

Comparative analysis of hedonic rents and maximum bids in a land-use simulation context

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Abstract

The choice and bid-auction approaches for location choice modeling are analyzed and compared, with a focus in their rent estimation models: hedonic prices and expected maximum bids, respectively. A simulation experiment is performed over synthetic data, comparing several specifications for hedonic rent models with the expected maximum bid. Results show that the hedonic approach generates rents that diverge from the maximum bids. This results indicate that hedonic rent models can be improved by accounting for elements like household's heterogeneity in preferences and market conditions or constraints.

Keywords

location choice, hedonic rents, equilibrium, auction market, real estate

1 Introduction

Land use simulation models, and particularly microsimulation models, are becoming an increasingly used tool to forecast the future states of cities and to evaluate policy scenarios and their effects in location and general conditions in a city.

Modeling the land use market is a complicated task due to the dynamics and interactions that take place between agents and goods. The (re)location dynamics of the city generate constant changes in the attributes of the different locations, making the location choice of one agent depend on the choices of the other agents. This phenomena, known as location externalities (or agglomeration economies in the case of firms), is one of the main forces shaping the socioeconomic landscape of the city and generating effects like spatial segregation or agglomeration. At the same time the growth of the population and the economy, or changes in the general market conditions (like the population's income distribution or zoning regulations), trigger changes in the agents' perceptions and in the way they "compete" for real estate properties, with the expected effect in location patterns and prices or rents.

The modeling approach for the location choice process underpinning most land use models can be roughly subdivided in two groups: bid-based or choice-based. The bid approach (Alonso, 1964; Ellickson, 1981) assumes that real state units are traded through auctions, where the best bidder wins the location and, simultaneously, defines the price (in case of buying) or rent (in case of renting) of the property. This approach is theoretically sound and consistent with urban economics. However, most of the operational models that use the bid-auction approach are equilibrium-based and treat agents and real estate units in an aggregated manner (Wegener, 2004).

The choice approach (McFadden, 1978; Anas, 1982) is more widely used, specially in microsimulation (disaggregate) models. It assumes that decision makers observe the attributes of the locations, one of them being the price or rent, and choose the location that maximize their utility. In most operational models using this approach, rents are calculated through hedonic models, supported by the theory proposed by Rosen (1974); this means that rents are described by an econometric function of the location's attributes, considering households as price-takers.

If the real estate market is assumed to operate as an auction market, the use of the bid or the choice approach for modeling location choice will, in theory, generate identical location distributions (Martinez, 1992, 2000). However this equivalence will depend on how the rents are calculated. In the bid approach rents are calculated as the expected maximum bid across households; in the choice approach rents are the outcome of hedonic models. Consistency between these two elements is not guaranteed.

Hedonic models (with the proper specification) are able to account for complex phenomena like

spatial autocorrelation and spatial heterogeneity (Anselin, 1988; Sheppard, 1999), including relocation dynamics and location externalities. However, some of the shifts in perceptions or changes in the willingness to pay from households are not considered in standard hedonic specifications. An example of this is what happens when there is a change in the population's income distribution. In the case of an increase in the number of rich households not only the location across zones will change, but also the scale of the prices in general. This is result of a stronger competition for unique goods between households with a higher acquisitive power which (in the case of an auction market) will increase the general value of the bids. Since standard hedonic models don't account for market clearing mechanisms nor the preferences of a particular sub-group of the population, they will be unable to react to this kind of phenomena. On the other hand, the expected maximum bid will aggregate the willingness to pay of all households, therefore being able to react to changes in their preferences.

This paper analyzes the differences that result from using a maximum bid versus a hedonic approach for rent estimation. For this purpose a simulation over synthetic data is performed and several specifications for hedonic rent models are compared with the bid approach. The objective is to build better hedonic rent models and to identify relevant elements that should be considered when modeling real estate prices.

The paper is organized as follows: Section 2 reviews the bid-auction approach for location choice modeling. Section 3 explains the theoretical equivalence between the bid and the choice approaches. Section 4 analyzes the relation between hedonic rent models and the expected maximum utility approach. Section 5 describes the simulation experiment, together with the specification and of the tested hedonic models; results are shown in section 6. Finally, Section 7 concludes the paper and identifies further research.

2 The bid approach

Since Alonso (1964), the real estate market has been understood as an auction market, where households bid their willingness to pay for a particular good (residential unit) which is assigned to the best bidder. This process simultaneously defines the price of the good, understood as the maximum bid in the auction process.

The willingness to pay, from an economic point of view, can be derived from the classical consumer's problem of maximum utility, given income constraints:

$$\max_{x,i} U(x, z_i)$$

$$s.t. px + r_i \le I$$
(1)

In the previous problem, the consumer maximizes his utility by choosing a vector of continuous goods (x) and a discrete location (i), described by a set of attributes (z_i) . The budget constraint states that the total amount spent in goods (with price p) plus the price of the selected location (r_i) must be smaller that the consumer's available income (I). Solving the problem on x and assuming equality in the budget constraint, the problem can be re-written as

$$\max_{i} V(p, I - r_i, z_i) \tag{2}$$

where V is the indirect utility function, conditional on the he location. Conditional on the level of maximum utility (\overline{U}), the indirect utility can be inverted in the rent variable:

$$r_i = I - V^{-1}(\overline{U}, p, z_i) \tag{3}$$

Under the auction market assumption, the rent variable can be understood as the willingness to pay for a particular location, therefore the bid function B can be expressed as:

$$B_{hi} = I_h - V_h^{-1}(\overline{U}, p, z_i) \tag{4}$$

In the bid function, the index h has been included to take into account heterogeneity in preferences within different households. If we assume bids to be random variables, with an extreme value distributed error term, it is possible to express the probability of a household (h) being the best bidder for a particular location (i) as follows:

$$P_{h/i} = \frac{\exp(\mu B_{hi})}{\sum_g \exp(\mu B_{gi})}$$
(5)

Under the auction market assumption, the price or rent of a good will be the maximum bid. The extreme value distribution assumption allows to write the expected maximum bid for a particular location as the logsum of the bids

$$r_i = \frac{1}{\mu} \ln\left(\sum_g \exp(\mu B_{gi})\right) \tag{6}$$

3 The bid-choice equivalence

The choice approach (McFadden, 1978; Anas, 1982) assumes that households choose the location that maximize their utility. The utility a household perceives can be defined as a function of the attributes of the location ($V_{hi} = f(z_i)$). Assuming an extreme value distribution for the error term of the utility function, the probability of a household h choosing a location i is:

$$P_{i/h} = \frac{\exp(\mu V_{hi})}{\sum_{j} \exp(\mu V_{hj})}$$
(7)

It is possible to demonstrate that, under the assumption of an auction market, the location where the agent is the highest bidder is also that of the maximum surplus or maximum utility (Martinez, 1992, 2000). This assures that the auction outcome yields an allocation consistent with maximum utility behavior of consumers. The consumer surplus is defined as the difference between the willingness to pay for a good and the actual price of the good. If the utility is written in terms of consumer surplus it will take the following form:

$$V_{hi} = B_{hi} - r_i \tag{8}$$

Replacing (8) in (7), the probability of a household h choosing a location i is:

$$P_{i/h} = \frac{\exp(\mu(B_{hi} - r_i))}{\sum_{j} \exp(\mu(B_{hj} - r_j))}$$
(9)

If prices are the outcome of an auction process and the market clears, the distribution of households across locations obtained through (9) will be the same as the distribution obtained from (5).

4 The hedonic rents model

Following Rosen (1974)'s approach, real estate prices or rents can be expressed as a function of the attributes of the location ($r_i = f(z_i)$). In fact, most of the operational land use microsimulation models, like UrbanSim (Waddell, 2002) or ILUTE (Salvini and Miller, 2005), use hedonic prices in their formulations. The most common form for a hedonic price model is a linear in parameters function:

$$r_i = \sum_k \alpha_k z_{ik} \tag{10}$$

where k is an index for the k^{th} attribute of the location. The parameters in a hedonic prices model can be interpreted as the market value of each of the attributes:

$$\alpha_k = \frac{\partial r_i}{\partial z_{ik}} \tag{11}$$

Under the assumption of an auction market (bid approach), the market value for each of the attributes (that is, the price at which this attribute would be bought) can be expressed as the derivative of the logsum (equation 6) with respect to the attribute. Since the attributes appear in the bid function of each household, the derivative takes the following form

$$\frac{\partial r_i}{\partial z_{ik}} = \sum_h \left(\frac{\partial \left(\ln \left(\sum_g \exp(B_{gi}) \right) \right)}{\partial B_{hi}} \cdot \frac{\partial B_{hi}}{\partial z_{ik}} \right)$$
(12)

If the bid function is also linear in parameters $(B_{hi} = \sum_k \beta_{hk} z_{ik})$ we have:

$$\frac{\partial r_i}{\partial z_{ik}} = \sum_h \left(P_{h/i} \cdot \beta_{hk} \right) \tag{13}$$

Therefore, if the prices are the outcome of an auction, the standard hedonic model will be an approximation of the maximum expected bid, where the parameter α tries to reproduce a weighted average of the individual households preferences β . Assuming that land is sold in auctions we conclude that there is a direct mapping between consumers utility functions and the corresponding hedonic rent functions. This implies first, that only a subset of functions are supported by the bid-auction theory and can be used for hedonic rent models, and second and perhaps more constraining, that once some utility function has been chosen to model location probabilities, the corresponding hedonic rent function is identified; any other function is not supported by the theory.

In the next section we analyze the difference in rents that result from using hedonic functions or maximum bids, through the simulation of a location choice process in a synthetic city. For comparison purposes we define two hedonic rent functions: first a "naive" one, following (10), and an improved one with market values for the attributes following (13). The specification of each of the hedonic rent models will be explained in detail in Section 5.4.

zone(i)	1	2	3	4	5	6	7	8	9	10
z_i	0.0	0.2	0.5	0.5	1.0	1.0	0.5	0.5	0.2	0.0

Table 1: Synthetic zonal attributes

5 Simulation experiment

5.1 Synthetic data

A synthetic data set is built, representing a city with 10 zones (i) and 3 different types of residential units (v). Three types of households (h) are defined: high income (h = 1), medium income (h = 2) and low income (h = 3) households. The number of households by income level (H_h), or cluster size, is arbitrarily defined.

Zones are characterized by a zone specific attractor $(z_i \in [0, 1])$ that variates across zones but keeps a constant value over time. This attractor can be interpreted as the accessibility of the zone or as the amount of amenities (commerce, services, green areas, etc.) in each zone. Table 1 show the values for z_i in each zone; the city is exogenously defined to be more attractive at the "center" and symmetrically less attractive towards the edges. Zones are also characterized by the percentage of located households by income level (H_{hi}) ; this variable represents the location externalities (the location of a household affects the location of other households) and will variate over time, allowing to account for phenomena like spatial agglomeration or segregation. Residential units are characterized by a single attribute (y_v) that can be interpreted as the size of the unit. Values for y_v are arbitrarily defined in order to have big $(y_1 = 1)$, medium $(y_2 = 0.6)$ and small houses $(y_3 = 0.3)$.

Each zone contains 500 residential units, uniformly distributed across the 3 sizes. The initial values for the located households by income level in each zone (H_{hi}) are randomly defined for the initial period. The total number of households is set to be equal to the total number of residential units.

In order to simulate location choices in our synthetic city, parameters that represent the preferences of each type of household need to be defined. The values of the parameters are arbitrary, but attempt to represent the willingness to pay of each type of household for each of the location attributes. Therefore, high income households have a high valuation for the zonal attractor (β_{hz}) , the size of the dwelling (β_{hy}) and the presence of other high income households (β_{hH_1}) , but assign a negative value to the presence of low income household (β_{hH_3}) . Preferences of medium income households are similar to those of the high income households but valuation of the attributes is in general lower (this can be interpreted as a lower willingness to pay). We assume that low income households are neutral regarding their preferences. The "true" parameters are shown in table 2.

parameter	h = 1	h=2	h = 3
β_{hz}	1.5	1.0	0
β_{hy}	1.5	1.0	0
β_{hH_1}	1.5	1.0	0
β_{hH_3}	-1.5	-1.0	0

Table 2: True parameters for the simulation of choices

5.2 Bid and choice probabilities

The probability of a household being the best bidder for a particular dwelling/zone (vi) follows (5), but needs to be corrected by the cluster size (H_h). This is consistent with a sampling of alternatives process, where the utilities need to be corrected by the probability of sampling (Ben-Akiva and Lerman, 1985) in order to assure unbiased results. For simplicity, we assume the scale parameter to be equal to one ($\mu = 1$).

$$P_{h/vi} = \frac{H_h \exp(B_{hvi})}{\sum_g H_g \exp(B_{gvi})}$$
(14)

where

$$B_{hvi} = \beta_{hz} z_i + \beta_{hy} y_v + \beta_{hH_1} H_{1i} + \beta_{hH_3} H_{3i} + b_h$$
(15)

The term b_h accounts for the maximum utility level that can be attain at the market clearing condition where every household is located somewhere. This can be interpreted a shift in the bid levels of each household type and is consistent with the alternative specific constant that needs to be estimated in discrete choice models to reproduce market shares.

Following (6), but accounting for the size correction, the rent for each type of dwelling in each zone can be calculated as the maximum expected bid:

$$r_{vi} = \ln\left(\sum_{g} H_g \exp(B_{gvi})\right) \tag{16}$$

The adjustment b_h is calculated by solving the market clearing condition which imposes that every household must be located somewhere:

$$H_h = \sum_{vi} S_{vi} P_{h/vi} \quad \forall h \tag{17}$$

Replacing (14) and (15) in (22) and clearing b_h we get:

$$b_{h} = -\ln\left(\sum_{vi} S_{vi} \exp\left(B_{hvi} - r_{vi}\right)\right) \quad \forall h$$
(18)

The previous equation represents a fixed point problem, since rents (r_{vi}) depend on b_h through (16).

The probability of a household h choosing a location vi (equation 9) also needs to be corrected by the group size of the sampled alternative.

$$P_{vi/h} = \frac{S_{vi} \exp(B'_{hvi} - r_{vi})}{\sum_{wj} S_{wj} \exp(B'_{hwj} - r_{wj})}$$
(19)

where S_{vi} is the total number of housing units type v in zone i and

$$B'_{hvi} = B_{hvi} - b_h = \beta_{hz} z_i + \beta_{hy} y_v + \beta_{hH_1} H_{1i} + \beta_{hH_3} H_{3i}$$
(20)

Note that (19) does not change if we replace B'_{hvi} by B_{hvi} , because the term b_h cancels out.

The market clearing can be equivalently solved by ensuring that every dwelling is used, following Anas (1982):

$$S_{vi} = \sum_{h} H_h P_{vi/h} \quad \forall h \tag{21}$$

The previous equality is true if the rents are calculated following (16)

5.3 Simulation algorithm

In the initial period (t = 0) bids functions are evaluated over the observed attributes and the term b_h is calculated in what can be interpreted as an adjustment to the current conditions of the willingness to pay of the households.

Once the bid functions are evaluated, rents are calculated following (16) and location choices are simulated. This last part can either be done following the distribution given by the bidauction approach (14) or by the choice approach (19), obtaining statistically identical distributions, as explained in Section 3. However, it is important to notice that, in period t = 0 the new location distributions will not be consistent with the observed distribution of households by income level and zone, which was arbitrarily defined for this first period. Therefore the city can be considered to be in a state of disequilibrium.

In order to make the simulation more realistic and consistent with standard microsimulation models, we allow relocation only for a fraction ρ of the households, therefore generating a transient that will tend to an equilibrium in the long term but which is not solved completely in one simulation period.

In period t + 1 the new location distribution of households changes the attributes H_{hi} of each zone following:

$$H_{hi}^{t+1} = (1-\rho)H_{hi}^{t} + \rho \sum_{v} S_{vi}P_{h/vi}^{t} \quad \forall hi$$
(22)

With the new location distributions, the bid functions are re-evaluated, the adjustment term b_h is re-calculated and a new relocation process takes place. We consider this to be a plausible approximation of the non-equilibrium relocation processes observed in reality, where house-holds are unable to account for the changes triggered by their own relocation, but do observe the attributes of the locations at the time of their decision.

5.4 Specification and estimation of the hedonic rent models

In period t = 0 of the simulation, the hedonic rent models are estimated. The dependent variable is the vector of rents calculated as the expected maximum bid and the explanatory variables are the attributes of each location vi at the beginning of the period (before any relocation of households)

The "naive" or standard hedonic model assumes a standard linear specification as follows:

$$r_{vi} = c + \alpha_z z_i + \alpha_y y_v + \alpha_{H_1} H_{1i} + \alpha_{H_3} H_{3i}$$
(23)

Since B_{hvi} is linear in parameters, this hedonic form is consistent with the bid-auction theory, with parameters (α) being an approximation of (13).

It is important to notice that, given the simulation algorithm, the attributes of the location that enter the hedonic rent model are those observed at the beginning of the period, and are therefore influenced by the previous prices. This is specially relevant for the income distribution by zone variables (H_{1i}, H_{3i}) .

Estimation results over for this model are shown in Table 3. The estimated parameters for the

parameter	estimate	std-error			
С	8.555	0.011			
α_z	0.825	0.005			
α_y	0.927	0.004			
α_{H_1}	1.007	0.013			
α_{H_3}	-0.822	0.018			
R^2 =0.991					

 Table 3: Estimation results for the standard hedonic rent model

Table 4: Estimation results for the pseudo-logsum rent model*

parameter	estimate for $h = 1$	estimate for $h = 2$	estimate for $h = 2$		
С		8.776 (3.21E-05)			
α_{hz}	1.232 (2.09E-04)	0.634 (1.09E-04)	0.302 (1.56E-04)		
α_{hy}	1.241 (1.79E-04)	0.629 (1.30E-04)	0.306 (2.03E-04)		
α_{hH_1}	1.238 (5.03E-04)	0.630 (3.16E-04)	0.305 (3.25E-04)		
$lpha_{hH_3}$	-1.244 (1.26E-03)	-0.626 (6.48E-04)	-0.308 (1.90E-04)		
R^2 =0.995					

* values between parenthesis indicate the standard-error

hedonic rent model have the expected signs, following the general trend of the true parameters. We also consider a model accounting for the value of attributes as defined in (13):

$$r_{vi} = c + \sum_{h} P_{h/vi} \left(\alpha_{hz} z_i + \alpha_{hy} y_v + \alpha_{hH_1} H_{1i} + \alpha_{hH_3} H_{3i} \right)$$
(24)

The previous model, which we call "pseudo-logsum model", also uses the bid probabilities and income distributions by zone at the beginning of the period. Estimation results for this model are shown in table 4. It is possible to see that the sign of the parameters keeps the structure observed in the parameters for the hedonic rent and the true parameters. The scale of the parameters for each household also follows the general structure of the true parameters, however the estimates for the pseudo-logsum are statistically different from the true parameters.

Since the assumption of the households being able to observe the probabilities is strong, a simplified version of the previous model is proposed, using the observed location by income and zone (H_{hi}) as an approximate value of $P_{h/vi}$. This makes the model more realistic, by assuming that households observe the zonal income distribution with a temporal lag of one period. We call this model "pseudo-logsum2" and is described by the following equation:

$$r_{vi} = c + \sum_{h} \frac{H_{hi}}{H_i} \left(\alpha_{hz} z_i + \alpha_{hy} y_v + \alpha_{hH_1} H_{1i} + \alpha_{hH_3} H_{3i} \right)$$
(25)



Figure 1: Average logsum rents by zone (scenario A)

where $H_i = \sum_h H_{hi}$ is the total number of households located in zone *i*.

6 Results

The location choice is simulated over 100 periods in two scenarios:

- Scenario A: the income distribution across the population remains constant in time ($H_1 = 1000, H_2 = 2500, H_3 = 1500$)
- Scenario B: in every period, the number of high income households is increased in 10 units while the number of low income households is decreased in the same amount. The initial number of households by income level is the same as in scenario A.

6.1 Results for scenario A

The city starts in a "disequilibrium" state but, as time advances, households relocate because they adjust their utility levels (b_h) and their perception of the location externalities (H_{hi}) up to the the static equilibrium when (logsum) rents stabilize, as seen in Figure 1. Figure 2 compares the average logsum rents to the rents generated by the hedonic models proposed in Section 5.4; it is possible to see that the pseudo-logsum model performs well, generating rents that are close to the logsum. The standard hedonic model and the pseudo-logsum2 models underestimate the rents systematically.

When comparing results by type of housing unit (shown in Figures 3, 4 and 5) the pseudo logsum model again performs well compared to the logsum, for every type of unit. The standard hedonic model systematically underestimates the rent for every type of dwelling, while the pseudo-logsum2 model underestimates the rents for big houses (type1) and overestimates for medium and small houses. This is explained by the lack of a factor accounting for the



Figure 2: Average rents (scenario A)





heterogeneity in preferences for different types of housing in both the hedonic and the pseudo-logsum2 model.

Similar results are obtained when analyzing the average rents by zone. Figures 6 and 7 show the predicted rents for each model for zones 1 and 5, as an example of what happens in other zones. For zones with a tendency of high rents, like zone 5, all models seem to adjust well to the logsum rents in the long term. This is probably explained by the bigger presence in this zone of high income households, who's willingness to pay is already high and, therefore, requires













little adjustment (b_h) in order to ensure location. This makes the logsum rents to be similar to the hedonic rents. The slower convergence of the pseudo-logsum2 model is explained by the lag in the adjustment of income distribution by zone.







Figure 8: Average logsum rents by zone (scenario B)





6.2 **Results for scenario B**

As in scenario A, the city starts in a disequilibrium state, but it never reaches an equilibrium since the general income distribution among households constantly changes. The increase in number of high income households and simultaneous decrease of low income households generates a positive shift in the bid at each period, which can be understood as the result of higher bids from high income households, that compete amongst them more intensively as their numbers grow. This explains the constant increase in prices after the initial periods seen in Figure 8.

When comparing the average rents generated by the hedonic models, it is possible to see that both pseudo-logsum models overestimate the rents while the standard hedonic model underestimates. As seen in Figure 9, the distance between the logsum and the rents estimated with the hedonic models increases in time, therefore generating a divergence that will be significant in the long term. The pseudo-logsum2 model generates bad results for the first periods, due to the slow adjustment of the variable H_{hi} as results of the partial relocation of households in each period.

Figures 10, 11 and 12 show estimated rent results for each housing unit type. In all cases



Figure 10: Average rents for housing unit type 1 (scenario B)





the pseudo-logsum models overestimate the rents, due to the bigger presence of high income households and the lack of adjustment for bids (b_h) . The standard hedonic model underestimate rents for dwellings of type 1 (big and expensive), does well for dwellings of type 2 (medium size) and overestimate rents for dwellings of type 3 (small and cheaper). This is a expected result since the standard hedonic model can be understood as an average of the different household's valuation of the dwelling's attributes. In all models, when over or underestimating, the difference between the estimated rents and the logsum rents increases with time.







Figure 13: Average rents for zone 1 (scenario B)





Figures 13 and 14 show the average zonal rents for low rent (zone 1) and high rent (zone 5) examples. For the higher rent zones, both pseudo-logsum approaches perform well, due to the bigger relevance of high income household's bids and their increasing number in time. The standard hedonic model performs well in the initial periods, but diverges from the logsum rents as the general income distribution among households variates in time. For low rent zones, all models deviate from the maximum bid rents. The pseudo-logsum models systematically overestimate the prices, since the bid adjustment (b_h) for household locating in this zone (low income) is relevant but not considered. The standard hedonic model underestimate rents in the first half of the simulation and overestimates in the second half. This is also due to the lack of a bid-adjustment term.

7 Conclusions

This paper shows that, in a land-use simulation context, the rents generated by hedonic models differ from the rents calculated as the expected maximum bids. This results are relevant considering that state of the practice in land use simulation usually utilizes hedonic functions for calculating (and forecasting) rents. If the assumption of an auction market for real estate goods is taken into account, the maximum bids (or logsums) are theoretically correct. Still, if other assumptions about the real estate market are considered, there is no guarantee that a standard hedonic model will be able to account for heterogeneity of household's preferences and changes in income distribution.

Hedonic prices do not take into account the adjustment in the willingness to pay of households that might occur when market conditions change. In the bid approach this adjustment comes from the constraint of ensuring that every household is located somewhere. Land use microsimulation models do not enforce this constraint explicitly, but still simulate location of households until a complete relocation is achieved. Therefore, some perception or willingness to pay adjustment mechanism is should take place, but is not modeled explicitly.

If the auction market assumption is confirmed, the bid-choice equivalence is valid and, therefore, maximum expected bids could be used in land use microsimulation models. Although, the practical feasibility of this solution requires further analysis and will depend on the structure of the model and availability of data.

Further research will analyze the relevance of bid adjustments by location-alternative (together with the adjustment by household type already analyzed in this paper), a probable cause of the constant difference in values between logsums and hedonic models observed in scenario A. Also, estimation and validation of models with real data should be a priority for future research.

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