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

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Overview

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

Spatial comparisons of the cost of living are needed to measure poverty rates, inequality, real incomes, the relative size of economies, convergence/divergence, etc.

Housing rents are difficult to compare internationally due to the lack of harmonized data.

We show how freely available harmonized micro-level Airbnb data can help to overcome these difficulties, allowing us to shed light on a number of issues related to international and city-level comparisons.

Main Contributions

1. We construct a hedonic Airbnb index for rents in 60 cities for the year 2019 across Europe, the Americas, Asia, Africa, and Australia.

We do this using a multilateral method from the price index literature that helps avoid the representativity bias problem that can arise when estimating the hedonic model over the full sample of cities.

For example, we find that Airbnb rents in San Francisco are 55 percent higher than in London and five times higher than in Mexico City.

2. We compare short-term Airbnb rents with long-term rents from Numbeo (60 cities) and the International Service for Remunerations and Pensions (ISRP) at the OECD and Eurostat (23 cities). We find that the Airbnb rent premium (the difference between short and long-term rental costs) is higher in cities with lower income levels for Numbeo but not for the ISRP.

3. We attribute this fining to the Airbnb and ISRP rent indices being more quality adjusted than the Numbeo rent indices.

Main Contributions

4. We impute long-term rents for the 37 cities missing from the ISRP dataset using Airbnb, ISRP and pcGDP data.

5. With this combined long-term spatial rent index, we demonstrate the pivotal role rents play in determining the price level.

6. We show that differences in housing affordability, as measured by the rent-income ratio, are smaller across countries when Numbeo rents are used. Housing affordability is noticeably worse in poorer cities when the rent indices are properly quality adjusted.

Most spatial models that include housing fail to account for these quality differences. Using a Cobb-Douglas model of housing and non-housing consumption they typically assume that the rental share of income and hence housing affordability is the same everywhere.

Related Literature

1. The International Comparisons Program (ICP) computes purchasing power parity (PPP) exchange rates for almost all countries in the world (World Bank, 2020).
Uses of ICP include:
Measuring poverty
Measuring inequality
Monitor progress toward the United Nations Sustainable Development Goals
Measuring the relative size of economies
Construct the Penn World Table
Cross-country growth regressions.

Housing rents are one of the weakest links in the ICP.

Related Literature

2. Urban economics: City size increases until the benefits of agglomeration are offset by their costs. Rents (real and imputed) are probably the main cost of agglomeration. Hence rent comparisons across cities at an international level are needed to calibrate the size distribution of cities.

3. Urban economics: 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). This implies that the share of housing expenditures does not vary across cities.

But they do not allow for quality differences in housing across locations.

Airbnb data

	N	Rent per Night in US Dollars median price	mean price	std price	MER
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

		Rent per Night in US Dollars			
	N	median price	mean price	std price	MER
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

Airbnb rent indices

407 773 rental observations for the year 2019 from 60 cities in Europe, the Americas, Asia, Africa and Australia.

Semi-log hedonic model:
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 washer,
Dummy for dryer,
Dummy for dishwasher,
Dummy for wifi,
Dummy for gym,
Dummy for Bathtub,
Dummy for Patio or balcony.
Dummy for inner, middle and outer ring of city,
Dummy for laptop friendly workspace,
Dummy for paid parking off premises,

Regression Results

	R-Squared = 0.57				
	Coefficient	Standard error		Coefficient	Standard error
nt	5.58***	0.002	Non-Professional	reference	
perhost	reference		Professional	0.13***	0.001
ost	0.04***	0.001	1 Bedroom	reference	
1	reference		2 Bedroom	0.23***	0.001
2	0.05***	0.001	3 Bedroom	0.41***	0.001
3	0.06***	0.001	City distance 1	reference	
4	0.05***	0.001	City distance 2	-0.08***	0.001
oom	reference		City distance 3	-0.19***	0.001
hroom	0.26***	0.001			

Multilateral city dummy versus GEKS city dummy

Multilateral city dummy: one hedonic model including dummies for each region. The multilateral rent indices are derived from the city dummies.

GEKS city dummy: hedonic model estimated over pairs of cities. The resulting bilateral rent indices are transitivized using the GEKS formula.

This entails taking a geometric mean of star comparisons, each with a different city at the centre.

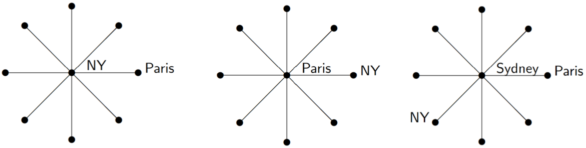


Figure 1: Airbnb spatial price indices

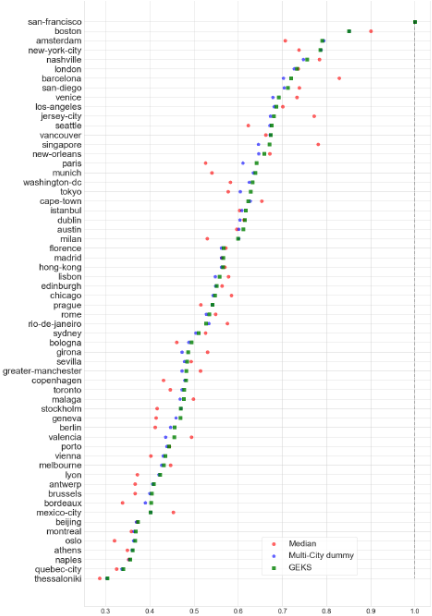


Figure 2: Airbnb rent versus income

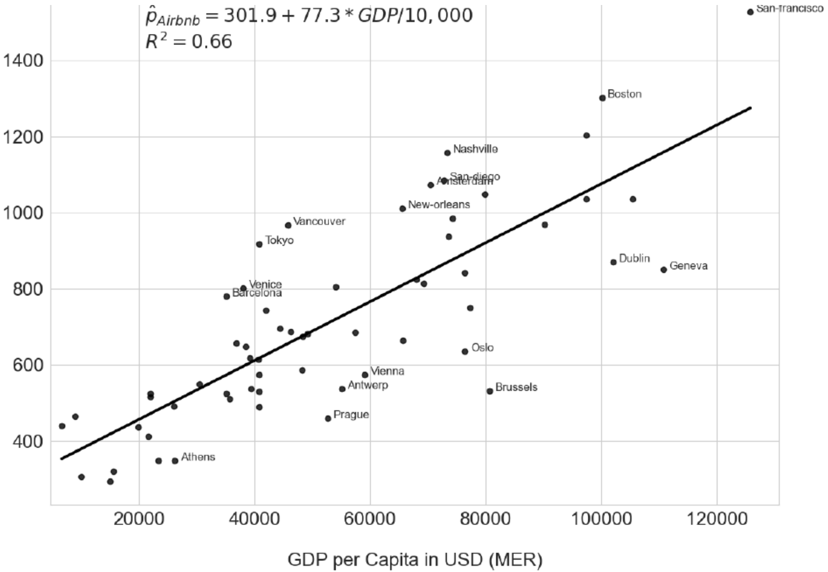


Figure 3: OLS Regression Results for Airbnb Rent Indices

ln Airbnb rent	M1	M2	M3	M4	M5	M6
Const	-1.547***	-1.567***	-1.378***	-1.398***	-1.282***	-1.304***
ln p.c. GDP	0.482***	0.483***	0.466***	0.465***	0.411***	0.416***
ln Airbnb penetration		-0.003	0.029	0.025	0.037	0.032
ln p.c. Tourists			-0.105***	-0.105*	-0.065	-0.061
ln Population (1 mil.)				-0.005	0.018	0.016
US-Dummy					0.183	0.175
Trade Openess						-0.001
Adj. R-squared	0.64	0.63	0.70	0.70	0.71	0.70

(b) Market exchange rates

Airbnb rent and income

Airbnb rents are increasing in per capita income.

Weekly Airbnb rent increases by \$77 for every \$10 000 increase in GDP per capita.

Outliers: The US cities tend to be above the best fit line, implying that Airbnb rents are higher than one would expect based on their income. A number of European cities are below the line.

This suggests there is high demand relative to supply for Airbnb in US cities.

Comparing short and long-term rents

We have two long-term rent series:

(i) Numbeo - crowdsourced - only partly quality adjusted (medians by number of bedrooms and inner/outer) - covers all 60 cities in our sample.

(ii) ISRP data - constructed by Eurostat/OECD from micro data - covers only 23 cities in sample.

We compare Airbnb and long-term rents as follows:

$$\text{Airbnb rent premium} = \frac{\text{Airbnb rent}}{\text{Long-term rent}}$$

This ratio os larger than 1.

The Airbnb rent premium is decreasing in income when Numbeo is used as long-term rent but not when ISRP is used.

Why? The Airbnb and ISRP indices are carefully quality adjusted while the Numbeo indices are only partially quality-adjusted.

The omitted variables (for Numbeo) are positively correlated with price (e.g., number of bathrooms, xxx).

Three possible alternative explanations for the downward sloping ARP for Numbeo are all rejected.
(i) Sample selection. When we restrict the Numbeo sample to the same 23 cities in the ISRP dataset, we get the same downward sloping ARP (next slide) xxx.
(ii) In equilibrium the ARP could be downward sloping if the Airbnb vacancy rate is higher in poorer cities. But this is not the case.
(iii) The extra costs of Airbnb landlords (e.g., cleaning) as a share of total rent are higher in poorer cities. Labour costs are far lower in poorer cities, so the share of cleaning costs should be lower.

Figure 4: Airbnb rent premia (Numbeo)

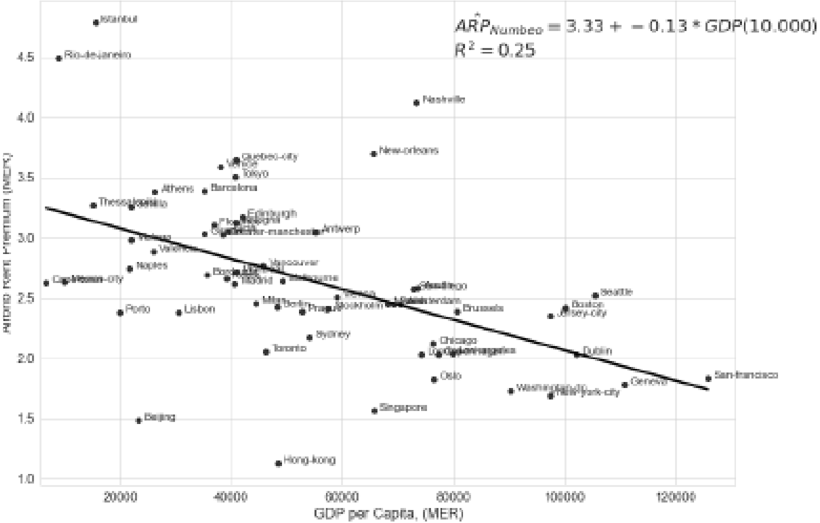


Figure 5: Airbnb rent premia (Numbeo – US and Canadian cities)

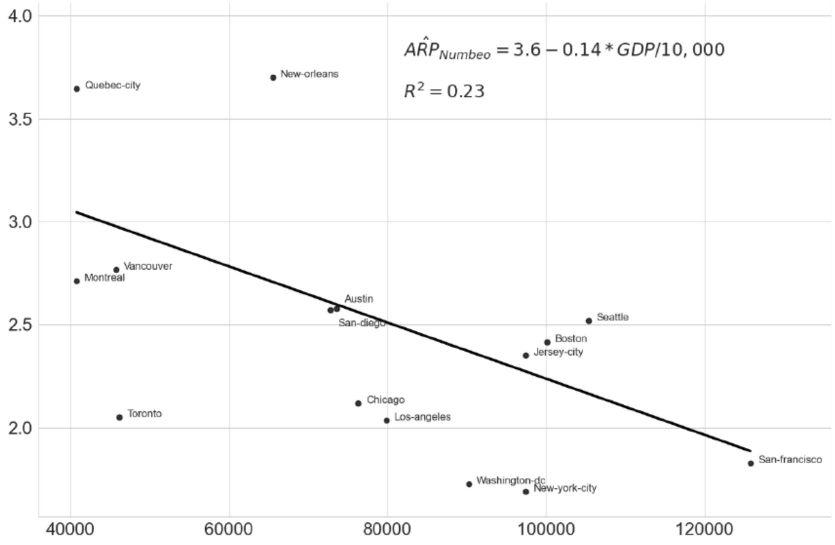
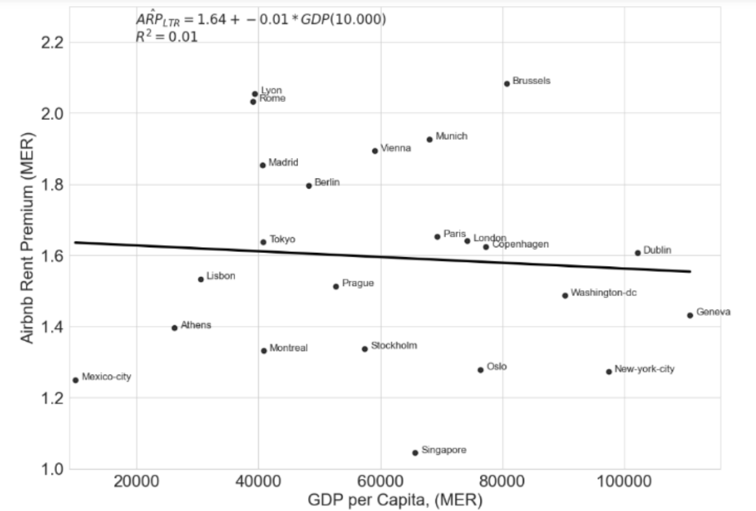


Figure 6: Airbnb rent premia (ISRP)



Using Airbnb to Improve the Long-Term rent Indices

We construct a long-term rent dataset for 60 cities. We take the rent indices for the 23 cities in the ISRP dataset as they are.

The challenge is extending the comparison to the other 37 cities. We do this in two different ways and then tale the average.

Method 1:
For the 23 cities in the ISRP dataset, run the following regression:

$$(Numbeo/ISRP) = a + b(pcGDP) + e.$$

For the remaining 37 cities indexed by k, we impute quality adjusted long-term rents (QALRs) as follows:

$$Q\hat{A}LR_k^+ = \frac{Numbeo_k}{\hat{a} + \hat{b}(pcGDP_k)}.$$

Method 2:
For the 23 cities in the ISRP dataset, compute the following ratio:

$$Z = \prod_{j=1}^{23} \left(\frac{Airbnb_j}{ISRP_j} \right)^{1/23} .$$

For the remaining 37 cities indexed by k, we impute quality adjusted long-term rents (QALRs) as follows:

$$Q\hat{A}LR_k^* = \frac{Airbnb_k}{Z}.$$

Our overall imputed rents are obtained by averaging these two sets of results as follows:

$$Q\hat{A}LR_k = \sqrt{Q\hat{A}LR_k^+ \times Q\hat{A}LR_k^*}.$$

Figure 7: Airbnb rent premia (LTR - 60 cities)

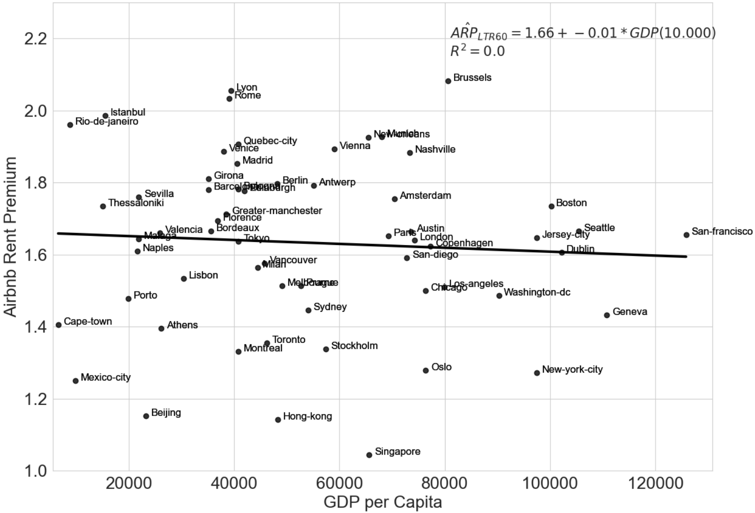


Figure 8: Airbnb rent premia (LTR - 37 cities)

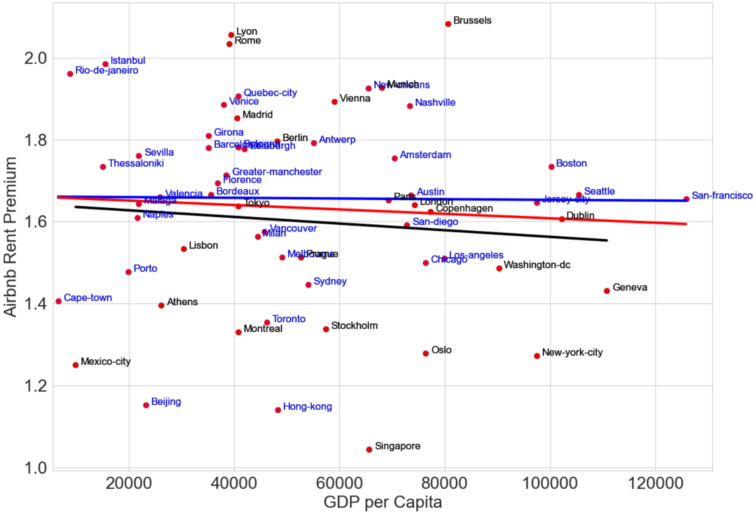
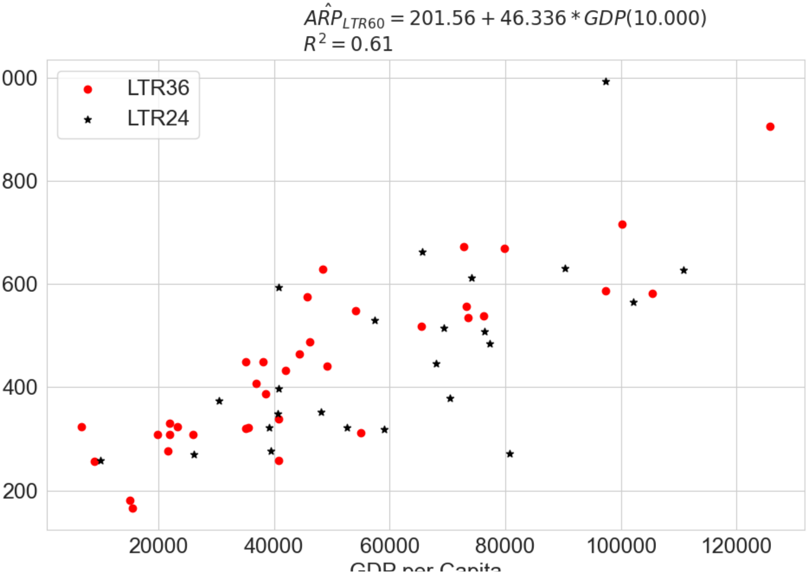


Figure 9: Long-Term Rent Indices



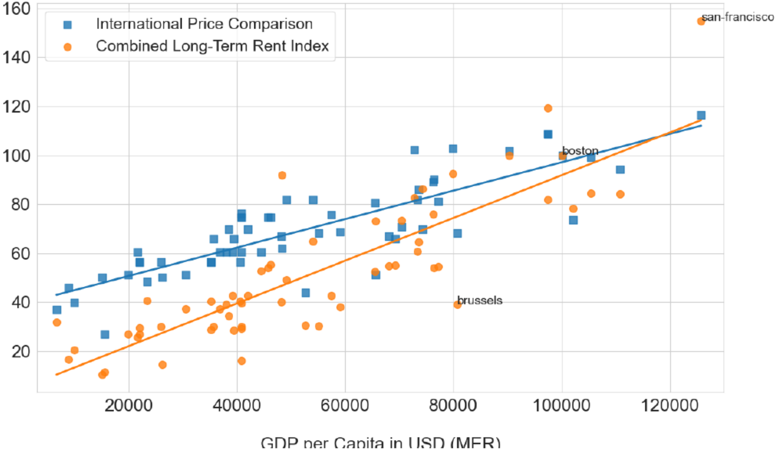
The cost of housing versus the cost of living

Compare ICP national price levels with our city housing rental price levels (based on Numbeo and QALR indices).

The positive slope of the price level with respect to income is well known. Non-traded services are more expensive in richer countries.

The slope is steeper for housing rents. Perhaps not surprising since housing is a key non-traded service.

Figure 10: Price level indices



Example:
p^U = log price level in US
p^G = log price level in Greece
P_T^U = log price level of traded goods in US
P_H^U = log price level of housing in US
P_T^G = log price level of traded goods in Greece
P_H^G = log price level of housing in Greece

Assume in each country the log price level is a weighted arithmetic mean of the log price levels of traded goods and housing:

$$p^U = \beta p_T^U + (1-\beta)p_H^U;$$

$$p^G = \beta p_T^G + (1-\beta)p_U^G.$$

Assume also that β is the same in both countries and that law of one price holds for traded goods (i.e., $p_T^U = p_T^G$).

It follows that:

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

Generalizing to our sample of 60 cities, with Boston as the base, we estimate the following equation:

$$p^k - p^B = \alpha + (1-\beta)(p_H^k - p_H^B),$$

where k indexes the other 59 cities in the dataset.

Consistent with our simple model, the constant is not significantly different from zero.

We obtain a value for $1-\beta$ of between 0.38 (with a constant) and 0.45 (without a constant).

Implication: a 1% increase in the rent price level of a city will increase its overall price level by about 0.45%.

This finding suggests that rents account for nearly half of differences in the overall price level across cities.

Dependent Variable $(p^k - p^B)$			
	α	$(1-\beta)$	R^2
Coeff. (with const.)	0.083	0.379***	0.58
std. err	0.043	0.043	
Coeff. (no const.)		0.448***	
std. err		0.025	

(v) How housing affordability differs across cities

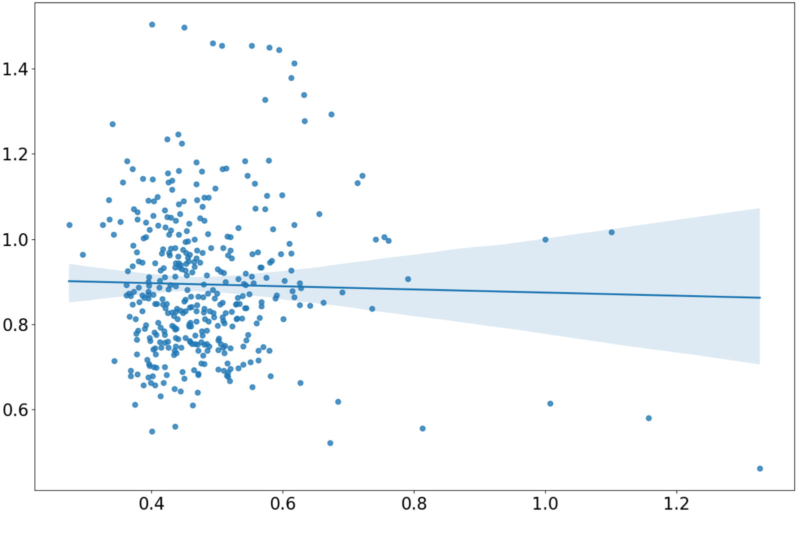
A standard assumption in models that incorporate housing into the utility function is that there is a unit elasticity of substitution between consumption and housing.

This implies that the rent-income ratio should be the same across cities.

Previous studies, focusing on cities within the same country, have tended to find this is the case, e.g., Davis and Ortalo-Magne (2011) for US cities.

We confirm their finding for US MSAs.

Figure 11: Housing affordability – US cities



But should rents be quality adjusted when comparing housing affordability?

One measure is rent divided income. An alternative is quality adjusted rent divided by income.

For US cities, there is no clear pattern either way. But in our sample of international cities, we find that the more rents are quality adjusted, the worse housing affordability looks in poorer cities.

Figure 12: Housing affordability – International Cities (Numbeo)

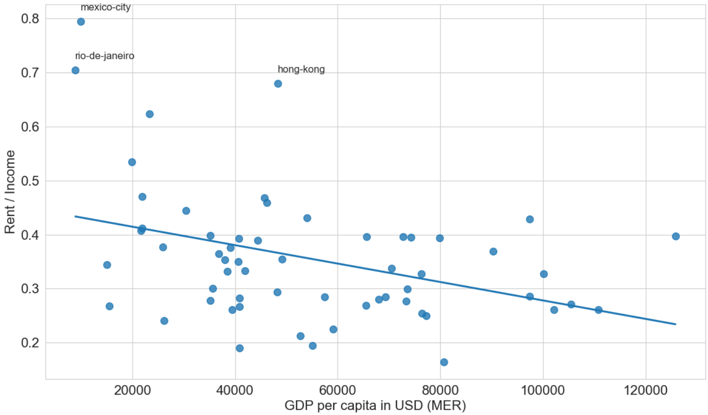
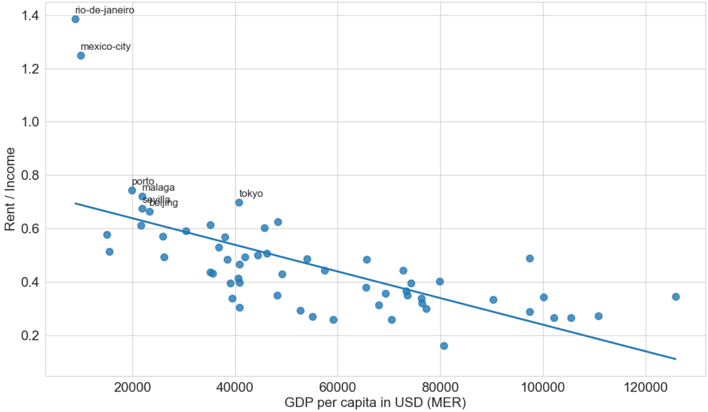


Figure 13: Housing affordability – International Cities (LTR)



Results for $HA = a + b \times pcGDP + error$:

LTR60 (all countries): $0.85^{***} - 0.00659^{***} \times pcGDP$ (in 10k) //
R2: 0.33, p-value on pcGDP: 0.00

Numbeo (all countries): $0.53^{***} - 0.00293^{**} \times pcGDP$ (in 10k) //
R2: 0.16, p-value on pcGDP: 0.002

LTR60 (57 countries): $0.64^{***} - 0.00346^{***} \times pcGDP$ (in 10k) //
R2: 0.47, p-value on pcGDP: 0.00

Numbeo (57 countries): $0.39^{***} - 0.00097^{*} \times pcGDP$ (in 10k) //
R2: 0.07, p-value on pcGDP: 0.049

Conclusion

(i) Airbnb rent across cities rises with income.

(ii) The Airbnb rent-premium is decreasing in income.

(iii) Airbnb rents can be used to construct optimal weights for combining long-term rent series.

(iv) Housing rents are a major determinant of differences in the price level across countries.

(v) Housing affordability as measured by the rent-income ratio is worse in poorer cities (when rents are sufficiently quality adjusted. This contradicts the standard result based on comparisons across cities in the same country and the common assumption in teh literature of a unit elasticity of substitution between consumption and housing.