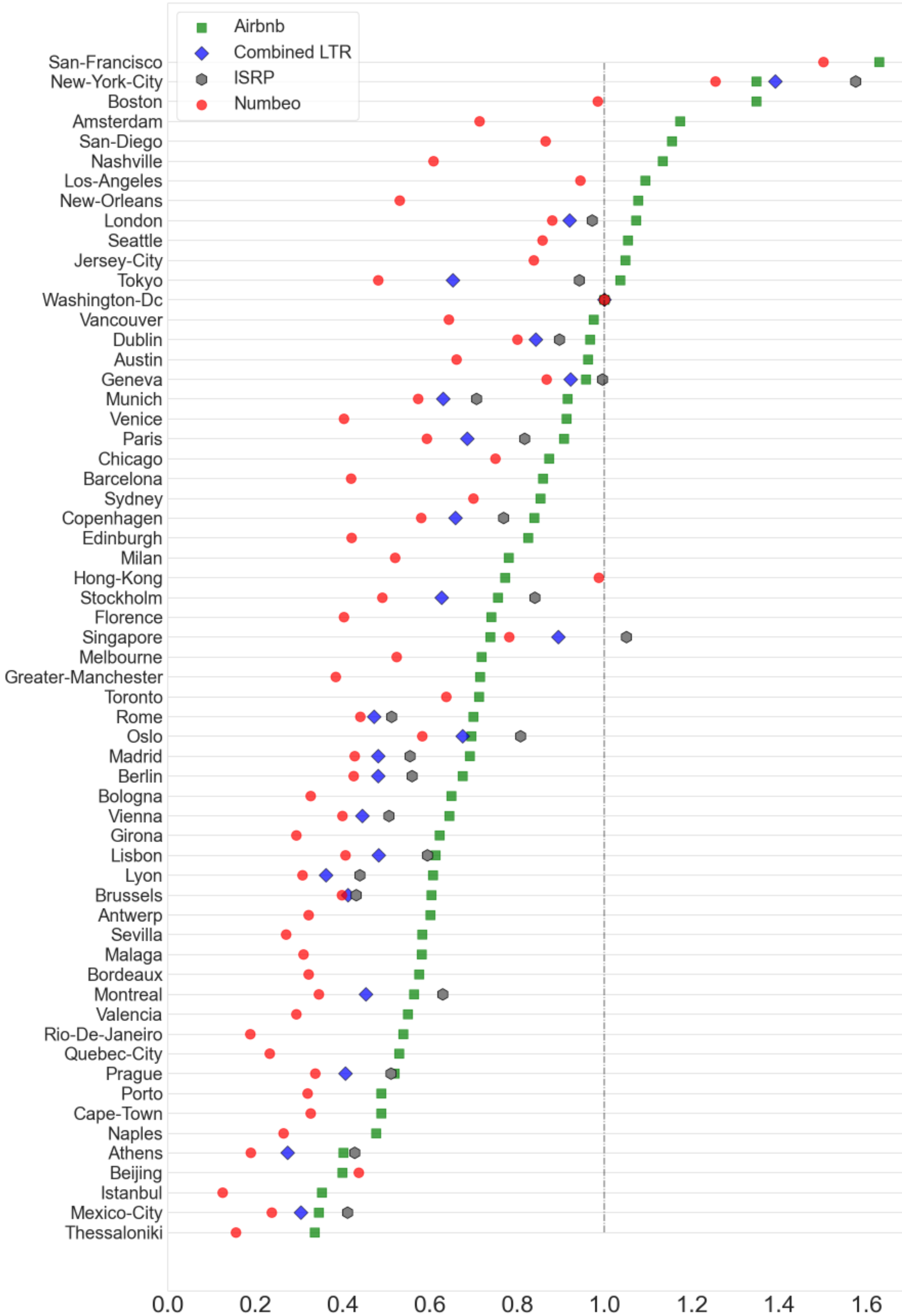


Figure 3: Comparison between the Airbnb and long-term rent indices

Note: Spatial rent indices for Airbnb, Numbeo, ISRP and the Combined index are shown with Washington DC = 1. The full numerical results are presented in Table A3 in Appendix A.

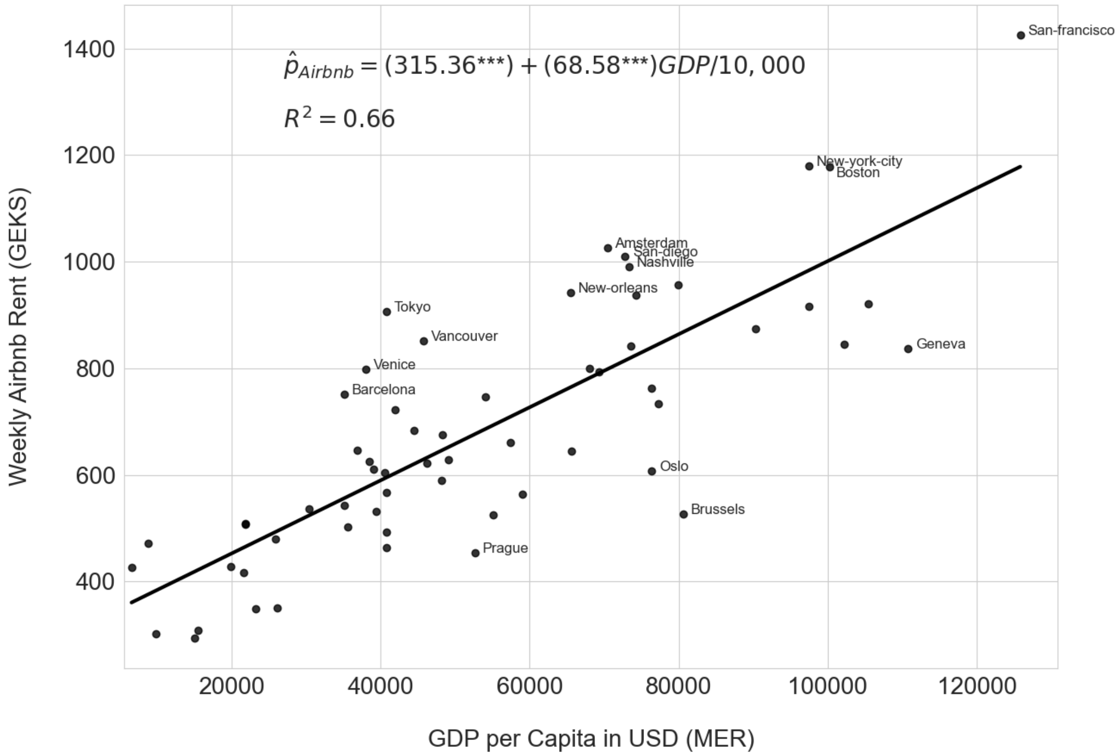


Figure 4: The Relationship Between Weekly Airbnb Rent and Per Capita GDP

Note: The weekly Airbnb rent is calculated by taking the spatial Airbnb rent indices with Washington DC as the base and multiplying them by the median weekly Airbnb rent in Washington DC. Asterisks in the least-squares equation represent significance as follows: * p-value <= 0.05; ** p-value <= 0.01, *** p-value <= 0.001.

Figure 4 shows the relationship between per capita GDP at the city level and weekly Airbnb rent calculated by taking the spatial Airbnb rent indices and multiplying them by the median weekly Airbnb rent in Washington DC. The estimated slope in Figure 4 is 68.6, meaning that Airbnb rent increases by about $69 per week for for every $10 000 increase in per capita GDP.

It is noticeable that Airbnb rents in US cities are higher than predicted by the best-fitting regression lines in Figure 4. This could be because Airbnb originated in the US and has had more time to establish itself there as an alternative to hotels. As a result, controlling for income, demand is higher than elsewhere. Also, the other cities above the Airbnb best-fit line (Barcelona, Venice, Tokyo, London, Vancouver, Amsterdam) are all popular destinations with a relatively long Airbnb presence.

In Table 2, we regress log Airbnb rent on log per capita GDP, log Airbnb penetration, log per capita tourism income, log Population, a US dummy and trade openness.[20] Per capita GDP is highly significant in Table 2, but none of the other explanatory variables are significant in specifications (5) and (6).

ln Airbnb rent	(1)	(2)	(3)	(4)	(5)	(6)
Const	1.714***	1.742***	2.019***	1.810**	2.042**	2.011**
ln p.c. GDP	0.443***	0.442***	0.429***	0.433***	0.387***	0.402***
ln Airbnb penetration		0.002	0.031	0.044	0.053	0.050
ln p.c. Tourists			-0.093***	-0.093***	-0.056	-0.059
ln Population				0.016	0.037	0.029
US-Dummy					0.167	0.124
Trade Openness						-0.001
Adj. R-squared	0.64	0.63	0.69	0.69	0.70	0.70

Table 2: OLS Regression Results for Airbnb Rent Indices

Note: Asterisks represent significance as follows: * p-value <= 0.05; ** p-value <= 0.01, *** p-value <= 0.001. The regressors are discussed in Appendices B and C.

5.2 The relationship between Airbnb and long-term rents

Average long-term rents at the city level for the Numbeo and ISRP datasets are calculated as shown in (5) and (6), respectively. The Airbnb rent premium is defined here as the percentage difference between weekly Airbnb rent and weekly long-term rent as follows:

$$\text{Airbnb Rent Premium (ARP)} = 100\left(\frac{Airbnb_k - Long\text{-}Term_k}{Long\text{-}Term_k}\right), \tag{13}$$

[20]The sources of these regressors are discussed in Appendix B (for city-level per capita GDP) and Appendix C (for all other regressors). We are not able to include the Airbnb Tourist Intensity variable since we focus here on all 60 cities. Tourist visitors are only available for a subset of these cities.

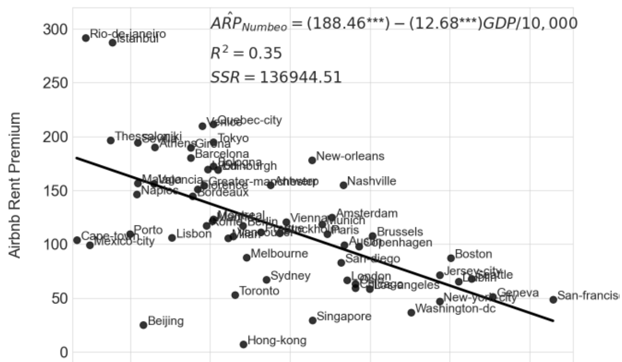
where $Airbnb_k$ denotes the Airbnb weekly rent in city k and $Long\text{-}Term_k$ is the corresponding weekly long-term rent (Numbeo, ISRP or Combined). Our combined long-term rent index is then calculated using the Numbeo and ISRP weights from (12) as follows:

$$\text{Combined long-term rent}_k = (\text{Numbeo rent index}_k)^{0.546} \times (\text{ISRB rent index}_k)^{0.454}.$$

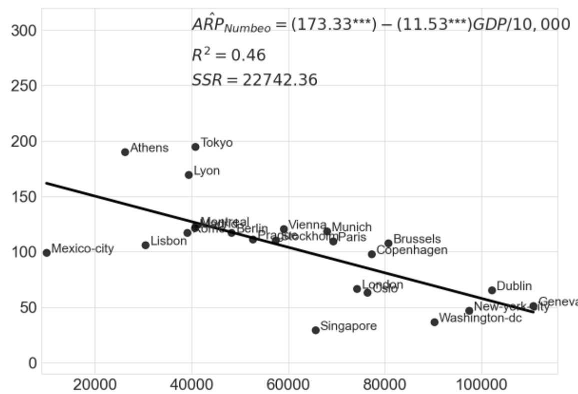
From a landlord's perspective, the Airbnb rent premium compares the relative attractiveness of the Airbnb market to the long-term rental market (Hill, Pfeifer, and Steurer, 2023). For example, if $ARP_k = 20$, the average Airbnb rent for an apartment is 20% higher than the average long-term rent.

Figure 5 illustrates four different calculations of the Airbnb rent premium. The first two panels are based on Numbeo data for the full 60-city and 23-city samples, respectively, while the last two panels are based on ISRP data and the Combined Long-term Rent Indices for the 23-city sample. The sum of squared residuals (SSR) of the least squares regression line for the combined rent indices is smaller than the SSR of both the Numbeo-23 and ISRP indices. This is an indication of the success of the errors-in-variables approach used to construct the Combined Indices in terms of reducing noise.

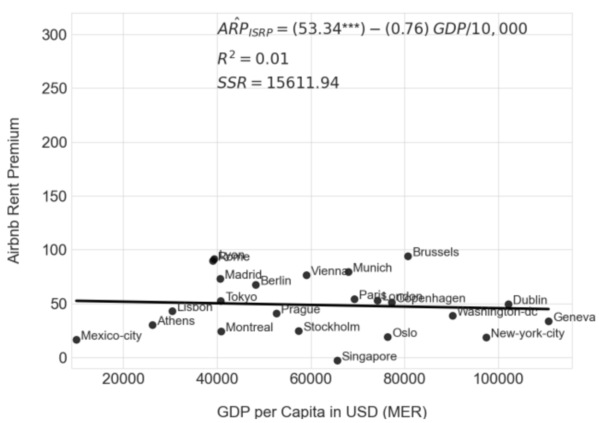
Two features of the Airbnb rent premia in Figure 5 are notable. First, they are positive regardless of which long-term rent series is used (although the Airbnb rent premia are systematically highest for Numbeo and lowest for ISRP). And second, the Airbnb rent premia are decreasing in the per capita GDP for Numbeo but not for ISRP (at the 5% significance level).



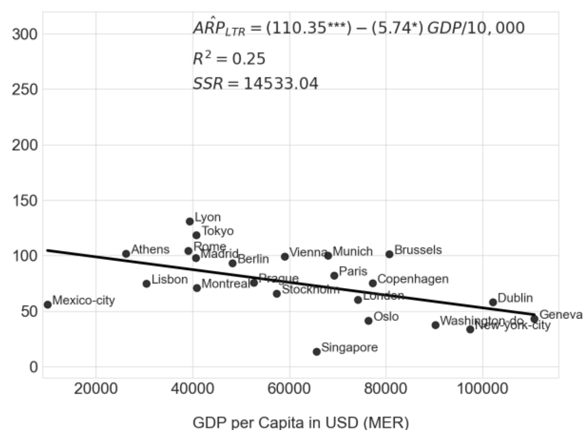
(a) Numbeo 60 Cities Rental Data



(b) Numbeo 23 Cities Rental Data



(c) ISRP 23 Cities Rental Data



(d) Combined 23 Cities Rental Data

Figure 5: The Relationship Between the Airbnb Rent Premium and Per Capita GDP

Note: The Airbnb Rent Premium (ARP) is calculated using the formula in (13). An ARP of 50, for example, indicates that a landlord in that city can earn 50 percent more on Airbnb than on the long-term rental market (other things equal). Asterisks in the least-squares equations represent significance as follows: * p-value <= 0.05; ** p-value <= 0.01, *** p-value <= 0.001.

There are three reasons why our finding that the Airbnb rent premium is positive does not necessarily imply that landlords should prefer Airbnb to the long-term rental market. First, the Airbnb rent premium is a gross measure that does not include additional costs such as furniture, utilities, and cleaning that landlords may incur in the Airbnb market. Second, it does not account for differences in vacancy rates between short-term and long-term rentals.

Adjusting for these factors would reduce the measured premium. Third, the hedonic model may not fully capture some quality aspects of Airbnb properties. We explore this issue further in Appendix D, where we compare web-scraped long-term rent data with Airbnb data for three of the cities in our sample (i.e., London, Sydney, and Rio de Janeiro).

To the extent that the Airbnb rent premium is still positive after these adjustments, this would imply that the long-term rental market is at risk of being crowded out by Airbnb. There is a substantial body of evidence supporting this crowding out hypothesis.[21]

Concerning the observed negative relationship between the Airbnb rent premium and per capita GDP, the slope of the regression line is -12.7 for Numbeo (60 cities), -11.5 for Numbeo (23 cities), -0.8 for ISRP (23 cities), and -5.7 for the combined index (23 cities). For example, in the case of Numbeo (60 cities), this means that a 10 000 decrease in GDP per capita increases the Airbnb rent premium by about 13 percent.

To the best of our knowledge, this negative relationship between Airbnb rent premia and per capita GDP is a new finding in the literature.[22] It suggests that Airbnb crowding-out of long-term rentals could be a bigger problem in poorer cities than in richer cities. However, before accepting this conclusion, we should consider other possible explanations that could also lead to this negative relationship between Airbnb rent premia and per capita GDP. First, the negative relationship may reflect the share of extra costs borne by Airbnb landlords being

[21] For example, Combs, Kerrigan, and Wachsmuth (2020) estimate that 31 000 units have switched from the long-term rental market to Airbnb in Canada as of April 2018. Horn and Merante (2017) estimate that each standard deviation increase in Airbnb density in Boston from September 2014 to January 2016 reduced the number of long-term rental offers by 5.9 percent and increased rents by about 0.4 percent. Barron, Kung, and Proserpio (2021) calculate that across the United States, a 1 percent increase in Airbnb listings leads to a 0.018 percent increase in rents. Garcia-López, Jofre-Monseny, Martínez-Mazza, and Segú (2020) find that Airbnb increased rents by 1.9% in Barcelona, Spain. Concerns about crowding out long-term rentals have led many cities around the world to limit the number of days per year that properties can be rented on Airbnb. For example, Amsterdam has a maximum of 30 days, Munich 56 days (i.e., eight weeks), New Orleans, San Francisco, London, Berlin, and Reykjavik 90 days, Los Angeles and Paris 120 days, and Tokyo 180 days (see Airbnb Help Center (https://www.airbnb.at/help and Lagrave (2018).

[22] It should be noted though that the negative slope is not significant at the 5% level for ISRP.

lower in higher-income cities. We think this explanation unlikely to be true since a major part of these extra costs – cleaning fees – should be lower (rather than higher) in poorer cities where labor is cheaper. Second, the Airbnb vacancy rate could be higher in poorer cities. Although we do not directly observe vacancy rates in the Inside-Airbnb dataset, we do observe the number of days since the last review. Plotting the average time since the last review against per capita GDP (see Figure 6), we do not observe any relationship between the two. So, this explanation also does not seem correct. Third, the negative relationship could be a consequence of the particular selection of cities. Again, this explanation seems unlikely as our results are almost identical for the Numbeo 60 and Numbeo 23 samples, suggesting that sample selection is not a big issue.

Our fourth and final explanation for why the observed negative relationship between Airbnb rent premia and per capita GDP may not lead to more crowding out of long-term rentals in poorer cities is that it may simply be a statistical artifact of how the rent indices were constructed. More specifically, the indices differ in the extent to which they are quality-adjusted, with Airbnb being the most quality-adjusted, followed by ISRP, with Numbeo being the least quality-adjusted.[23] Differences in the degree of quality adjustment, when combined with a general tendency for properties in richer cities to be of higher quality, can explain both the negative relationship between the Airbnb rent premium and per capita income itself and why the strength of this negative relationship in Figure 5 varies depending on which measure of long-term rents is used (Numbeo, Combined, or ISRP).

[23] The Airbnb rents are constructed from a hedonic model that adjusts for a number of characteristics. From the discussion of the compilation of ISRP rents in section 4, it is clear that the ISRP and Eurostat take great care to control for property features and location. By contrast, the Numbeo dataset is crowd-sourced, and the rent indices are calculated as simple averages of medians defined on four categories (1-bedroom inner, 3-bedroom inner, 1-bedroom outer, and 3-bedroom outer).

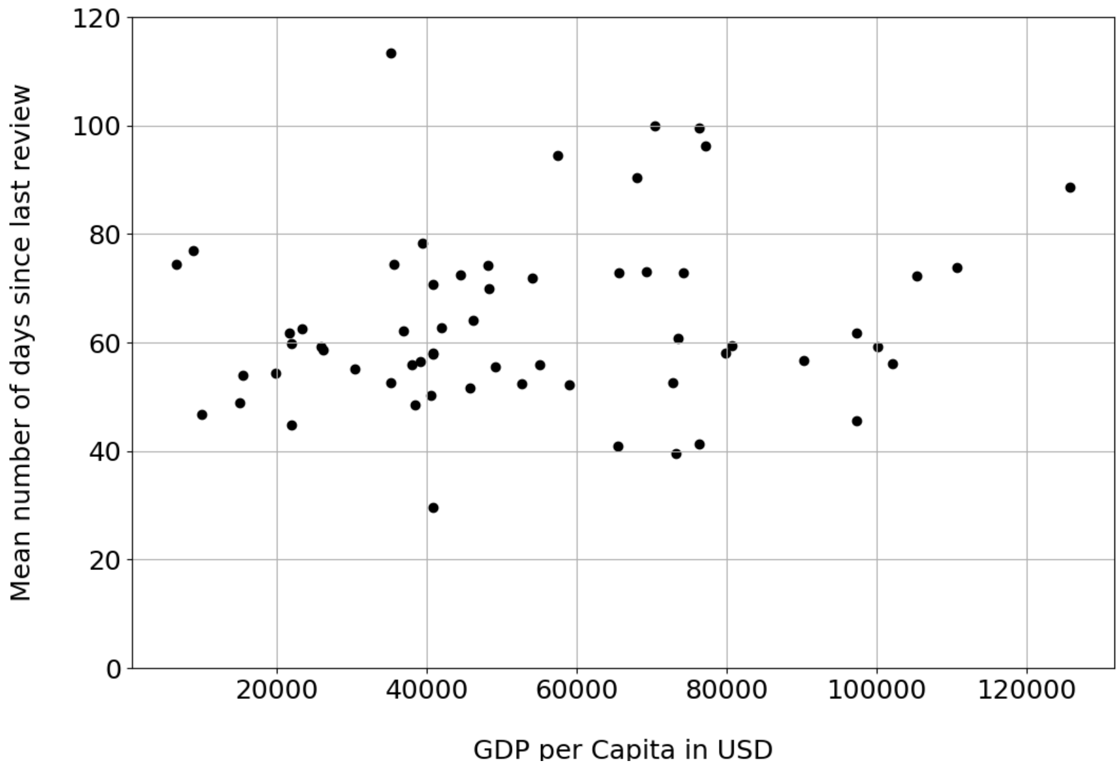


Figure 6: Mean number of days since last review

5.3 Spatial comparisons of the cost of living

A well-known finding of the International Comparisons Program (ICP) is that a country's price level (i.e., the ratio of the PPP to the corresponding MER) rises with per capita income (Deaton and Heston, 2010; World Bank, 2020). The Balassa-Samuelson hypothesis attributes these price level differences to higher productivity of the traded sector in richer countries. This higher productivity raises wages in both the traded and non-traded sectors and, as a result, non-traded services become more expensive in richer countries (see for example Hassan, 2016; Bordo et al., 2017).

As housing is a key element of the non-traded sector, this suggests that rents should rise at a faster rate than the overall price level as incomes rise. Figure 7, which illustrates how both the overall price level (World Bank, 2022) and rents (our combined rent index) vary with income in our sample of cities, confirms this pattern.

To further explore how rent differences affect the aggregate price level, consider the following stylized example. Let p^U and p^G denote the log price levels in the U.S. and Greece, respectively. Also let P_T^U and P_H^U denote the log price levels for traded goods and housing in the U.S., while P_T^G and P_H^G denote the corresponding log price levels in Greece. We assume that the log price level in each country is a weighted arithmetic mean of the log price levels of traded goods and housing, as follows:

$$p^U = \beta p_T^U + (1-\beta) p_H^U; \tag{14}$$

$$p^G = \beta p_T^G + (1-\beta) p_U^G. \tag{15}$$

We further assume that the housing share β is the same in both countries (see next section). Assuming the law of one price holds for traded goods (i.e., $p_T^U = p_T^G$), it follows from (14) and (15) that

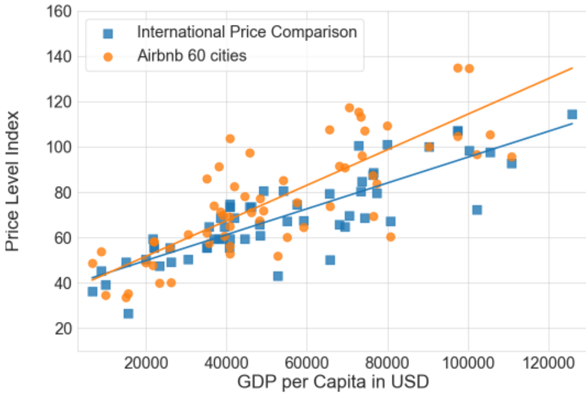
$$p^G - p^U = (1-\beta)(p_H^G - p_H^U).$$

We generalize this idea to cities. Washington DC is again the base, with p^W and p_H^W in (16) denoting the overall log price level and the log price level for housing rents in Washington DC. We then estimate the following equation:

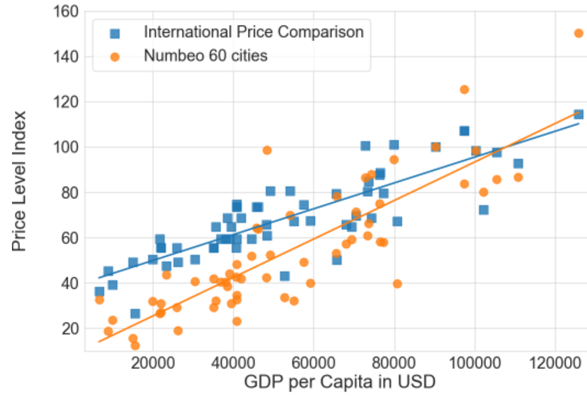
$$p^k - p^W = (1-\beta)(p_H^k - p_H^W), \tag{16}$$

where k indexes the other 59 (or 22) cities in the dataset. The overall log price level p^k is taken from the ICP (World Bank, 2022). These are national price levels, except for US cities, where we adjust them using the MSA price levels provided by the BEA. The terms p_H^k are the log price levels for housing rents from our combined rent index.

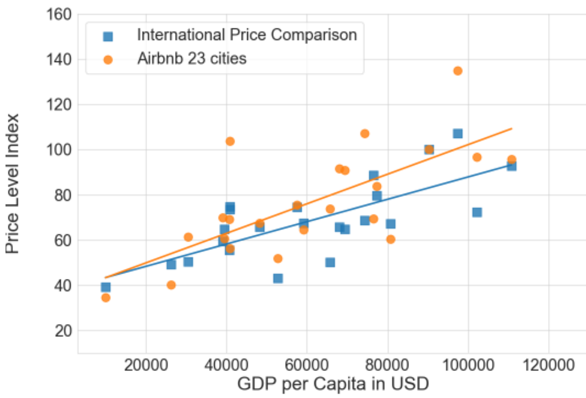
The results of the estimation in (16) are shown in Table 3. The estimated value of $1-\beta$ ranges from 0.507 (Numbeo-60) to 0.952 (Airbnb-23). These results indicate that a 1% increase in a city's rental price level will increase its overall price level by between 0.5% and 1%, depending on which measure of rents is used. The implied elasticity of the overall price level with respect to rents is between 0.5 and 1.



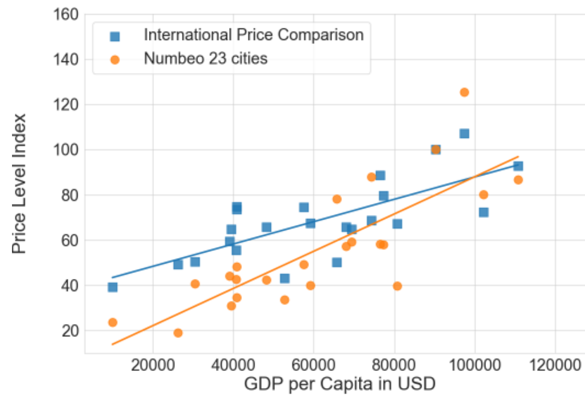
(a) Airbnb (60)



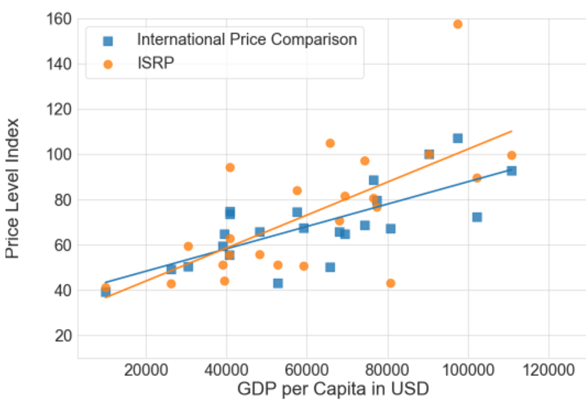
(b) Numbeo (60)



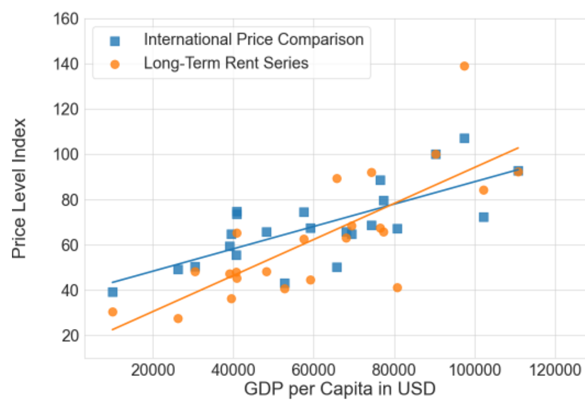
(c) Airbnb (23)



(d) Numbeo (23)



(e) ISRP



(f) Combined Long-Term Rent

Figure 7: Price level indices - Washington, DC = 100

Note: The price level is defined as the PPP exchange rate divided by the market exchange rate (all multiplied by 100). A price level of 120 means that prices are 20% higher than in Washington, DC.

Dependent Variable $(p^k - p^W)$						
	Airbnb (60)	Numbeo (60)	Airbnb (23)	Numbeo (23)	ISRP	LTR
$(1-\beta)$	0.948***	0.507***	0.952***	0.532***	0.809***	0.646***
std. err	0.064	0.026	0.108	0.050	0.102	0.064

Table 3: The Contribution of Rents to Price Level Differences based on the combined Long-Term Rent Index

Note: This Table relates to equation (16). p^k denotes the log price level in city k and p^B the log price level in Washington DC. Asterisks represent significance as follows: * p-value <= 0.05; ** p-value <= 0.01, *** p-value <= 0.001.

5.4 Housing affordability

5.4.1 The elasticity of substitution between housing and consumption and its implications

Following Davis and Ortalo-Magné (2011), suppose an economy is populated by identical agents. They each choose which of N regions to live in, where regions are indexed by $n = 1, \ldots, N$. Income and housing rent in each region are denoted by y_n and r_n. From the perspective of each agent, both are given exogenously. The price of the consumption good is normalized to 1. Each agent decides how much non-housing consumption c_n to buy and how much housing h_n to rent. Davis and Ortalo-Magné (2011) assume Cobb-Douglas preferences. We here generalize the model to the case of CES preferences. Each agent in region n solves the following problem:

$$\text{Max}\left[(1-\alpha)c_n^\rho + \alpha h_n^\rho\right]^{1/\rho}, \tag{17}$$

subject to the budget constraint: $c_n + r_n h_n = y_n$.

Solving (17) yields the following solutions for c_n and h_n:

$$\hat{c}_n = (1-\alpha)^\sigma \frac{y_n}{\alpha^\sigma r_n^{1-\sigma} + (1-\alpha)^\sigma}; \tag{18}$$

$$\hat{h}_n = \left(\frac{\alpha}{r_n}\right)^\sigma \frac{y_n}{\alpha^\sigma r_n^{1-\sigma} + (1-\alpha)^\sigma}, \tag{19}$$

where σ is the elasticity of substitution between consumption and housing, defined as follows:

$$\sigma = \frac{1}{1-\rho}.$$

The housing share of income is now obtained as follows:

$$\frac{\hat{h}_n r_n}{y_n} = \frac{\alpha^\sigma r_n^{1-\sigma}}{(1-\alpha)^\sigma + \alpha^\sigma r_n^{1-\sigma}}.$$

The parameter ρ can take any value between $-\infty$ and 1. For the elastic case, where $0 < \rho < 1$ ($\sigma > 1$), the housing share of income is decreasing in r_n. For the inelastic case $-\infty < \rho < 0$ ($0 < \sigma < 1$), the housing share of income increases in r_n. For the Cobb-Douglas special case, where $\rho = 0$ ($\sigma = 1$), the housing share of income is the same in all regions.

An interior equilibrium in which agents live in all regions requires that $U(\hat{c}_m, \hat{h}_m) = U(\hat{c}_{,n}, \hat{h}_n)$ for any pair of regions m and n. Substituting the solutions of (18) and (19) into the utility function yields the following:

$$U = \frac{y_n}{[(1-\alpha)^\sigma + \alpha^\sigma r_n^{1-\sigma}]^{1/(1-\sigma)}}. \tag{20}$$

It can be seen from (20) that if $y_n > y_m$ while utility is the same in both regions, it must follow that $r_n > r_m$. In other words, in equilibrium, regions with higher incomes have higher rents.

While inelastic substitution between consumption and housing is one way that the housing share of income can be higher in poorer cities, an alternative way that this can happen is if there is a lower bound on the observed level of h_n in our dataset due to its focus on expatriates and tourists rather than locals. For example, suppose we add the constraint that $h_n \geq \bar{h}$. In poorer cities, many locals may live in properties with quality levels lower than $\bar{h}$. However, we do not observe these properties in our dataset. Thus, we may observe a rapidly rising housing share of income in the poorest cities, which is unrelated to the true value of the elasticity of substitution between consumption and housing. We will return to this point when we discuss our results for the three poorest cities in our dataset in Section 5.4.3.

5.4.2 Housing affordability across cities in the US

Housing affordability is a growing concern in many countries (Fetzer, Sen and Souza, 2023). We use the rent/income ratio as our measure of housing affordability. So far, most of the literature on city-level housing comparisons has focused on a single country. Before discussing our international results, we provide a brief overview of this literature.

Davis and Ortalo-Magné (2011) and Albouy, Ehrlich, and Liu (2016) emphasize the importance of determining whether the rent/income ratio changes with income. If it does, the results of many economic models would need to be re-examined, since it is often assumed that the utility function for consumption and housing has a Cobb-Douglas form, which implies a uniform rent/income ratio across income levels.[24] Initial empirical support for the Cobb-Douglas assumption comes from Davis and Ortalo-Magné (2011), who find little difference across Metropolitan Statistical Areas (MSAs) in the United States in the share of housing expenditures that renter households spend. Their study is based on data from the 1980, 1990, and 2000 Decennial Census of Housing surveys and is therefore necessarily limited to the United States.[25]

Here we update the results of Davis and Ortalo-Magné to 2019 with data from the BEA. Figure 8 plots average personal income on the x-axis against the rent/income ratio on the y-axis for MSAs in 2019.[26] Our results in Figure 8 confirm the finding of Davis and Ortalo-Magné that there is no clear relationship between city income and affordability. The slope of the rent/income line in Figure 8 while negative is not statistically significant at the 5% level.

[24] See for example Eeckhout (2004), Michaels, Rauch, and Redding (2012), Guerreiri, Hartle, and Hurst (2013) and Berger et al., 2018).

[25] In contrast, when the price-to-income ratio is used, a clear upward sloping relationship between income and housing affordability is observed. This difference between the results obtained using the rent/income and price/income ratios can be attributed to the upward-sloping relationship between income and the price/rent ratio, as documented by Bracke (2015), Hill and Syed (2016), Katz (2017), Aten (2018), and Halket, Nesheim, and Oswald (2020).

[26] https://www.bea.gov/itable/regional-gdp-and-personal-income

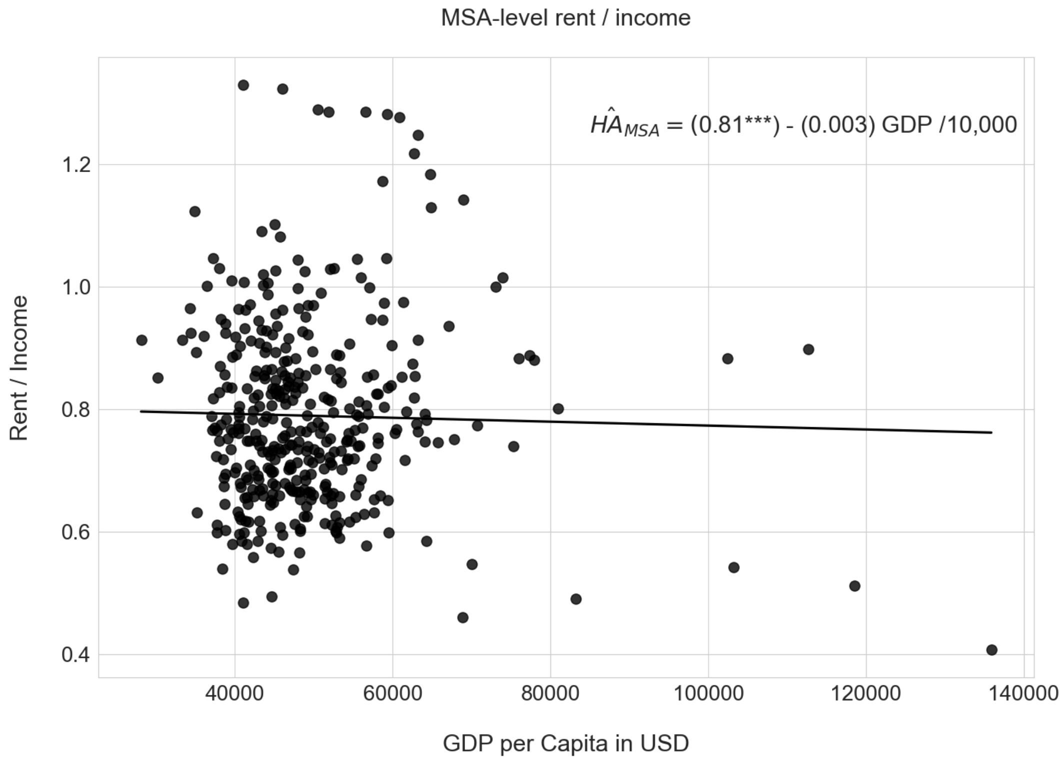


Figure 8: Housing affordability across US MSAs (rents) in 2019.

Note: The data were obtained from the Bureau of Economic Analysis. Rent/income is normalized to 1 for the Washington-Arlington-Alexandria MSA. Hence, for example, a value of 1.2 implies that rent/income in that MSA is 20% higher than in the Washington-Arlington-Alexandria MSA. Asterisks in the least-squares equation represent significance as follows: * p-value <= 0.05; ** p-value <= 0.01, *** p-value <= 0.001.

5.4.3 Housing affordability across our sample of international cities

Switching now to our international datasets, we need to replace per capita income with per capita GDP, since for most cities only per capita GDP is available. Figure 9 plots the relationship between per capita GDP and the city-level rent/income ratio for six cases: these are Numbeo (57 cities), Airbnb (57 cities), Numbeo (22 cities), ISRP (22 cities), Combined (22 cities) and Airbnb (22 cities). The three cities excluded from the 60 city sample are Cape Town, Rio de Janeiro and Mexico City. The city excluded from the 23 city sample is Mexico City. The reason for excluding these cities is that their rent/income ratios are extreme outliers on the high side. Cape Town, in particular, has a rent/income ratio of 1.64, which implies that rent is 64% higher than income!

There are two main explanations for these outliers. First, there was no city-level GDP available for these three cities (see Appendix B), and we had to use the national GDP figures instead. The city-level GDP figures would have been higher for all three cities. Second, these three cities are the poorest in our sample, and it is highly likely that there is a qualitative discrepancy between the rental properties in our dataset and those in which a city's residents actually live. One reason for this discrepancy is that our long-term and Airbnb rental datasets are skewed towards expatriates and tourists rather than locals. In addition, the share of informal housing is likely to be much higher in these cities than elsewhere, and this type of housing is typically not included in any rental dataset (not just ours). Thus, it is likely that there is a lower bound on housing quality in our rental datasets, implying an additional constraint that $h_n \geq \bar{h}$ in (17). This constraint becomes binding for the three poorest cities in our sample, implying that even with Cobb-Douglas preferences, the rent/income ratio rises beyond this point as income falls.[27]

From Figure 9 it can be seen that the rent/income ratio is more or less independent of income according to both the Numbeo 57 and 22 samples. The slope of the per capita GDP coefficient is -0.010 for Numbeo 57 and -0.004 for Numbeo 22. While the first of these coefficients is statistically significant at the 5% level for Numbeo 57, the effect is still very slight. However, for the Airbnb 22 and ISRP 22 samples, the rent/income ratio is clearly decreasing in income. The Combined 22 sample is an average of Numbeo 22 and ISRP 22 and hence also shows a rent/income ratio that is decreasing with income, but at a lower rate than with ISRP 22.

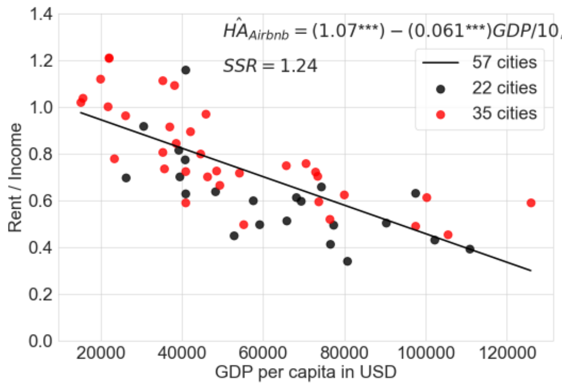
The most plausible explanation for the findings in Figure 9 is that the slope of the rent/income ratio line depends on how quality-adjusted the rent indices are. As was noted in subsection 5.2, the Airbnb and ISRP rent indices are more quality-adjusted than the Numbeo rent indices. This is why the rent/income best-fit lines are downward sloping for Airbnb and ISRP, but flat for Numbeo.

[27] Another factor that may contribute to the high rent/income ratios in the poorest cities is that there are, on average, more income earners per household in these cities (Lanjouw and Ravallion, 1995).

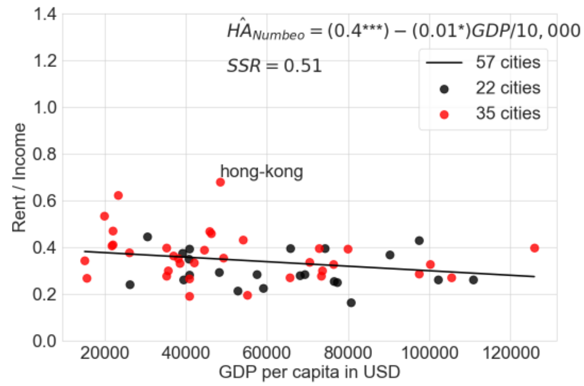
This finding raises a fundamental issue about the concept of housing affordability. The standard approach for measuring housing affordability is to simply divide rent by income (or price by income). This housing affordability measure implies that all cities with the same rent-to-income ratio have the same housing affordability score. If this is the concept being used, then the Numbeo results are more relevant. An alternative approach would be to consider the *quality-adjusted* rent-to-income ratio instead. This implies that if the raw rent/income ratio is the same in cities A and B, but the quality of rented properties is higher in A, then city A has the better housing affordability. Under this second concept, the ISRP results are more relevant.

When comparing price levels across countries, the ICP invests considerable resources to ensure that products of equal quality are being compared. The question is whether the same should be done when measuring housing affordability. Many residents in poor cities live in poor-quality informal housing. Indeed, Brueckner and Lall (2015) interpret the prevalence of informal housing and slums as a symptom of the lack of affordability in cities in poorer countries. In this sense, the quality-adjusted rent/income ratio may be a more informative measure of housing affordability.

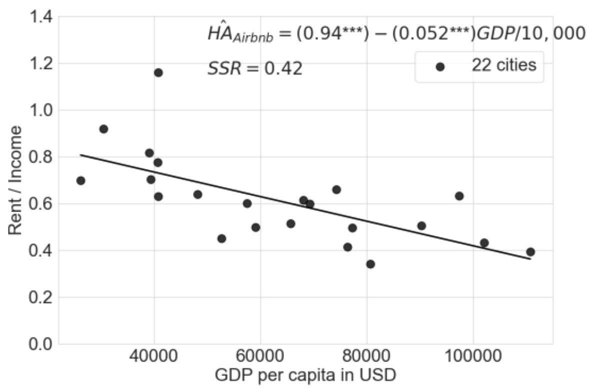
In summary, based on the Numbeo results, we find that the housing expenditure share is reasonably stable across our international sample of cities. This is broadly consistent with the findings of Davis and Ortalo-Magné (2011) for US cities and the assumption of a unit elasticity of substitution between consumption and housing. However, our results also indicate that when spatial rent differences are better quality-adjusted (as, for example, when ISRP rents are used), measured housing affordability (defined as quality-adjusted rent divided by income) is significantly worse in poorer cities.



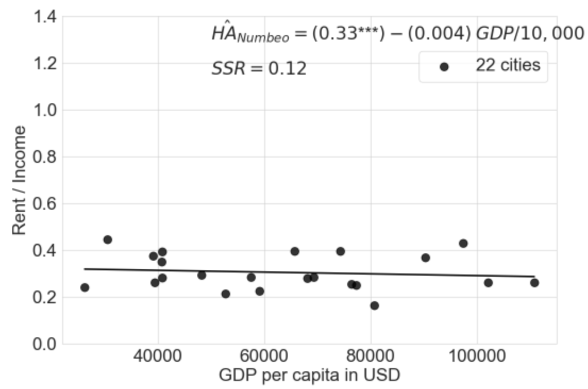
(a) Airbnb (57)



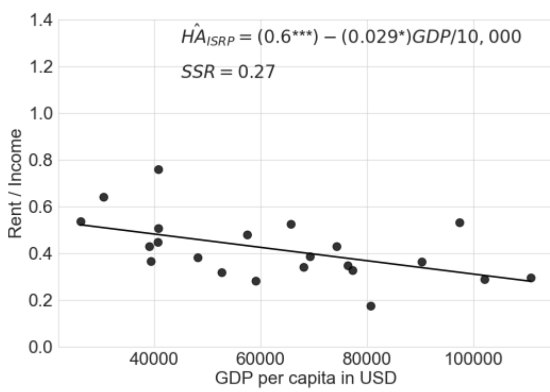
(b) Numbeo (57)



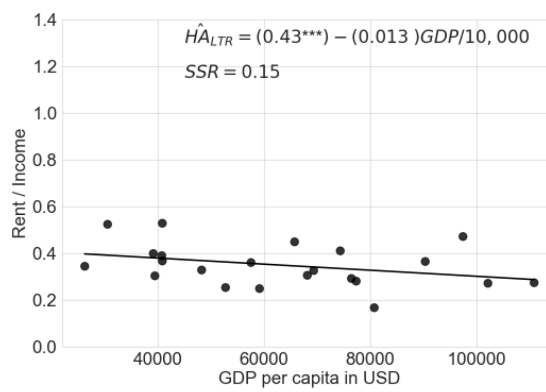
(c) Airbnb (22)



(d) Numbeo (22)



(e) ISRP



(f) Combined Long-Term Rent

Figure 9: Housing affordability based on rent indices

Note: The derivation of per capita GDP at the city level is explained in Appendix B. Cape Town, Rio de Janeiro and Mexico City are excluded since their rent/income ratios are implausibly high. In particular, Cape Town's rent/income ratio is 1.64, implying that rent exceeds income by 64%. An explanations for these outliers is provided in the text. Asterisks in the least-squares equations represent significance as follows: * p-value <= 0.05; ** p-value <= 0.01, *** p-value <= 0.001.

6 Conclusion

Airbnb rents are a valuable source of internationally harmonized micro-level rent data. This paper shows that Airbnb data can be used to better understand spatial differences in housing costs across cities worldwide. We used a hedonic approach, incorporating insights from the multilateral price index literature, to calculate quality-adjusted spatial Airbnb rent indices for 60 cities. We found a generally linear relationship between Airbnb rents and per capita GDP, with Airbnb rents increasing at around \$69 per night for every \$10,000 increase in per capita GDP.

When comparing Airbnb and long-term rents, we found that the Airbnb rent premium is positive (implying that landlords can earn more per week than on the long-term rental market). This does not necessarily imply that landlords should prefer Airbnb as there are other factors that need to be considered (such as the costs of furniture, utilities, and cleaning and differences in the vacancy rate). We also found that the Airbnb rent premium is downward sloping in per capita GDP when Numbeo long-term rents are used but this relationship is no longer statistically significant when ISRP long-term rents are used. We believe this is due to differences in the degree of quality adjustment of the Numbeo and ISRP rents. Our conjecture is that this downward sloping relationship disappears When the Airbnb and long-term rent indices are equally quality-adjusted.

We then showed how Pinkovskiy and Sala-i-Martin's (2016, 2020) method for optimally combining two series can be applied to rent indices. Using short-run Airbnb rent indices as the benchmark for combining long-term rent indices, the resulting combined index gave approximately equal weight to the Numbeo and ISRP indices.

Housing rents are an important part of the non-traded sector. We showed that rent differences across cities are larger than differences in the overall price level, irrespective of which spatial rent index is used. Furthermore, for each 1% increase in rents, we found that the price level rises by between 0.5% and 1%, depending on the reference rent index.

The standard approach to measuring housing affordability is to simply focus on the ratio of rent to income without attempting to quality adjust the rent estimate. We found that the rent/income share is relatively stable across our international sample of cities when using Numbeo rents. This is consistent with previous findings for cities within the same country and supports the common assumption in the academic literature of a unit elasticity of substitution between housing and non-housing consumption. However, when comparing more quality-adjusted rents (such as ISRP) with income, we found that housing affordability is worse in poorer cities. This raises important questions about the meaning of housing affordability in spatial comparisons and the appropriate methodology for measuring it.

Our findings also highlight the need for further investigation. In particular, our sample of cities focuses on those that are attractive to tourists. It remains to be seen how many of our results generalize to a wider international sample of cities.

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Appendix A: Additional Tables

	N	Rent per Night in US Dollars			MER
		median price	mean price	std price	
Amsterdam	13519	218.82	220.89	87.75	0.89
Antwerp	1148	113.90	113.63	51.47	0.89
Athens	7504	79.05	80.53	40.43	0.89
Austin	2219	223.79	225.43	145.63	1.00
Barcelona	7027	203.03	214.25	103.87	0.89
Beijing	6720	78.65	80.26	36.89	6.94
Berlin	10154	122.81	123.97	62.95	0.89
Bologna	2211	128.13	129.21	69.81	0.89
Bordeaux	4242	104.94	105.18	54.14	0.89
Boston	2442	322.05	327.66	158.76	1.00
Brussels	4276	112.36	113.57	55.91	0.89
Cape-Town	5570	114.61	115.66	69.71	14.45
Chicago	3467	214.62	222.84	121.70	1.00
Copenhagen	18541	153.61	154.82	68.88	6.67
Dublin	3052	201.73	202.67	94.22	0.89
Edinburgh	7213	176.20	182.24	90.08	0.78
Florence	7334	156.41	159.91	76.69	0.89
Geneva	1559	180.86	180.43	94.69	0.99
Girona	2537	133.84	133.87	89.77	0.89
Greater-Manchester	1367	156.25	156.84	65.69	0.78
Hong-Kong	3478	153.55	153.40	70.98	7.80
Istanbul	4943	76.99	77.64	46.19	5.67
Jersey-City	1371	267.68	271.06	117.87	1.00
Lisbon	12578	130.07	133.39	55.69	0.89
London	25268	236.85	238.12	125.06	0.78
Los-Angeles	10655	244.00	245.38	103.01	1.00
Lyon	6439	113.83	114.94	63.31	0.89
Madrid	10152	147.38	153.04	89.04	0.89
Malaga	3530	124.57	127.55	54.61	0.89
Melbourne	10089	157.74	159.37	62.52	1.44

	N	Rent per Night in US Dollars			MER
		median price	mean price	std price	
Mexico-City	6818	84.95	85.37	50.34	19.26
Milan	10682	153.52	154.75	88.22	0.89
Montreal	10254	120.82	125.33	69.50	1.33
Munich	4718	175.34	175.92	105.01	0.89
Naples	3450	94.80	95.70	42.94	0.89
Nashville	1631	270.55	271.65	115.31	1.00
New-Orleans	2309	240.00	246.56	113.67	1.00
New-York-City	20034	259.10	262.56	124.76	1.00
Oslo	4746	131.49	132.03	62.03	8.80
Paris	39454	165.89	168.19	101.35	0.89
Porto	5280	100.40	102.36	41.45	0.89
Prague	8697	109.69	112.29	73.01	22.93
Quebec-City	1639	110.42	112.68	57.64	1.33
Rio-de-Janeiro	9253	128.46	132.30	87.02	3.94
Rome	15280	149.83	153.73	76.67	0.89
San-Diego	2475	262.14	264.85	129.13	1.00
San-Francisco	1700	355.00	362.16	162.17	1.00
Seattle	2223	200.00	227.83	106.21	1.00
Sevilla	4059	112.43	129.94	67.46	0.89
Singapore	1142	163.10	176.22	82.54	1.36
Stockholm	4713	128.92	144.54	71.14	9.46
Sydney	13545	173.42	187.65	83.05	1.44
Thessaloniki	2165	57.70	63.28	25.44	0.89
Tokyo	5271	178.96	202.72	94.00	109.01
Toronto	4570	134.08	147.87	70.96	1.33
Valencia	3928	114.91	124.45	48.14	0.89
Vancouver	1437	198.79	216.07	88.94	1.33
Venice	5512	178.75	197.48	87.07	0.89
Vienna	7376	111.88	124.83	59.20	0.89
Washington-DC	2807	186.64	206.04	90.61	1.00

Table A1: Summary of uncleaned Airbnb dataset

R-Squared = 0.60					
	Coefficient	Standard error		Coefficient	Standard error
Constant	5.36***	0.002	Non-Professional	reference	
Non-Superhost	reference		Professional	0.12***	0.001
Superhost	0.02***	0.001	1 Bedroom	reference	
Quarter 1	reference		2 Bedroom	0.22***	0.001
Quarter 2	0.05***	0.001	3 Bedroom	0.40***	0.001
Quarter 3	0.06***	0.001	4+ Bedroom	0.56***	0.001
Quarter 4	0.05***	0.001	City distance 1	reference	
1 Bathroom	reference		City distance 2	-0.06***	0.001
2 Bathroom	0.21***	0.001	City distance 3	-0.18***	0.001
3+ Bathroom	0.40***	0.002	Washing machine	0.03***	0.001
Dryer	0.07***	0.001	Dishwasher	0.10***	0.001
Wifi	0.12***	0.001	Gym	0.09***	0.001
Laptop friendly workspace	0.01***	0.001	Bathtub	0.01***	0.001
Paid parking off premises	0.02***	0.001	Patio or balcony	0.00***	0.001
Amsterdam	0.17***	0.003	Antwerp	-0.50***	0.003
Athen	-0.91***	0.003	Austin	-0.05***	0.003
Barcelona	-0.16***	0.003	Beijing	-0.92***	0.003
Berlin	-0.41***	0.003	Bologna	-0.43***	0.003
Bordeaux	-0.56***	0.003	Boston	0.31***	0.003
Brussels	-0.50***	0.003	Cape Town	-0.69***	0.003
Chicago	-0.13***	0.003	Copenhagen	-0.17***	0.003
Dublin	-0.04***	0.003	Edinburgh	-0.18***	0.003
Florence	-0.30***	0.003	Geneva	-0.06***	0.003
Girona	-0.48***	0.003	Greater Manchester	-0.35***	0.003
Hong Kong	-0.25***	0.003	Istanbul	-1.04***	0.003
Jersey City	0.08***	0.003	Lisbon	-0.49***	0.003
London	0.08***	0.003	Los Angeles	0.10***	0.003
Lyon	-0.49***	0.003	Madrid	-0.37***	0.003
Malaga	-0.55***	0.003	Melbourne	-0.36***	0.003
Mexico City	-1.05***	0.003	Milan	-0.23***	0.003
Montreal	-0.56***	0.003	Munich	-0.08***	0.003
Naples	-0.73***	0.003	Nashville	0.14***	0.003
New Orleans	0.03***	0.003	New York City	0.30***	0.003
Oslo	-0.37***	0.003	Paris	-0.13***	0.003
Porto	-0.70***	0.003	Prague	-0.65***	0.003
Quebec City	-0.63***	0.003	Rio de Janeiro	-0.60***	0.003
Rome	-0.34***	0.003	San Diego	0.12***	0.003
San Francisco	0.50***	0.003	Seattle	0.08***	0.003
Sevilla	-0.54***	0.003	Singapore	-0.38***	0.003
Stockholm	-0.27***	0.003	Sydney	-0.16***	0.003
Thessaloniki	-1.08***	0.003	Tokyo	0.04***	0.003
Toronto	-0.33***	0.003	Valencia	-0.63***	0.003
Vancouver	-0.03***	0.003	Venice	-0.08***	0.003
Vienna	-0.44***	0.003	Washington	reference	

Table A2: Multilateral Hedonic City-Dummy Estimation Results (Airbnb)

City	Numbeo	Airbnb	Combined	ISRP	City	Numbeo	Airbnb	Combined	ISRP
San-Francisco	150.2	163.0			Melbourne	52.4	71.8		
New-York-City	125.4	134.9	139.2	157.6	Greater-Manchester	38.4	71.5		
Boston	98.4	134.8			Toronto	63.7	71.2		
Amsterdam	71.4	117.3			Rome	44.1	70.0	47.2	51.2
San-diego	86.4	115.5			Oslo	58.2	69.4	67.6	80.7
Nashville	60.8	113.3			Madrid	42.7	69.2	48.1	55.5
Los-Angeles	94.5	109.3			Berlin	42.5	67.5	48.1	55.9
New-Orleans	53.0	107.7			Bologna	32.6	64.9		
London	88.0	107.3	92.1	97.2	Vienna	40.0	64.4	44.5	50.6
Seattle	85.8	105.3			Girona	29.4	62.2		
Jersey-City	83.7	104.8			Lisbon	40.7	61.3	48.3	59.4
Tokyo	48.1	103.6	65.3	94.3	Lyon	30.8	60.8	36.2	44.0
Washington-DC	100.0	100.0	100.0	100.0	Brussels	39.8	60.3	41.3	43.1
Vancouver	64.3	97.5			Antwerp	32.3	60.1		
Dublin	80.1	96.7	84.3	89.6	Sevilla	27.1	58.2		
Austin	66.1	96.3			Malaga	31.0	58.1		
Geneva	86.7	95.8	92.3	99.5	Bordeaux	32.2	57.5		
Munich	57.3	91.6	63.0	70.7	Montreal	34.6	56.4	45.4	62.9
Venice	40.3	91.3			Valencia	29.4	55.0		
Paris	59.2	90.8	68.6	81.7	Rio-de-Janeiro	18.8	53.9		
Chicago	75.0	87.3			Quebec-City	23.3	53.0		
Barcelona	42.0	85.9			Prague	33.7	51.9	40.7	51.1
Sydney	69.9	85.3			Porto	32.0	48.9		
Copenhagen	57.9	83.9	65.9	76.8	Cape-Town	32.7	48.8		
Edinburgh	42.0	82.5			Naples	26.5	47.7		
Milan	52.0	78.1			Athens	18.9	40.2	27.4	42.8
Hong-kong	98.7	77.3			Beijing	43.7	39.9		
Stockholm	49.1	75.6	62.7	84.0	Istanbul	12.5	35.3		
Florence	40.3	74.0			Mexico-City	23.7	34.5	30.5	41.1
Singapore	78.2	73.8	89.4	105.1	Thessaloniki	15.5	33.6		

Table A3: Rent Indices with Washington DC = 100

Appendix B: Control Variables in the Combined Rent Index

(i) Per capita GDP at the city level

For countries in Europe, per capita GDP at the Nomenclature of Territorial Units for Statistics 2 (NUTS-2) level is available from Eurostat.[28] For example, there are 21 NUTS-2 regions in Italy. While the NUTS-2 level is typically a larger area than individual cities, it is the smallest area for which per-capita GDP is available. Eurostat provides per capita GDP at the NUTS-2 level for 32 European cities in our dataset (including Istanbul).[29] For the 12 US cities, we use the relevant Metropolitan Statistical Areas (MSAs) per capita GDP estimates.[30] For the UK cities, we take per capita GDP at the International Territorial Level 2 (ITL-2), which is essentially equivalent to NUTS-2 and available from the Office of National Statistics.[31] Per capita GDP for the Geneva region is available from the Swiss Federal Statistical Office.[32] Provincial-level per capita GDP for Toronto, Vancouver, Montreal, and Quebec City are available from Statistics Canada.[33] State-level per capita GDP for Sydney and Melbourne are available from the Australian Bureau of Statistics.[34] For Singapore and Hong Kong, national and city-level per capita GDP numbers are equivalent. For Mexico city, Rio de Janeiro, Cape Town, and Tokyo, we could not find regional per capita GDP and used national per capita GDP instead. Finally, the per capita GDP for the Beijing region is available from the CEIC data website.[35] All per capita GDPs are converted into US dollars using the PPP-exchange rates from the World Bank (2022).

(ii) Airbnb Tourist Density

Information on the number of tourists visiting a city annually is obtained from two main

[28] https://ec.europa.eu/eurostat/databrowser/view/TGS00005/default/table

[29] https://ec.europa.eu/eurostat/web/regions/data/database

[30] https://www.bea.gov/data/gdp/gdp-county-metro-and-other-areas.

[31] https://www.ons.gov.uk/economy/grossdomesticproductgdp/datasets/regionalgrossdomesticproductallnutslevelregions

[32] https://www.bfs.admin.ch/bfs/en/home/statistics/national-economy/national-accounts/gross-domestic-product-canton.html

[33] https://www150.statcan.gc.ca/t1/tbl1/en/cv.action?pid=3610022201

[34] https://www.abs.gov.au/statistics/economy/national-accounts/australian-national-accounts-state-acco 2020-21

[35] https://www.ceicdata.com/en/china/gross-domestic-product-prefecture-level-city-per-capita/cn-gdp-per-capita-beijing

sources. The first source is Euromonitor.[36] The second source is Mastercard.[37, 38] Here we are only focusing on the 23 cities in the ISRP dataset. When available, we used the number of visitors reported by Euromonitor. When a city was not available in Euromonitor, we used a scaled up estimate of the number stated in the Mastercard report. The scaling factor (λ) was calculated from all cities that were represented in both datasets as follows:

$$\lambda = \prod_{k=1}^{K} \left(\frac{V_k^{EM}}{V_k^{MC}} \right)^{1/K},$$

where $k = 1 \ldots, K$ indexes the cities in both datasets and V_k^{EM} and V_k^{MC} denote the number of annual visitors to city k in the Euromonitor and Mastercard datasets, respectively. Two cities (Lyon and Oslo) were not represented in either dataset. Data on the number of annual visitors to these cities were obtained from local websites.[39]

Our Airbnb Tourist Intensity variable was then constructed by dividing annual visitors by the number of Airbnb listings from in this city from the Inside Airbnb website.http://insideairbnb.com/)

Appendix C: Additional Explanatory Variables Included in Table 2

(i) Airbnb penetration index

We define the Airbnb penetration index as the number of distinct Airbnb listings per city divided by its population. As cities may differ in the number of web-scraping events in the InsideAirbnb dataset, we randomly select one such event per city to determine the number of Airbnb listings.

(ii) Per capita tourism income

We take the per capita tourism income (at the national level) from the World Tourism Organization (UNWTO) (2019). It is defined as the total spending of tourists visiting a country divided by the population of that country.

[36] https://go.euromonitor.com/white-paper-travel-2019-100-cities.html

[37] https://www.mastercard.com/news/media/wexffu4b/gdci-global-report-final-1.pdf

[38] See also the following website: https://en.wikipedia.org/wiki/List_of_cities_by_international_visitors.

[39] The sources are https://presse.lyon-france.com/en/tool-box/key-figures and https://tourismteacher.com/tourism-in-oslo/, respectively.

(iii) City population

City population data are taken from United Nations (2018).

(iv) Trade openness

Data on trade openness at the national level are taken from World Bank (2022). Trade openness is defined as the sum of imports and exports divided by GDP.

Appendix D: A Micro-Level Comparison of the Quality of Airbnb and Long-Term Rentals

In Table D1, we compare web-scraped micro-level long-term rental data for London, Sydney, and Rio de Janeiro with our Airbnb data. We find that in all three cities Airbnb properties are on average smaller (fewer bedrooms and bathrooms) but located closer to the city center than long-term rental properties (see Table D1). The hedonic model controls for observable differences such as the number of bedrooms and bathrooms, but perhaps not fully for the locational difference. Hence these results suggest that uncontrolled for quality differences could be contributing to the positive measured Airbnb rent premium.

2019	London		Rio De Janeiro		Sydney	
	Airbnb	webscraped	Airbnb	webscraped	Airbnb	webscraped
bathrooms						
mean	1.23	1.38	1.55	1.87	1.23	1.37
std.	0.45	0.59	0.67	0.98	0.43	0.50
bedrooms						
mean	1.60	2.00	1.79	2.28	1.60	1.78
std.	0.69	0.99	0.83	0.87	0.63	0.69
distance to center in km						
mean	10.80	11.92	10.25	13.59	6.59	11.67
std.	5.64	4.88	5.64	9.04	5.63	7.74
price /month						
mean	3,826.45 GBP	2,165.03 GBP	10,717.02 BRL	3,337.32 BRL	1166.47 AUD	505.66 AUD
std.	2,012.00	1,203.70	7,048.31	2,942.18	515.13	147.76
count						
	25,542	317.868	9,534	12,939	13,613	20,236

Table D1: Comparison of characteristics in Airbnb dataset and online listing dataset

Note: The data for London were web-scraped throughout 2019. For Rio de Janeiro, the data are from 2020, and for Sydney, they were web-scraped between April and August 2021. The numbers for London and Rio de Janeiro prices correspond to monthly rent. In contrast, we took weekly rent for Sydney, where rent is usually stated as a weekly figure. For Rio de Janeiro, we calculated the distance to the city center based on the 6,716 observations for which exact coordinates were available.