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Abstract

In this paper, the heterogeneity of the Paris apartment market is addressed. For this purpose, quantile regression is applied – with market segmentation based on price deciles – and the hedonic price of housing attributes is computed for various price segments of the market. The approach is applied to a major data set managed by the Paris region notary office (Chambre des Notaires d'Île de France), which consists of approximately 156,000 transactions over the 2000 – 2006 period. Although spatial econometric methods could not be applied due to the unavailability of geocodes, spatial dependence effects are shown to be adequately accounted for through an array of 80 location dummy variables. The findings suggest that the *relative* hedonic prices of several housing attributes differ significantly among deciles. In particular, the elasticity coefficient of the apartment size variable, which is 1.09 for the cheapest units, is down to 1.03 for the most expensive ones. The unit floor level, the number of indoor parking slots, as well as several neighbourhood attributes and location dummies all exhibit substantial implicit price fluctuations among deciles. Finally, the lower the apartment price, the higher the potential for price appreciation over time. While enhancing our understanding of the complex market dynamics that underlie residential choices in a major metropolis like Paris, this research provides empirical evidence that the QR approach adequately captures heterogeneity among house price ranges, which simultaneously applies to housing stock, historical construct and social fabric.

Keywords: Hedonics; market segmentation; housing sub-markets; quantile regression; heterogeneity.

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1. Introduction

Paris is France's capital and its most populous city. However it is by no means homogeneous in terms of neighbourhood, building, and population features. Its growth over the centuries has resulted from an organic process that started from the inner areas (originally, Lutece) and extended progressively into the surrounding suburbs that now form the inner, *intramuros* Paris, which is the subject of this paper. Inner Paris, which represents around 20% of the population in the Paris region, is divided administratively into twenty boroughs ("*arrondissement*s"), conveniently known by their numbers and mostly delineated by *Boulevard Périphérique.* The latter are sequentially grouped, so as to form a snail-like pattern (see online appendix, Figure A-1), divided into four administrative precincts, referred to as "*quartiers*". The inner Paris housing dynamics can therefore be analysed on the basis of those 80 neighbourhoods (see online appendix, Figure A-2).

In fact, Paris apartments are highly heterogeneous with regard to their price, size, number of rooms, construction period, and location characteristics. It can be assumed that all market segments do not follow the same rationale when it comes to value attributes. For that reason, it is likely that the shadow price of many housing attributes varies substantially across product price ranges. It should be noted that traditional hedonic models are based on the premise that the full hedonic price envelope function is homogenous (Rosen, 1974). This, however, does not preclude the existence of distinct sub-markets. As put by Rosen (1974, p. 40), who notes that the overall "quality" in the consumption bundle of a complex good may not necessarily increase with income…:

> *" However, in general there is no compelling reason why the overall quality should always increase with income. Some components may increase and others decrease (cf. Lipsey and Rosenbluth 1971). Be that as it may, a clear consequence of the model is that there are natural tendencies toward market segmentation, in the sense that consumers with similar value fonctions purchase products with similar specifications. This is a well-known result of spatial equilibrium models. In fact, the above specification is very similar in spirit to Tiebout's (1956) analysis of the implicit market for neighborhoods, local public goods being the "characteristics" in this case. He obtained the result that neighborhoods tend to be segmented by distinct income and taste groups (also, see Ellickson 1971).*"

In the presence of such sub-markets, the ability of traditional hedonic methods to capture the true market value of specific bundles of housing attributes may be questioned. Consequently, the model must be designed so as to account for heterogeneity that may otherwise render hedonic prices unreliable for any given sub-market, since the latter are measured at the overall mean of the price distribution. As suggested by our literature review, several approaches have been used to deal with this issue. For example, in this context, Paris notary house price indices are based on a series of reference sets of relatively similar properties (see Clarenc *et al.*, 2014).

While mean house prices convey a broad picture of local market structure, they may be inadequate for providing an in-depth understanding of how economic agents belonging to different price segments of the market value housing attributes. Indeed, the existence of price segment sub-markets has a direct impact on real estate prices and rent dynamics. In order to address that issue, this paper uses quantile regression (QR) to identify the implicit price of housing characteristics for different points in the distribution of house prices. Since quantile regression uses the entire sample, the problem of truncation and of biased estimates is avoided (Heckman, 1979; Newsome and Zietz, 1992). The Paris notary database for the 2000-2006 period, which provides apartment sale prices together with an array of both structural and neighbourhood descriptors, is used for this purpose.

By using quantile regression, this paper extends the existing literature on hedonic models in the presence of market heterogeneity, in line with Zietz *et al*. (2008), Farmer *et al*. (2010), Mak *et al*. (2010) and Liao and Wang (2012). Its contribution is twofold. First, it provides new evidence that housing-attribute pricing may vary, in *relative* terms, across quantiles, a conclusion that applies to both structural and neighbourhood dimensions. Second, it highlights the relevance of using QR for investigating the price-formation process in major metropolitan areas, such as Paris, where market heterogeneity is the norm, despite rather strict planning constraints. Finally, it yields findings that diverge from mainstream research in the field with respect to the marginal influence of unit size on values. Although other approaches can be used for handling the issue, the QR approach offers the clear advantage of circumventing a major constraint of hedonic modelling, *i.e*. market homogeneity, by estimating multiple coefficients for housing attributes, depending on the asset price range.

The paper is organized as follows. Following a literature review, the hedonic and QR methods are first presented. Secondly, the dataset is introduced with a short descriptive analysis of the variables. Finally, selective QR findings (for deciles 0.1, 0.3, 0.5, 0.7 and 0.9) are reported and their impact on apartment unit prices discussed. A general conclusion ends the paper.

2. Literature review

Real estate is all about sub-markets, an assertion about which there is general consensus. As underlined by Islam and Asami (2009), there are many ways to define sub-markets, according to how they will be used in the regression equation. More often than not, they are defined as geographical areas based on either pre-existing geographic or political boundaries or on socio-economic and/or environmental characteristics. They may also be derived from statistical techniques (*e.g.* factor analysis, principal component analysis, cluster analysis) or spatial econometrics (spatial autoregressive models). For instance, Des Rosiers *et al*. (2000) use principal component analysis to identify sub-markets and show how it separates influences that would otherwise be intermingled.

Accounting for sub-markets is essential for obtaining greater accuracy of hedonic models and more effectively modelling spatial and temporal patterns present in house prices. As stated by Goodman and Thibodeau (2003, 2007), model performance improves with the number of sub-markets hence defined.

Emphasizing market segmentation, Goodman and Thibodeau (1998, 2003) turn to hierarchical linear modelling for delimiting sub-markets and obtain significant gains in hedonic prediction accuracy, compared to the market-wide model. In the same vein, Bourassa *et al*. (2003) concluded that price predictions are most accurate when appraisal-based market delineation is used, as opposed to sub-markets derived from factor and cluster analyses. Leishman (2001) pointed out that housing markets may be segmented both spatially and structurally, and may be considered as a set of inter-related sub-markets. Leishman *et al*. (2013) apply multilevel modelling in order to improve the predictive accuracy.

The development of the geographically weighted regression approach proposed by Brunsdon *et al*. (1998) makes it possible to generate spatially varying coefficients that capture local sub-market specificities and account for spatial autocorrelation (SA). Following Can and Megbolugbe (1997), Thériault *et al*. (2003) use interactive variables together with Casetti's expansion method to reveal marginal price impacts that would go unnoticed when only mean estimates are derived. More recently, Biswas (2012) examines various definitions of housing sub-markets in the context of foreclosures. He shows how the traditional approach based on spatial proximity and on the stock homogeneity assumption, is superseded by an approach accounting for both housing stock heterogeneity and non-contiguity in space. Koschinsky *et al*. (2012) compare the results from non-spatial and spatial econometrics methods to examine the reliability of coefficient estimates for locational housing attributes in Seattle, WA. They conclude that, while OLS generates higher coefficient and direct effect estimates for both structural and locational housing characteristics than spatial methods, OLS with spatial fixed effects rank second to spatial methods when SA is taken into consideration.

Finally, Bhattacharjee *et al*. (2012) investigate the sub-market delineation issue through the dwelling substitutability concept. Their model incorporates both spatial heterogeneity and endogenous spatial dependence, and shows that house substitutability is achieved by combining similarity in housing attributes with similarity in hedonic prices. In that respect, Pryce (2013) suggests that the cross-price elasticity concept is most useful in exploring the degree of substitutability, compared to distance, spatial contiguity or neighbourhood attribute clustering.

Heterogeneity is one of the main characteristics of real estate. Over the past forty years, several authors have addressed the market heterogeneity issue in various ways (Xu, 2008). As suggested by Bhattacharjee *et al*. (2012) and in considering the dwelling substitutability concept, heterogeneity in housing attributes can reasonably be assumed to vary among apartment price ranges. In that context, QR (Koenker and Bassett, 1982; Koenker and Hallock, 2001) reveals itself as a most appropriate device for capturing heterogeneous utility functions and for bringing out differences in homebuyer preference maps. QR is estimated simultaneously and thus retains all the information available from the dataset and provides greater in-depth insight into the effects of the covariates than would a series of independent standard linear regressions (Benoit and Van den Poel, 2009). QR focuses on the interrelationship between a dependent variable and its explanatory variables for a given quantile. QR is of interest when explanatory factors are expected to exhibit different variations for different ranges of the dependent variable.

Coulson and McMillen (2007) are among the first to use quantile regression for addressing market heterogeneity in housing research. They use quantile regression to create price indices for various housing quantiles. Based on sales from three municipalities in Chicago, their findings support theoretical expectations and show cointegration between the supply side and price indices, with a prevalence of high-quality units. In addition, their study identifies significant variations in how physical attributes are valued across quantiles. Using 1999-2000 home sales from the Orem/Provo area in Utah, Zietz *et al*. (2008) also find that the coefficients of some, although not all, variables vary considerably across quantiles. Above all, they account for SA and show that quantile effects largely outweigh SA effects.

In the same vein, using a dataset of nearly 6,000 cross-sectional, intertemporal (1997-2004) sales from City One, a major residential project in Sha Tin, Hong Kong, Mak *et al*. (2010) apply QR in order to identify the implicit prices of housing characteristics for different price ranges. The empirical findings suggest that homebuyer tastes and preferences for specific housing attributes vary greatly across different price quantiles. Among other things, and in line with Zietz *et al*. (2008), optimal square footage emerges as larger for upper quantiles than for lower quantiles. Higher-priced properties also command a larger market premium for a view than do lower-priced properties. Finally, Liao and Wang (2012) apply quantile regression to Changsha, an emerging Chinese city. More than 46,000 sales were recorded in 113 residential developments over a one-year period, from September 2008 to September 2009. The authors conclude, yet again, that the pricing of housing attributes may vary across their conditional distribution. The findings initially suggest that the price of nearby properties has a greater value impact on high- and low-priced homes than on mid-priced homes. A clear upward trend of the quantile effects for floor area is also revealed.

Farmer and Lipscomb (2010) investigate the role sub-market competition plays in setting the price of housing attributes, particularly in a context of fixed supply and evolving homebuyer profiles. Using household information from both direct stated-preference surveys and Multiple Listing Service data, the authors use QR to track variations in implicit prices for specific attribute bundles in those price ranges where two sub-markets overlap. The findings support the hypothesis that, where cross-sub-market competition is expected, newcomers with particular needs and preferences are willing to pay more than average implicit prices for specific bundles of housing attributes. They also confirm the relevance of QR for adequately handling the selective heterogeneity of hedonic coefficients.

Zahirovic-Herbert and Chatterjee (2012) considered the effects of historic designation on residential property values in Baton Rouge, Louisiana. The results support the well-established notion in the urban economics literature that historic preservation has a positive impact on property values. Using QR, the authors show that low-end properties gain most from a historic preservation designation.

3. Methodology: the quantile hedonic regression approach

Hedonic theory states that the market price of a complex, or heterogeneous, good is a direct function of the utility derived from the quantity of the *n* known attributes it is composed of and results from the market equilibrium for such attributes. In spite of its theoretical and methodological limitations (Rosen, 1974), the hedonic price method has proved very reliable for isolating the marginal contribution of market value determinants, time included.

The basic, traditional general form of the hedonic price equation can be written as:

$$\text{Log } Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon = X\beta + \varepsilon \text{ ,}$$

where Y is the sale price; X_i is the vector of k housing attributes; β_0 is the intercept; β_i is the implicit or hedonic, price of each i attribute; and ε is the stochastic error term (the X_i may be logged as well, for instance the unit surface area, as in the log-log model). Under such an approach, hedonic prices are usually computed as the mean value of the parameter estimate distribution, although the median may also be used for that purpose. However, where it is assumed that the marginal price of a given attribute changes over space and/or time, relying on the mean value of the distribution is no longer adequate and other methods ought to be applied. This is where quantile regression comes into play.

The "mean" regression model assumes that the expected value of variable y can be expressed as a linear combination of a set of regressors X_i, $E(Y|X) = X\beta$, where β represents the vector of the variable coefficients. QR produces different coefficients for each pre-specified quantile (decile or centile) of the error distribution. QR allows for raising such a question for any quantile of the conditional distribution function, thereby generalizing the concept of a univariate quantile to a conditional quantile, given one or more covariates.

This single mean curve $X\beta$ is sometimes not informative enough and provides only a partial or overall view of the relationship of interest. It might therefore be useful to describe the link between Y and the X_i's at different points of the conditional cumulative distribution of y. QR provides that capability by using different conditional quantiles of y according to X[2]. They can be denoted $Q_\tau(Y|X)$, where τ is a given probability ($0 < \tau < 1$).

Without any information on X, the quantile function $Q_\tau(Y)$ returns a value of y, which splits the data into proportions τ below, and $(1 - \tau)$ above it. Hence $Q_\tau(Y)$ is linked to the cumulative distribution function of y as follows:

$$F_y\left(Q_\tau(Y)\right) = \text{Prob}\left(Y \le Q_\tau(Y)\right) = \tau,\ 0 < \tau < 1$$

[2] The QR approach is also known as the L1-norm method.

As with the classical regression model that defines the "mean" of y as a linear function of the X_i's, $E(Y|X) = X\beta$, the quantile regression model defines the quantile associated with probability τ as $Q_\tau(Y|X) = X\beta$. Hence, there may be an infinite number of quantile regressions, while there is only one "mean" regression.

Koenker and Bassett (1978) initially developed this method. QR minimizes the weighted sum of the absolute deviations, noted S (β_τ | Y,X), with asymmetric weights, τ for positive residuals and (1 - τ) for the negatives ones:

$$S\left(\beta_\tau \mid Y, X\right) = \sum_{i:Y_i \geq X_i^{'}\beta_\tau}^{n} \tau \left|Y_i - \beta_\tau X_i^{'}\right| + \sum_{i:Y_i < X_i^{'}\beta_\tau}^{n} \left(1-\tau\right)\left|Y_i - \beta_\tau X_i^{'}\right|$$

Then, S is minimized as a function of the vector β_τ.

Quantile effects lend themselves to a straightforward interpretation that follows directly from the hedonic price index estimators. For instance, the marginal effect of X at the median is $\beta_{0.5}$, while the marginal effect at the 90th per centile is $\beta_{0.9}$.

4. The database

The database is that of the Paris region Chamber of Notaries and consists, after filtering, of some 156,000 apartment sales from Q1-2000 to Q2-2006 for inner Paris. In France, all property sales have to be registered by a notary, who collects the realty transfer fee to be paid to Inland Revenue. The database is publicly accessible for a fee. It includes, for each transaction, information on the sale price, apartment size, floor level, number of rooms, number of bathrooms, number of cellars, the construction period, the presence of a garage, of an elevator, the type of street (boulevard, square, alley, etc.) and the date of transaction. Moreover, the postal code and administrative precinct information are available for each unit. They indicate the *arrondissement* as well as the district, or *quartier*, where the asset is located within the *arrondissement*. Paris *arrondissements* are divided into four districts[3] - thereafter referred to as *quartiers* - and sequentially numbered so as to form a snail-like, spiral pattern that extends from the centre to the periphery. Only second-hand apartments are considered in the study, as new dwellings and houses represent a small share of total transactions for the Paris Region, with prices and structural attributes that greatly differ from those of second-hand apartments.

The main housing attributes (essentially dummy variables with the exception of the size descriptor) include apartment size, construction period of the building, floor level, number of bathrooms, presence of a lift,[4] and street type (e.g. Street, Avenue, Boulevard, etc.). Time and spatial trends are accounted for through 26 quarter dummies (Q1 2000 through Q2 2006) and 80 neighbourhood dummies (*quartiers* 1 through 80), respectively.

For reasons of conciseness, statistics on apartment attributes and on sale prices are not displayed here, but are available online as an appendix. The most important points can be summarized as follows:

(i) Mean price and standard deviation are €226,000 and €242,000 respectively;

(ii) Half of the properties sold were built before the First World War, far exceeding the share this category of units accounts for in the Paris housing stock (roughly 30%). This shows the particular interest in Haussmann-style buildings (1850-1913 period);

(iii) Some 60% of sales relate to apartments smaller than 50 sq.m. This is consistent with the standard two-room Parisian apartment and with an investment market that is driven by small dwellings, which form its most active segment;

(iv) Only 5% of apartments are located above the seventh floor, inner Paris buildings usually having between four and six floors;

[3] Thus, the 1st *arrondissement* comprises *quartiers* 1 through 4, the 2nd "arrondissement" of *quartiers* 5 through 8, etc.

[4] The variable lift is poorly reported and should therefore be interpreted with care (see online appendix).

(v) More than two thirds of apartment sales belong to the peripheral districts (12^{th} through 20^{th} *arrondissements*). This is consistent with their respective size, which exceeds that of more central districts (1^{st} to 11^{th} *arrondissements*);

(vi) In contrast with the decile partition for which, by construction, there is no price overlap or discontinuity among deciles (*i.e.* each decile takes over where the previous one ends), the price distribution by size displays pronounced price overlaps. This emphasises the usefulness of quantile regression based on prices as a market segmentation device;

(vii) The sales are essentially uniformly distributed over time, ranging from a minimum of 22,100 (2002) to a maximum of 28,600 (2005). This is even more the case with regard to quarters, with Q1 through Q3 exhibiting some 40,000 sales, while Q4 displays a somewhat lower frequency, 35,000 sales (see online appendix).

The reference (included in the intercept) is an apartment located in 'Clignancourt' (*quartier* 70), in a street-type location ('*rue'*), on the ground floor of a building built between 1850 and 1913 (Haussmannian period) with a lift, a cave and without rooms service or a garage. Information about attributes is not always available. When this problem arises, a variable "attribute missing" has been added to the model, so as to generate an unbiased estimation of the intercept (and hence of the other parameters).

5. Empirical results

5.1. Overall model performance and functional form

Quantile regression findings are reported in Table 1 for deciles 10, 30, 50, 70 and 90. Table 1 gives the coefficient estimates with their statistical significance. The last column gives the slope of the quantile with its statistical significance. Most parameters emerge as highly significant (p-values are predominantly less than 0.0001, as indicated by three stars ***). Regarding overall model performance, pseudo R-Squared statistics pertaining to deciles are relatively good, with the median decile R-Squared still standing at 0.739. Model explanatory power also rises with the price category, from 0.673 (1^{st} decile) to 0.766 (9^{th} decile). The tendency for the equations to fit better at higher quantiles is probably due to the heterogeneity of the housing stock at lower quantiles, which combine premises in all kinds of areas, either low-quality or high-quality, except for poorly maintained apartments. All the associated p-values of the estimates are reported in the online appendix (Tables A-25 and A-26), as well as findings pertaining to the other missing deciles (20, 40, 60 and 80). Finally, and as discussed below, the relationship between the selling price and basic hedonic pricing variables (size, floor, garage, bathrooms) is best captured using quantile regression.

As is usually the case with hedonic price models, the log-linear functional form is used here, with the natural logarithm of sale price as the dependent variable. Considering that a semi-log functional form is used for the model, all dummy variable coefficients must be transformed, so as to derive the actual marginal contribution of the variable to price[5]. For the remainder of the paper, actual marginal contributions are discussed, although original regression coefficients are reported in Tables 1 and A-25.

5.2. Addressing the spatial autocorrelation issue

SA is a common source of imperfection in house price modelling. Essentially, it can take two forms, *i.e.* spatial error dependence or spatial lag dependence. The former is commonly handled using a weight matrix approach designed for modelling the spatial pattern in the error term due to omitted variables, while a "spatially lagged" dependent variable is generally used to account for the spatial lag dependence. As geocodes are not available, the geographical location of apartments is used instead. In this sense, we follow Gregoir *et al*. (2012), who also use administrative areas as location dummies and Zahirovic-Herbert and Chatterjee (2012), who base location parameters on census blocks.[6] As mentioned earlier, each of the 20 Paris *arrondissements* is an amalgamation of four administrative *quartiers*, each of which has its own specific features and price

[5] This is achieved by using the exponential of the coefficient, minus 1. For instance, a coefficient of 0.1367 (6^{th} floor) yields a marginal contribution to price of 14.6%. This applies to all variables in the model, with the exception of the size coefficient; since the variable is log-transformed, its regression coefficient is interpreted as the size-elasticity of price.

[6] Gregoir *et al*. (2012) and Zahirovic-Herbert and Chatterjee (2012) use a smaller administrative area (respectively the land register unit level and the census blocks, each corresponding to a few building blocks).

determinants operating at a micro-spatial level. While a second-best solution, referring to these 80 dummy variables captures a large amount of the SA potentially present in the residuals. Indeed, as shown in Table A-28 (online appendix), regressing the model residuals on the location dummies yields R-Squared values that fall below 0.02 for all deciles where the latter are included in the model, as opposed to values ranging between 0.35 and 0.38, where they are not. Such findings corroborate Koschinsky *et al*. (2012), as to the relevance of fixed effect location dummy models for adequately handling spatial dependence common in residential transaction prices. They are also in line with Zietz *et al*. (2008), who state that quantile effects largely dominate SA effects. Consequently, it is assumed that most SA influences are accounted for in this paper.

As can be seen in Figure 1 for the median (see online appendix for findings on other deciles), the (standardized) market premium assigned to apartments located in the 18th, 19th and 20th *arrondissements* (*quartiers* 71 to 78) proves to be substantially lower than those assigned to units belonging to the 5th through 8th *arrondissements* (*quartiers* 20 to 29). In addition, the premium per *quartier* decreases with the price range, although its ranking among *quartiers* is somewhat constant across quantiles (see Figures A-7 to A-11, online appendix).

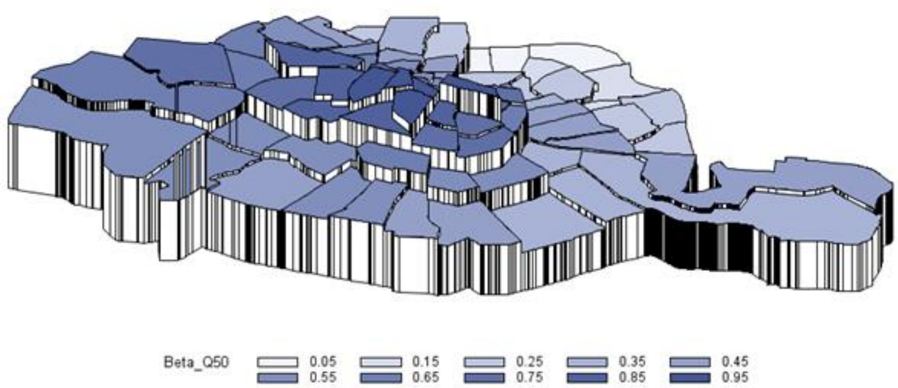

Figure 1. Standardized neighbourhood premium per Paris *quartier*

5.3. Main empirical findings

5.3.1. Apartment size

Starting with the size parameter displayed in Figure 2[7], the findings tend to confirm the existence of distinct sub-markets in the Paris apartment market, as well as the relevance of using quantile regression to estimate the hedonic prices of housing attributes. Given our dataset, and in line with other studies using QR, such as Zietz *et al*. (2008), Coulson and McMillen (2007) or Liao and Wang (2012), the quantile effect appears to be very important for the size parameter. However, in contrast to previous research[8], we find that the higher the price category, the lower the size-elasticity of the sale price. Indeed, while the elasticity coefficient reaches 1.09 for the lowest decile, it is down to less than 1.03 for upper-end units. Therefore, a 10% increment in apartment size results in an almost 10.9% price increase for the former, as opposed to a 10.3% raise for the latter. The negative slope of the size-elasticity of price corroborates the fact that size increments command a substantially higher willingness-to-pay for smaller, cheaper units, than for more expensive ones.[9] Such a finding is at odds with the QR literature, in which an additional size unit adds substantially more to *relative* sale prices (although not necessarily to absolute ones) for higher quantiles. Orford (2000), in his study on Cardiff, Wales, also provides empirical evidence of a positive linear relationship between the average house price and the hedonic prices of floor area. Whether the pattern emerging from this research is generalizable to large and expensive metropolises or remains specific to the Paris market, is an issue for further research.

[7] Here, the logged sale price is used as the dependent variable (as opposed to the logged unit price/sq.m.). The "Size" parameter is thus an estimation of the size-elasticity of price.

[8] For instance, Zietz *et al*. (2008) find that the price elasticity of square footage emerges as more than three times as high for upper-decile properties (0.419), than for those at the lower end of the spectrum (0.133).

[9] It has to be recalled here that price impacts are expressed in relative terms and that a higher *relative* willingness-to-pay for an incremental unit of living area in a low-end segment of the market may, and will most of the time, translate into an absolute price rise which remains substantially lower than the one observed for upper-segment properties.

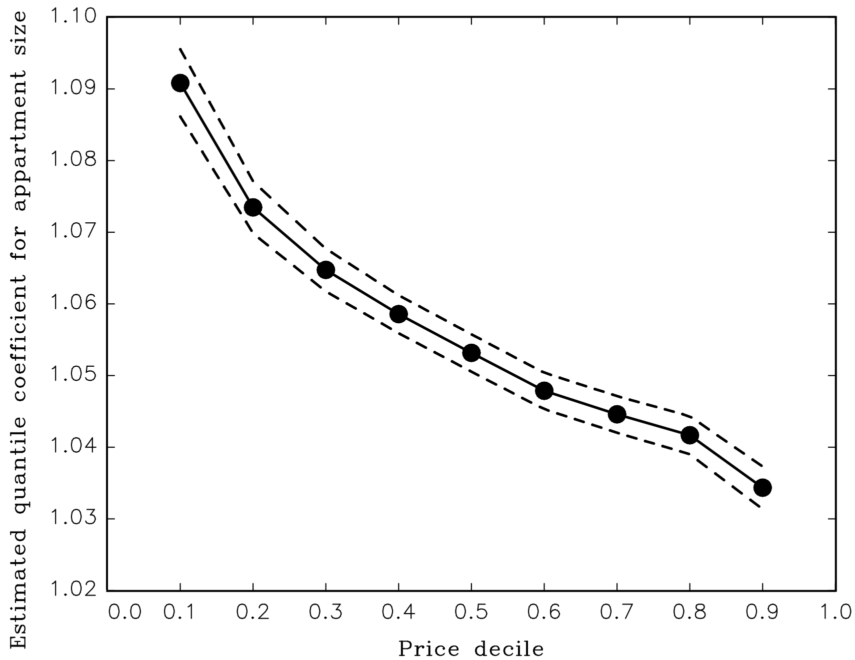

Figure 2. Size-elasticity coefficients of sale price by decile[10]

5.3.2. Price index

Turning to the price index, it is worth noting that price increases are not uniform among deciles and are clearly inversely related to value. Studies comparing appreciation rates across price ranges are scarce, despite abundant literature on house price index construction, estimation, and prediction. A notable exception is Coulson and McMillen (2008), who highlight differences in single-family house price appreciation rates among price ranges. For our Paris dataset, price appreciation over the 2000-2006 (mid-year) period is 113% (0.7557) for the lowest decile (Q10), thereby yielding an annual growth rate of 14.7%. It declines progressively for higher deciles and is down to 99% (0.6866, *i.e.* a 13.3% annual growth rate) for luxury apartments. Such a trend is consistent with theoretical expectations and rests on the fact that, in a context of relative housing scarcity, the lower the apartment price, the more affordable it is to homebuyers and the more sustained the demand for such units will be. Consequently, cheaper units are assigned

[10] Dotted lines represent the 95% confidence interval.

greater potential for relative price appreciation over time, which reflects a catch-up effect for low-price *quartiers*.

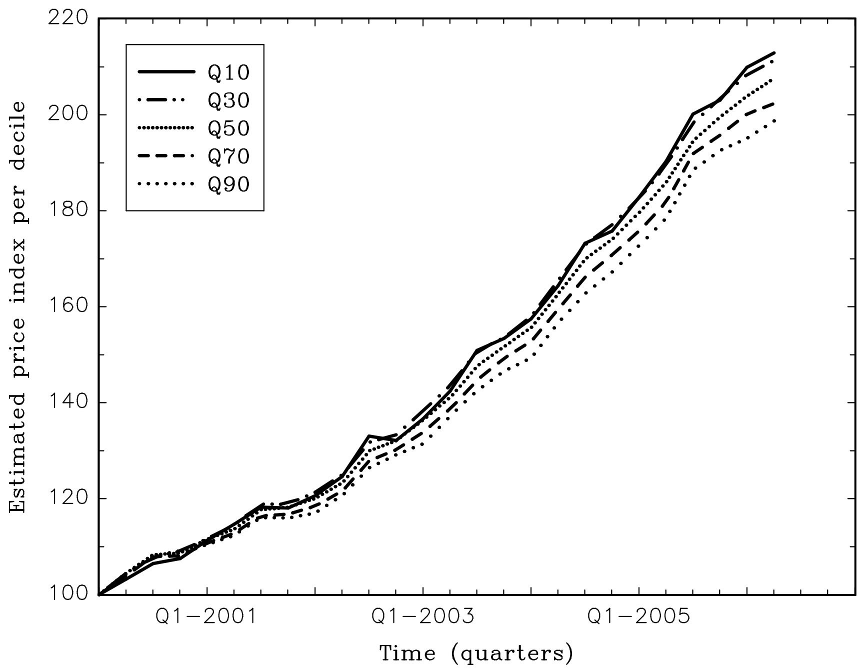

Figure 3. Price index for selected deciles

5.3.3. Floor level

With respect to the floor level variable, a ground floor apartment located in a building with a lift serves as the reference. As expected, the higher the floor, the higher the price. For the median quantile, the market premium stands at around 7.3% for the first floor, 10.9% for the second floor and rises to roughly 15% for upper floors (6th and above), which offer a panoramic view of Paris and its famous mansard roofs. However, as shown in Figure 3, the pricing of the floor level attribute is not constant along the price distribution; interestingly, the higher the price category, the lower the premium assigned to a given floor level.

Such a result may seem counterintuitive. For instance, Mak *et al*. (2010) find the opposite, as top floors are usually considered more prestigious. In that respect, it should be reiterated that in this paper, regression coefficients are expressed as percentages and not as absolute contributions to value. Consequently, a lower *relative* marginal contribution may still translate into a larger absolute price for the attribute, when applied to upper apartment price tags.

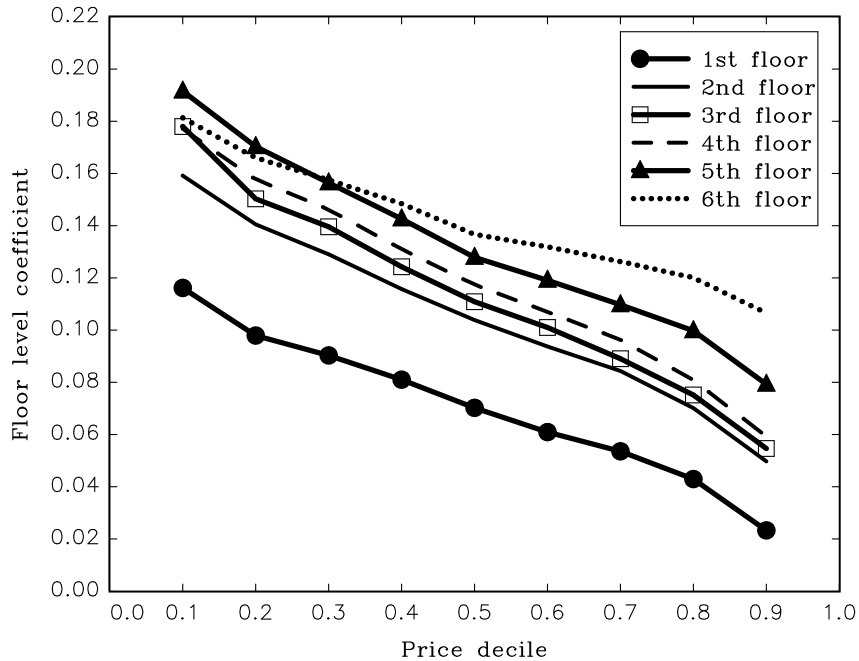

Figure 4. Floor Level (Ground floor with a lift as the reference)

5.3.4. Parking place

Parking in Paris[11] is quite problematic. While local residents have access to on-street parking permits that allow them to park at a small fraction of the parking fare faced by non-residents, some households prefer off-street parking (*e.g.*, those with expensive cars). The latter are thus assumed to apply to high-value apartment buildings with off-street, indoor parking places, even more so if they are located in the Central Business District where parking facilities are particularly scarce. This assumption is confirmed by the regression findings. At the median, a 4.7% premium is induced by the presence of one parking place, which rises to above 8.9% for two parking slots[12]. Yet again, applying QR provides additional insights into how attribute prices are structured. The findings clearly

[11] Ownership of cars in Paris is comparable to other European cities such as London or Berlin (about 300 cars per thousand inhabitants).
[12] Property owners in Paris seldom have garages at their disposal, which is why the reference is an apartment without a parking place.

suggest that the relative price of a parking place rises as the apartment value increases. Thus, while the market premium paid for one parking space ranges from roughly 4.0% (lower decile) to over 6.0% (upper decile) of apartment prices, it reaches 11.7% for two parking places in the case of high-end units. Unsurprisingly, no additional premium is assigned to a second parking spot for low-end (Q10) apartments whose owners, more often than not, cannot afford more than one car. In their study on Hong-Kong, however, Mak *et al*. (2010) reach the opposite conclusions, with lower quantiles commanding a higher premium.

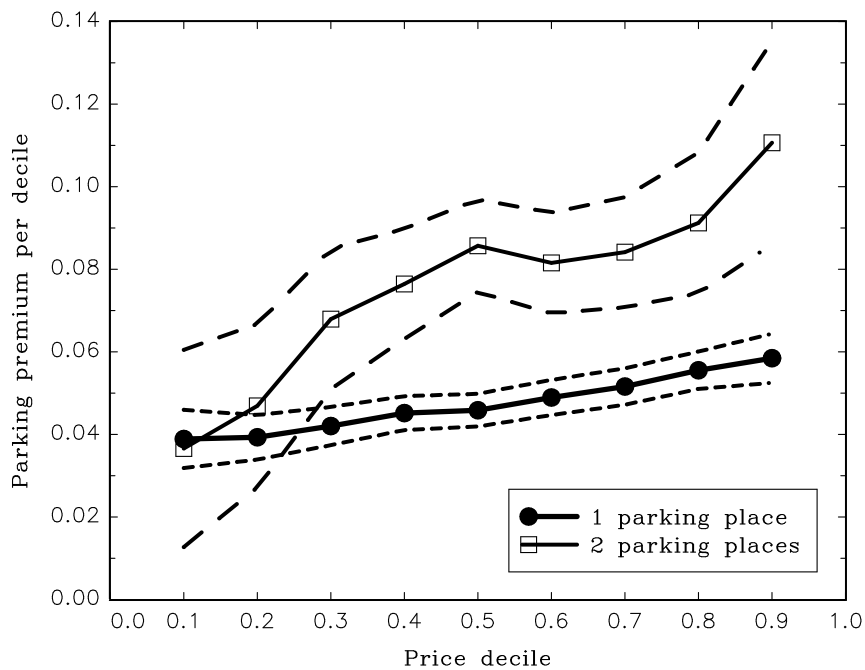

Figure 5. Parking place premium by decile[13]

5.3.5. Miscellaneous

Other attributes also yield interesting results. Regarding the construction period, the Haussmannian period (1850-1913) is set as the reference. This variable has a non-monotonic relationship with price, but displays little variation across deciles. Thus, apartments located in recently constructed buildings (1992-2000) sell at a quasi-constant premium of roughly 11% above Haussmannian prices. Such a premium can easily be

[13] Dotted lines represent the 95% confidence interval.

explained by the level of comfort such buildings provide, a functionality in line with the modern way of life and higher construction standards. By contrast, those dating from the interwar (1914-1947) and post-WWII (1948-1969) periods sell at a discount ranging between 0.7% and 2.0% for deciles Q30 and above, while it is not significant for apartments in the lowest decile. Finally, pre-1850 units benefit from a “historic building” premium over and above Haussmannian prices, varying from 1.6% to 3.1%, depending on the decile.

Other features relating to the unit or its neighbourhood are also assigned substantial price premiums or discounts. The presence of a mezzanine, for instance, commands an average premium of 13.5%, which proves constant along the price distribution. While the presence of a garden also generates a value increment, it steadily rises with the price segment, at 14.5% for the cheapest apartments and reaching 21.6% for the most expensive ones. Having an apartment located on a “place” or on a “quay” - as opposed to a plain street, used as the reference - similarly exerts a positive and growing influence on value, as the price of the unit increases. For a “place” location, and for the first (Q10) and last (Q90) deciles, the market premium grows from less than 3% (n.s.) to 9%, whereas it stands at 5% and 11.6%, respectively, for a “quay” location. The high premium attached to the latter stems from the view of the river Seine or of neighbouring canals. In contrast, being located on a boulevard results in a price discount that reaches 6% for low-end apartments, because of the noisy environment, but which is down to only 1.4% for high-end ones, considering that amenities such as trees may, to a large extent, lessen any inconvenience and due to the social image of a prestige address.

6. Conclusion and prospect for future research

In this paper, the heterogeneity of the Paris apartment market is addressed. For this purpose, quantile regression is applied – with market segmentation based on price deciles – and the hedonic price of housing attributes is computed for various prices segments of the market. The approach is applied to a major data set, which consists of approximately 156,000 transactions over the 2000 – 2006 period. Although spatial econometric methods could not be applied due to the unavailability of geocodes, spatial dependence effects are shown to be adequately accounted for through an array of 80 location dummy variables.

This research provides empirical evidence supporting the fact that QR estimates add some useful insight into interpreting the marginal impact of housing attributes on property values and clearly demonstrate that such nuances are overlooked when an OLS approach, based on mean estimates, is used instead. The findings suggest that hedonic *relative* prices of several housing attributes significantly differ among deciles, although discrepancies tend to vary greatly in magnitude, depending on the attribute. Among other findings, the elasticity coefficient of the apartment size variable, which stands at 1.09 for the cheapest units, is down to 1.03 for the most expensive ones. Similarly, a majority of housing descriptors, including several neighbourhood attributes and location dummies, exhibit significant implicit price fluctuations over the price distribution. Using QR makes it possible to sort out attributes that are assigned a constant, relative contribution to apartment value, irrespective of the price segment, as opposed to those whose marginal influence rises or lessens with price. The research thus enhances our understanding of the complex market dynamics that underlies residential choices in a major metropolis like Paris, where heterogeneity simultaneously operates on the housing stock, historical construct and social fabric.

As this research highlights the virtues of QR as a modelling device for handling heterogeneity in housing markets, it also raises a series of issues that need to be addressed in future research. First, it would be useful to replicate the analysis over a longer period of time to test whether the patterns emerging for the 2000-2006 period – characterized by a buoyant real estate market - still hold through slumps or a bearish market. In particular, it might be interesting to focus on price index behaviour, thereby highlighting investment opportunities for various price segments of the Paris residential market. The issues warranting further investigation include where to invest, when to invest, and which attributes should be focused on most, depending on the asset price range. Second, an inter-metropolis comparison of the market dynamics at stake in large, international cities would make it possible to assess whether price setting patterns obtained for Paris also apply elsewhere or whether they are a mere reflection of market features that are idiosyncratic to France’s capital.

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Table 1 - Regression results - QR estimates.

Quantile level	Q10	Q30	Q50	Q70	Q90	Trend and statistical significance of differences among quantiles ($\chi 2$ test)
Parameters						
Pseudo R2	67,3%	71,8%	73,9%	75,5%	76,6%	
Intercept	6.7644***	7.1395***	7.3706***	7.5696***	7.8238***	
Size (size-elasticity of price)	1.0908***	1.0647***	1.0532***	1.0446***	1.0344***	↘***
Q1 2000	*reference*					
Q2 2000	0.0319**	0.0432***	0.0439***	0.0383***	0.0414***	!!
Q3 2000	0.0629***	0.0756***	0.0795***	0.0765***	0.0766***	!!
Q4 2000	0.0726***	0.0864***	0.0829***	0.0775***	0.0875***	!!
Q1 2001	0.1070***	0.1098***	0.1090***	0.1017***	0.0988***	!!
Q2 2001	0.1370***	0.1352***	0.1277***	0.1206***	0.1163***	↘**
Q3 2001	0.1673***	0.1726***	0.1627***	0.1518***	0.1491***	↘*
Q4 2001	0.1658***	0.1724***	0.1672***	0.1551***	0.1479***	↘*
Q1 2002	0.1874***	0.1934***	0.1824***	0.1689***	0.1569***	↘**
Q2 2002	0.2199***	0.2228***	0.2092***	0.1950***	0.1877***	↘***
Q3 2002	0.2852***	0.2755***	0.2617***	0.2459***	0.2343***	↘***
Q4 2002	0.2786***	0.2875***	0.2781***	0.2636***	0.2555***	↘**
Q1 2003	0.3121***	0.3236***	0.3100***	0.2913***	0.2732***	↘***
Q2 2003	0.3535***	0.3611***	0.3442***	0.3268***	0.3164***	↘***
Q3 2003	0.4115***	0.4108***	0.3894***	0.3694***	0.3537***	↘***
Q4 2003	0.4279***	0.4288***	0.4166***	0.4001***	0.3823***	↘***
Q1 2004	0.4540***	0.4570***	0.4422***	0.4237***	0.4007***	↘***
Q2 2004	0.4971***	0.5042***	0.4870***	0.4670***	0.4492***	↘***
Q3 2004	0.5494***	0.5474***	0.5300***	0.5078***	0.4866***	↘***
Q4 2004	0.5638***	0.5713***	0.5542***	0.5351***	0.5139***	↘***
Q1 2005	0.6032***	0.6017***	0.5855***	0.5638***	0.5464***	↘***
Q2 2005	0.6435***	0.6395***	0.6205***	0.5978***	0.5794***	↘***
Q3 2005	0.6939***	0.6844***	0.6654***	0.6515***	0.6339***	↘***
Q4 2005	0.7083***	0.7096***	0.6906***	0.6716***	0.6550***	↘***
Q1 2006	0.7413***	0.7341***	0.7124***	0.6938***	0.6683***	↘***
Q2 2006	0.7557***	0.7482***	0.7302***	0.7046***	0.6866***	↘***
Before 1850	0.0235***	0.0164***	0.0156***	0.0206***	0.0303***	!!
1850 - 1913	*reference*					
1914 - 1947	-0.0062	-0.0123***	-0.0143***	-0.0098***	-0.0070**	!!
1948 - 1969	-0.0032	-0.0146***	-0.0198***	-0.0178***	-0.0145***	!!
1970 - 1980	0.0344***	0.0135***	0.0034	-0.0005	-0.0033	↘***
1981 - 1991	0.0496***	0.0493***	0.0466***	0.0491***	0.0458***	!!
1992 - 2000	0.1182***	0.1079***	0.1003***	0.0985***	0.1018***	!!
Building construction missing	-0.0228***	-0.0187***	-0.0141***	-0.0065**	0.0088**	!!
No bathroom	*reference*					

1 bathroom	0.1495***	0.0897***	0.0618***	0.0456***	0.0326***	↘***
2 bathrooms	0.1415***	0.0899***	0.0661***	0.0582***	0.0628***	↘***
3 bathrooms or more	0.0740***	0.0471***	0.0481***	0.0618***	0.0973***	!!
Ground floor (bldg with lift)	*reference*					
Entresol	0.0954***	0.0741***	0.0422***	0.0450**	0.0414*	↘*
1st floor	0.1161***	0.0903***	0.0702***	0.0536***	0.0233***	↘***
2d floor	0.1592***	0.1290***	0.1038***	0.0844***	0.0497***	↘***
3d floor	0.1780***	0.1396***	0.1109***	0.0890***	0.0547***	↘***
4th floor	0.1771***	0.1463***	0.1174***	0.0963***	0.0593***	↘***
5th floor	0.1915***	0.1564***	0.1278***	0.1097***	0.0792***	↘***
6th floor	0.1814***	0.1576***	0.1367***	0.1263***	0.1065***	↘***
7th floor and more	0.1785***	0.1577***	0.1459***	0.1394***	0.1281***	↘***
Floor missing	0.0865***	0.0726***	0.0755***	0.0720***	0.0574***	!!
Building without lift	-0.0364***	-0.0209***	-0.0193***	-0.0195***	-0.0210***	↗*
Lift missing	-0.0097**	-0.0074***	-0.0073***	-0.0080***	-0.0109***	!!
Duplex	0.0835***	0.0959***	0.1060***	0.1243***	0.1650***	↗***
Triplex	0.0864**	0.1063***	0.1400***	0.1473***	0.1391***	↗***
No parking	*reference*					
1 parking place	0.0389***	0.0420***	0.0459***	0.0516***	0.0584***	↗***
2 parking places	0.0366**	0.0679***	0.0857***	0.0841***	0.1107***	↗**
3 or more parking places	-0.0231	0.0068	0.0379	0.0603	0.1358	↗***
No room service	*reference*					
1 room service	0.0316***	0.0424***	0.0545***	0.0699***	0.0846***	↗***
2 rooms service or more	0.0131	0.0376***	0.0629***	0.0915***	0.1177***	↗***
No cave	-0.0356***	-0.0187***	-0.0078***	0.0014	0.0131***	↗***
1 cave or more	*reference*					
1 or more balcony	0.0144	0.0224**	0.0204***	0.0203***	0.0130	!!
Garden	0.1353***	0.1570***	0.1613***	0.1677***	0.1958***	↗
Mezzanine	0.1219***	0.1273***	0.1286***	0.1239***	0.1319***	!!
Street	*reference*					
Avenue	-0.0167***	-0.0024	0.0042*	0.0114***	0.0208***	↗***
Boulevard	-0.0602***	-0.0560***	-0.0403***	-0.0289***	-0.0142***	↗***
Place	0.0290	0.0311**	0.0518***	0.0640***	0.0859***	↗***
Quay	0.0490***	0.0790***	0.0804***	0.0891***	0.1098***	↗
1 St-Germain-l'Auxerrois	0.4919***	0.4565***	0.4040***	0.3768***	0.3723***	↘***
2 Les Halles	0.3507***	0.3574***	0.3314***	0.3050***	0.2686***	↘***
3 Palais-Royal	0.4475***	0.4614***	0.4324***	0.3980***	0.3781***	!!
4 Place Vendôme	0.5381***	0.4802***	0.4647***	0.4318***	0.4097***	↘***
5 Gaillon	0.3881***	0.3753***	0.3713***	0.3310***	0.3172***	!!
6 Vivienne	0.3191***	0.2973***	0.2772***	0.2663***	0.2588***	↘*
7 Mail	0.2605***	0.2913***	0.2724***	0.2389***	0.2080***	↘***
8 Bonne-Nouvelle	0.1317***	0.1922***	0.1863***	0.1781***	0.1531***	!!
9 Arts-et-Métiers	0.2482***	0.2512***	0.2313***	0.1946***	0.1468***	↘***

10 Enfants-Rouges	0.3510***	0.3253***	0.2979***	0.2750***	0.2381***	↘***
11 Archives	0.4795***	0.4769***	0.4416***	0.4116***	0.3805***	↘***
12 Sainte-Avoye	0.3680***	0.3531***	0.3228***	0.2732***	0.2332***	↘***
13 Saint-Merri	0.4811***	0.4316***	0.3910***	0.3574***	0.3310***	↘***
14 Saint-Gervais	0.4882***	0.4830***	0.4538***	0.4119***	0.3633***	↘***
15 Arsenal	0.4795***	0.4583***	0.4259***	0.3967***	0.4047***	↘***
16 Notre-Dame	0.7888***	0.7568***	0.7460***	0.7385***	0.7400***	!!
17 Saint-Victor	0.5766***	0.5554***	0.5098***	0.4626***	0.4219***	↘***
18 Jardin des Plantes	0.5132***	0.4774***	0.4366***	0.3839***	0.3169***	↘***
19 Val-de-Grâce	0.5870***	0.5407***	0.4988***	0.4571***	0.4085***	↘***
20 Sorbonne	0.5819***	0.5817***	0.5427***	0.5111***	0.4746***	↘***
21 Monnaie	0.7139***	0.6765***	0.6629***	0.6215***	0.5814***	↘***
22 Odéon	0.7013***	0.6737***	0.6769***	0.6575***	0.6927***	↘**
23 Notre-Dame-des-Champs	0.6317***	0.6039***	0.5787***	0.5418***	0.5167***	↘***
24 St-Germain-des-Prés	0.7953***	0.7452***	0.7284***	0.7147***	0.7369***	!!
25 St.-Thomas-d'Aquin	0.6851***	0.6719***	0.6615***	0.6572***	0.6691***	!!
26 Les Invalides	0.6370***	0.6130***	0.5925***	0.6080***	0.6131***	!!
27 Ecole-Militaire	0.5779***	0.5377***	0.4979***	0.4737***	0.4353***	↘***
28 Gros-Caillou	0.5835***	0.5336***	0.5058***	0.4731***	0.4350***	↘***
29 Champs-Elysées	0.5883***	0.5882***	0.5952***	0.6308***	0.7138***	↗*
30 Faubourg du Roule	0.4348***	0.4133***	0.3887***	0.3514***	0.3218***	↘***
31 La Madeleine	0.4137***	0.4204***	0.4120***	0.3752***	0.3852***	!!
32 Europe	0.3636***	0.3517***	0.3226***	0.2908***	0.2727***	↘***
33 Saint-Georges	0.2436***	0.2229***	0.1884***	0.1485***	0.0908***	↘***
34 Chaussée-d'Anlin	0.1824***	0.1965***	0.2079***	0.1922***	0.1755***	!!
35 Faubourg Montmartre	0.1671***	0.1595***	0.1371***	0.1065***	0.0652***	↘***
36 Rochechouart	0.2011***	0.1781***	0.1527***	0.1103***	0.0538***	↘***
37 St.-Vincent-de-Paul	-0.0094	-0.0272**	-0.0544***	-0.0816***	-0.1243***	↘***
38 Porte Saint-Denis	0.0532***	0.0441***	0.0268**	-0.0056	-0.0484***	↘***
39 Porte Saint-Martin	0.0894***	0.0792***	0.0471***	0.0135**	-0.0382***	↘***
40 Hopital St.-Louis	-0.0231	-0.0367***	-0.0549***	-0.0857***	-0.1295***	↘***
41 Folie-Méricourt	0.0866***	0.1001***	0.0638***	0.0347***	-0.0131*	↘***
42 Saint-Ambroise	0.2132***	0.1739***	0.1327***	0.0850***	0.0265***	↘***
43 La Roquette	0.1973***	0.1730***	0.1373***	0.0943***	0.0451***	↘***
44 Sainte-Marguerite	0.1985***	0.1684***	0.1196***	0.0643***	-0.0024	↘***
45 Bel-Air	0.2222***	0.1714***	0.1241***	0.0717***	-0.0023	↘***
46 Picpus	0.1824***	0.1515***	0.1086***	0.0667***	0.0015	↘***
47 Bercy	0.1205***	0.0811***	0.0592***	0.0170	-0.0379**	↘***
48 Quinze-Vingts	0.2251***	0.1856***	0.1469***	0.1062***	0.0568***	↘***
49 Salpétrière	0.3072***	0.2807***	0.2396***	0.1952***	0.1429***	↘***
50 Gare	0.0176	0.0027	-0.0143	-0.0418***	-0.0839***	↘***
51 Maison-Blanche	0.1534***	0.1370***	0.1150***	0.0766***	0.0276***	↘***
52 Croulebarbe	0.3745***	0.3365***	0.2951***	0.2518***	0.1892***	↘***

53 Montparnasse	0.4463***	0.4167***	0.3889***	0.3575***	0.3144***	↘***
54 Parc Montsouris	0.2762***	0.2407***	0.2055***	0.1629***	0.1146***	↘***
55 Petit Montrouge	0.3204***	0.2692***	0.2288***	0.1896***	0.1369***	↘***
56 Plaisance	0.2825***	0.2427***	0.2072***	0.1600***	0.1022***	↘***
57 Saint-Lambert	0.2998***	0.2505***	0.2061***	0.1540***	0.0940***	↘***
58 Necker	0.3831***	0.3331***	0.2888***	0.2475***	0.2015***	↘***
59 Grenelle	0.3900***	0.3380***	0.2991***	0.2514***	0.2190***	↘***
60 Javel	0.3349***	0.2788***	0.2371***	0.1825***	0.1133***	↘***
61 Auteuil	0.3820***	0.3239***	0.2807***	0.2380***	0.1847***	↘***
62 La Muette	0.4690***	0.4265***	0.3903***	0.3524***	0.3019***	↘***
63 Porte Dauphine	0.4597***	0.4353***	0.4054***	0.3749***	0.3386***	↘***
64 Chaillot	0.4650***	0.4278***	0.3945***	0.3660***	0.3283***	↘***
65 Ternes	0.3927***	0.3534***	0.3167***	0.2782***	0.2197***	↘***
66 Plaine Monceau	0.3847***	0.3535***	0.3163***	0.2716***	0.2222***	↘***
67 Batignolles	0.2502***	0.2307***	0.1911***	0.1465***	0.0916***	↘***
68 Epinettes	0.0198*	-0.0111*	-0.0404***	-0.0762***	-0.1080***	↘***
69 Grandes-Carrières	0.0703***	0.0715***	0.0602***	0.0431***	0.0349***	↘***
70 Clignancourt	*reference*					
71 La Gouttes-d'Or	-0.2614***	-0.2765***	-0.2889***	-0.3091***	-0.3284***	↘***
72 La Chapelle	-0.2477***	-0.2618***	-0.2904***	-0.3047***	-0.3237***	↘***
73 La Villette	-0.2035***	-0.2101***	-0.2259***	-0.2504***	-0.2812***	↘***
74 Pont de Flandre	-0.1874***	-0.2299***	-0.2497***	-0.2808***	-0.3076***	↘***
75 Amérique	-0.1188***	-0.1306***	-0.1493***	-0.1721***	-0.1945***	↘***
76 Combat	-0.0362**	-0.0368***	-0.0551***	-0.0896***	-0.1359***	↘***
77 Belleville	-0.0620***	-0.0795***	-0.1014***	-0.1338***	-0.1731***	↘***
78 Saint-Fargeau	-0.0021	-0.0462***	-0.0855***	-0.1279***	-0.1853***	↘***
79 Père-Lachaise	0.0687***	0.0297***	-0.0136**	-0.0607***	-0.1222***	↘***
80 Charonne	-0.0113	-0.0386***	-0.0601***	-0.0985***	-0.1434***	↘***

Dependent variable: natural logarithm of sale price

*: p-value less than 5%; **: p-value less than 1%; ***: p-value less than 0.01%
!!: no clear trend, ↘: marginal contribution decreases with price , ↗: marginal contribution increases with price