Market Heterogeneity and the Determinants of Paris Apartment Prices: A Quantile Regression Approach

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by

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Abstract

In this paper, the heterogeneity of the Paris apartment market is addressed through assessing the differences in the hedonic price of housing attributes over the 2000-2006 period for various price, hence income, segments of the housing market. For that purpose, quantile regression is applied to the 20 Paris "arrondissements" as well as to the 80 neighborhoods, called "quartiers" – or quarters - (each "arrondissement" is composed of four quarters), with market segmentation being based on price deciles (deciles 1 to 9). The database includes some 159,000 sales spread over a seven year period (2000 – 2006). Housing descriptors include, among other things, a price index, building age, apartment size, number of rooms and bathrooms, unit floor level, the presence of a lift and of a garage, the type of street and access to building (boulevard, square, alley, etc.) as well as a series of location dummy variables standing for both the "arrondissements" and the quarters.

Findings clearly 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 size variable, which stands at 1.07 for the first price decile (cheapest units), is down to 1.03 for units belonging to the ninth one (dearest units). The number of rooms, of service rooms, of bathrooms, the housing type, the apartment floor level as well as the number of parking slots all exhibit strong implicit price fluctuations among deciles while it is less so for the building period that affect prices in a more uniform way. Finally, the lower the apartment price, the higher the potential for price appreciation over time.

Key words: Hedonics, market segmentation, housing submarkets, quantile regression.
JEL Classification Code: C20, R1

Introduction

According to the INSEE database on second-hand apartment sales, overall apartment prices in Paris have been steadily growing from the first quarter of 1998 until the first half of 2009, when they dropped by an overall 7%, before resuming their ascent. Between the beginning of 2010 till the end of 2011, Paris apartment prices experienced a stunning growth of roughly 30% and have stabilized since. But some Paris “arrondissements” have been doing better than others and are still expected to experience value rises in the near future. In the presence of market heterogeneity, the ability of traditional appraisal methods to capture the true property market value may be questioned and emerges as a major issue for local authorities that collect property tax as well as for mortgage lenders confined to tight lending provisions in a crisis context. Assessing such differences in a reliable way is a step forward towards improving mortgage lending risk management.

As the first metropolis in Europe, Paris is a very specific city in the sense that space is limited by a peripheral highway and not expandable. For that very reason, it is called “intra muros” Paris. All the main developments take place in the suburbs and the number of apartments changes very little over time. The last census in 2009 reported 1,353,056 apartments compared to 1,322,540 in 1999 (a growth of 2.3% in 10 years) while, over the same period, the population grew from 2,126,000 inhabitants to 2,234,000 (+4.9%).

Apartments in Paris are very diverse regarding their size, the number of rooms, the construction period or the presence of parking places or not. Within a district or a neighborhood, the location along an avenue, a “boulevard” or a street may also have an influence on the pricing process as it expresses the social image given by the residence place.

If the transactions prices have followed a positive trend for 30 years in Paris (cf. Figure 1 in the Appendices section), the main reasons have probably to be found in macroeconomic factors and in the relatively short supply of space for residential purposes. This said, the analysis of a significant number of characteristics of each apartment upon sale can also be a way to better understand the proper dynamics of the different market segments.

These motivations are particularly important when prices are volatile and investors are looking for a portfolio management that integrates the specific risk of each market segment.

In this paper, the heterogeneity of the Paris apartment market is addressed through assessing the differences in the hedonic price of housing attributes over the 2000-2006 period for various price, hence income, segments of the housing market. For that purpose, quantile regression (QR) is applied to the 20 Paris "arrondissements" as well as to the 80 neighborhoods, referred to as "quartiers" – or quarters -, with market segmentation being based on price deciles (deciles 1 to 9). Each "arrondissement" is composed of four quarters that are sequentially grouped so as to form a snail-like pattern[1] (see Figure 2). The database includes some 159,000 sales spread over a seven year period (2000 – 2006). Housing descriptors include, among other things, a price index, building age, apartment size, number of rooms and bathrooms, unit floor level, the presence of a lift and of a garage, the type of street and access to building (boulevard, square, alley, etc.) as well as a series of location dummy variables standing for both the "arrondissements" and the quarters.

The paper is organized as follows. Following a brief literature review, the quantile regression method is being presented. In a second step, the dataset is introduced with a descriptive analysis of the variables. OLS results are then reported and compared with those obtained with QR. The most significant attributes are brought out and their impact on unit prices discussed. A general conclusion ends the paper.

1. Literature review

A major requirement for parameter estimates derived from hedonic price modeling to be reliable is that the market under analysis be homogeneous (Rosen, 1974). Real estate though is all about submarkets. According to Goodman and Thibodeau (1998), housing market segmentation stems from spatial differences in structural characteristics, neighborhood amenities, or some combination of both. As shown by Bourassa *et al*. (2003), submarkets do matter in the setting of residential prices, with location factors playing a paramount role.

Over the past forty years, several authors have addressed, in quite various ways, market heterogeneity while numerous improvements have been brought to the hedonic analytical framework in order to better handle the issue. Thus, in order to overcome the identification problem raised by Rosen, Bajic (1985) applies a two-stage regression procedure to the Toronto residential market so as to estimate the demand functions of housing attributes. In

[1] Thus, the 1st "arrondissement" is formed of quarters 1 through 4, the 2nd "arrondissement" of quarters 5 through 8, etc. By and large, quarters form the northwestern, northeastern, southwestern and southeastern quadrants of the "arrondissement".

their study on the metropolitan Dallas single-family housing market, Goodman and Thibodeau (1998) turn to hierarchical linear modeling (HLM) for delimiting submarkets on the basis of prevailing interactions between dwelling (house size) and neighborhood (school quality) attributes. They find evidence that variations in the house size coefficient is partly determined by the quality of public schools. In a subsequent paper, Goodman and Thibodeau (2003) show that spatial disaggregation obtained with the HLM approach also results in a better hedonic prediction accuracy.

Principal component analysis (PCA) may as well be used to identify submarkets and sort out influences that would otherwise be intermingled (Des Rosiers *et al.*, 2000). Resorting to interactive variables using Casetti's expansion method (Casetti, 1972) is yet another, and most convenient, way to bring out marginal price impacts that would go unnoticed where only mean estimates are derived (Thériault *et al.*, 2003 and 2005). In a similar methodological line, Xu (2008) applies expansion models to examine the spatial and socio-economic heterogeneities in housing attribute prices in Shenzhen, China. Findings support the evidence that the implicit prices of major housing features are not constant but vary with household profile and location within the city. Finally, in the late 1990s, the development of the geographically weighted regression (GWR) approach (Brunsdon *et al.*, 1998) has allowed to generate spatially varying coefficients designed at capturing local submarket specificities.

Considering the size and diversity of the Paris apartment market, heterogeneity in housing attribute hedonic prices is unavoidable and can reasonably be assumed to vary among characteristics, over space as well as depending on apartment price range. In that context, quantile regression (Koenker and Bassett, 1982; Koenker and Hallock**,** 2001), reveals itself as a most adequate device for capturing heterogeneous utility functions and for bringing out differences in homebuyer preference maps. A semi-parametric approach, QR is similar to generalized least squares (GLS) or spatial weights matrices (SWM). Since quantile regressions are estimated simultaneously, degrees of freedom are not calculated by quantile but as a system. By keeping in all the information available from the dataset, quantile regression thus provides the analyst with better in-depth insights into the effects of the covariates than would a series of independent standard linear regressions (Benoit and Van den Poel, 2009).

Ziets *et al.* (2008) are among the first authors to resort to quantile regression (QR) for addressing the market heterogeneity issue in housing research. Using 1999-2000 home sales from the Orem/Provo area, Utah, they apply the method while accounting for spatial autocorrelation and show that quantile effects largely outweigh spatial autocorrelation effects. Authors also find that the coefficients of some, although not all, variables vary considerably across quantiles. This is the case, for instance, for the price elasticity of square footage which emerges as being more than three times as high for upper-decile properties (0.419) as it is for those at the lower end of the spectrum (0.133).

Farmer and Lipscomb (2010) investigate the role submarket competition plays in setting the price of housing attributes, particularly in a context of fixed supply and evolving homebuyer profile (as is the case for neighborhoods under gentrification). Using household information from both direct stated preference surveys and Multiple Listing Service (MLS) data, authors use QR to track variations in implicit prices for specific attribute bundles in those price ranges where two submarkets overlap. Findings support the hypothesis that, where cross-submarket competition is expected, newcomers with particular needs and preferences are willing to pay higher 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.

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) applies QR in order to identify the implicit prices of housing characteristics for different price ranges. Empirical findings suggest that homebuyers' tastes and preferences for specific housing attributes vary greatly across different price quantiles. Among other things, optimal square footage emerges as being larger for upper quantiles than it is for lower quantiles. Higher-priced properties also command a larger market premium for a view than lower-priced properties do.

Finally, Liao and Wang (2010) apply Two Stage Quantile Regression (2SQR), as suggested by Kim and Muller (2004), to Changsha, an emerging Chinese city. More than 46,000 sales were recorded in 113 residential developments over a one-year period, that is from September 2008 to September 2009. Authors conclude, here again, that the pricing of housing attributes may vary across their conditional distribution. Findings first suggest that the price of nearby properties has a greater value impact on higher- and lower-priced homes than it has on medium-priced homes. A clear upward trend of the quantile effects of floor area is also brought out. As for the number of bedrooms, it exerts differential price impacts depending on the decile, with 2SQR estimates suggesting that implicit prices are highest for low-income households (1st decile) because of the greater number of persons per bedroom in that category. The coefficient peaks again around the 8th decile, thereby suggesting that high-income households have a strong demand for a study room, entertainment room, and so forth.

2. Analytical approach

Quantile regression generalizes the concept of a univariate quantile to a conditional quantile given one or more covariates. For a random variable *Y* with a probability distribution function

$$F(y) = \mathrm{P}(Y \leq y) \tag{1}$$

the τ^{th} quantile of Y is defined as the inverse function:

$$Q(\tau) = \inf\{y : F(y) \geq \tau\} \tag{2}$$

where 0 < τ < 1. In particular, the median is Q(1/2).

For a random sample $\{y_1, \ldots, y_n\}$ of Y, it is known that the sample median is the minimizer of the sum of absolute deviations:

$$\min_{\xi \in R} \sum_{i=1}^{n} \left| y_i - \xi \right| \tag{3}$$

Likewise, the general τ^{th} sample quantile $\xi(\tau)$, which is the analogue of $Q(\tau)$, may be formulated as the solution of the optimization problem

$$\min_{\xi \in R} \sum_{i=1}^{n} \rho_\tau \left(y_i - \xi \right) \tag{4}$$

where $\rho_\tau = z\left(\tau - \mathrm{I}_{z<0}\right), 0 < \tau < 1.$

The linear conditional quantile function $Q(\tau \mid X = x) = x'\beta(\tau)$ can be estimated by solving

$$\hat{\beta}(\tau) = \arg\min_{\beta \in R^p} \sum_{i=1}^{n} \rho_\tau \left(y_i - x_i^{'} \beta(\tau) \right) \tag{5}$$

for any quantile $0 < \tau < 1$. The quantity $\hat{\beta}(\tau)$ is called the τ^{th} regression quantile. The case τ = 0.5, which minimizes the sum of absolute residuals, corresponds to the median regression. Once developed, the quantile regression maximization function writes as:

$$\min_{\beta \in R^p} \left[\sum_{i \in \{i: y_i - x_i^{'}\beta \geq 0\}}^{n} \tau \left| y_i - x_i^{'}\beta \right| + \sum_{i \in \{i: y_i - x_i^{'}\beta < 0\}}^{n} (1-\tau) \left| y_i - x_i^{'}\beta \right| \right] \qquad (6)$$

or :

$$\min_{\beta \in R^p} \left[\sum_{i \in \{i: y_i - x_i^{'}\beta \geq 0\}}^{n} \tau \left(y_i - x_i^{'}\beta \right) + \sum_{i \in \{i: y_i - x_i^{'}\beta < 0\}}^{n} (\tau - 1) \left(y_i - x_i^{'}\beta \right) \right] \qquad (7)$$

There are two different sets of observations in the quantile regression: the ones which are below the regression hyperplane, and those located above it, with positive ($u_i = y_i - x_i^{'}\beta \geq 0$); and negative ($u_i = y_i - x_i^{'}\beta < 0$) residuals, respectively. These two sets differ by the weights attributed to the different observations. Except for the median case, where symmetric weights are used, the weights are asymmetric. The fewer the number of observations, the higher the weights. All the observations in the first set have a weight τ, the others having a weight $1-\tau$. For instance, with $\tau = 0.9$, the 10% of observations above the regression hyperplane have a weight nine times larger than the below-hyperplane observations.

Since the early 1950s, it has been recognized that the median regression can be formulated as a linear programming (LP) problem and solved efficiently with some form of the simplex algorithm. In particular, the algorithm of Barrodale and Roberts (1973) has been used extensively. The simplex algorithm is computationally demanding in large statistical applications. In theory, the number of iterations can increase exponentially with the sample size. However, this algorithm is still popularly used when the data set contains less than tens of thousands of observations. Several alternatives have been developed to handle L1 regression for larger data sets. The interior point approach of Karmarkar (1984) solves a sequence of quadratic problems in which the relevant interior of the constraint set is approximated by an ellipsoid. The worst-case performance of the interior point algorithm has been proved to be better than that of the simplex algorithm. More important, experience has shown that the interior point algorithm is advantageous for larger problems. Like L1 regression, general quantile regression fits nicely into the standard primal-dual formulations of linear programming. Besides the interior point method, various heuristic approaches have been provided for computing L1-type solutions. Among these, the finite smoothing algorithm of Madsen and Nielsen (1993) is the most useful. It approximates the L1-type objective function with a smoothing function, so that the Newton-Ralphon algorithm can be used iteratively to obtain the solution after a finite number of loops. The smoothing algorithm extends naturally to the general quantile regression.

This method corresponds to the resampling method for the confidence intervals. The Markov chain marginal bootstrap (MCMB) method is used. The standard errors of the coefficient estimates are estimated using bootstrapping as suggested by Gould (1992, 1997). They are significantly less sensitive to heteroskedasticity than the standard error estimates based on the method suggested by Rogers (1993).

As an illustration of what the quantile regression does, we apply it to the following single variable regression model on Ln Price for the quantiles 0.001, 0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95, 0.99, 0.999. Findings are displayed in Figure 3.

3. The database

The chosen database for our study is provided by the Chambre des Notaires de France and includes, after filtering, some 159,000 apartment sales spread over a seven year period, that is from 2000 to 2006. This database records all property transactions as registered by the Notaries since 1990. Due to computational constraints, we decided to analyze only a part of this database, with the selected sample though still being large enough to allow statistical significance.

3.1 Univariate description of the dataset

Each transaction provides a detailed description of the property. Housing descriptors include, among other things:

- Sale price (in Euros)
- Building age (construction period);
- Apartment size and number of rooms;
- Floor location in building;
- Number of bathrooms;
- Number of cellars;
- Presence of a lift;
- Presence of a garage with the number of parking places;
- Type of street and access to building (blvd, square, alley, etc.);

- Location dummy variables standing for the 20 districts (“arrondissements”) and 80 “neighborhoods” (quarters);
- Time dummy variables for sale year.

Descriptive statistics on some of these descriptors are reported in Tables 1 through 5 and can be summarized as follows

- ➢ As it can be easily noticed, one half of the sold properties were built before the First World War (Table 1). This proportion is much higher than the one found for similar properties in the overall real estate stock (estimated at around 30%). It shows the particular interest of the transactions market for Haussmann-style buildings in the city.

- ➢ More than 80% of sales relate to studios and to 2 or 3 room apartments, with the 2 room apartment, often considered as the standard Parisian apartment, forming the most active market (Table 2).

- ➢ The usual height of buildings is comprised between four and six floors. Thus, roughly 36% of apartments are located in such buildings, as shown in Table 3 which does reflect this peculiarity of the Parisian urbanism.

- ➢ Table 4 shows that apartments with a lift are two and a half times more likely to be sold than those without one. This corroborates INSEE’s figure stating that 63% of Paris apartment units are equipped with a lift[2].

We also add to this short analysis the distribution of sales by “arrondissement” (Table 5) together with a map of the latter (Figure 2) joined in appendix. It is noticeable that more than half of the transactions belong to the peripheral districts (from 15th to 20th “arrondissements”) that spread from west to east on the right bank of the seine[3] and which gather only 40% of Paris apartments. It may be concluded then that there is an excess of demand over supply for these locations.

3.2 Bivariate description of the dataset

The impact of a lift on prices is interesting to analyze where its presence is being crossed with the number of rooms. Results are summarized in Table 6. These figures show that except for

[2] Source from INSEE, 2008 census.
[3] With the exception of the 15th “arrondissement” which stands on the left bank of the river.

one case (9 room apartments, but not necessarily significant regarding the small number of transactions), the average price of apartments is significantly higher when there is a lift. However, this expected result may be biased by the fact that apartments with a lift are more frequent in the most expensive districts. Moreover, it also depends on apartment size. Thus, as brought out in Table 7, for the same number of rooms, apartments are most of the time larger when there is a lift.

4. Regression results

As is most often 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. As argued by Dubé *et al*. (2011), while the optimal functional form may depend on the type and level of market segmentation resorted to, the log-linear form provides many advantages over other, more sophisticated specifications. In particular, it allows parameter estimates to be easily interpreted while insuring that the dependent variable is normally distributed. Consequently, the log-transformed sale price is explained by the apartment living area – equally log-transformed so as to generate elasticity coefficients - and a set of dummy variables accounting for apartment and building features as well as for location attributes.

The most important characteristics are the number of rooms, the construction period of the building, the floor, the number of bathrooms and the street type ('Street', 'Avenue', 'Boulevard'…). The construction period is a discrete variable with seven categories: the building was built after 1991, between 1981 and 1991, between 1970 and 1980, between 1948 and 1969 (after the second World War), between 1914 and 1947, between 1850 and 1913 (the "Haussmannian" period) or before 1850. The floor price impact is linked to the presence or not of a lift. The reference (estimated in the intercept) is an apartment located on the ground floor in a building with a lift. As the information on the floor is not always available, a "floor missing" variable is added on to the model which enables to have an unbiased estimation of the intercept (and hence of the other parameters)[4]. This is done as well for the other variables where the problem may arise.

[4] Missing values can be handled by making imputations or by dropping observations with missing values altogether.

The presence of a bathroom is not the rule. There are apartments without a full bathroom (they could have a toilet instead or even a shared toilet[5]). The price effect of "not having a bathroom" varies depending on the number of rooms. While it is possible to have no bathroom at all (no private toilet as well) for small apartments, this is highly improbable for larger ones[6]. For that reason, an interactive dummy variable crossing the lack of bathroom with the number of rooms has been designed ("0 bathroom and 1 room", "0 bathroom and two rooms", etc.). While the interpretation of such variables may not be quite relevant[7], this specification will lead, once again, to unbiased estimations for the other parameters.

Year dummy variables are introduced to capture the trend, which may be interpreted as an annual residential real estate index for Paris apartments over the 2000-2006 period. Information on the number of service rooms ("chambres de bonnes") is used as well; so is the presence or not of a basement, an attic, a garden, a mezzanine and the number of parking spaces attached to the sale. Distinction is also made between a standard apartment and a duplex or a triplex.

As the information on the geocodes is not available, the geographical location of apartments is used instead. As mentioned earlier, each of the 20 "arrondissements" of Paris is the amalgamation of four quarters, each of which having its own specific features and price determinants operating at a micro-spatial level. While a second best solution, we believe that resorting to these 80 dummy variables captures a large amount of the spatial autocorrelation potentially present in the residuals as real estate prices are truly linked to them.

For both the ordinary least squares (OLS) and the median quantile estimations, all of the 159,074 observations are first used. In order to test for the model robustness though, the latter is then run after dropping the 1% of the most influential observations according to the Cook's distance procedure[8], which leaves 157,484 observations for analysis. As can be seen from Table 8, and apart from a few coefficients (pertaining, mainly, to the number of rooms and service rooms and to a few floor and street type dummies), regression parameter estimates are roughly equivalent whether the full or cleansed sample is used.

[5] It is common in Paris' old buildings to have toilets in the stairs (between two floors) or at the top floor (in the Hausmannian buildings where there are a lot of "chambres de bonnes" (service rooms).

[6] Les us notice that the distinction bathroom/toilet is not made properly in the database. Hence the analysis of these variables will be hazardous.

[7] The category 'no bathroom' is never documented in the dataset. Hence, cases with missing information about the bathroom are treated as "no bathroom" cases.

[8] Cook's distance is a commonly used estimate of the influence of a data point when performing least squares regression analysis.

4.1 Applying the OLS procedure

The OLS method leads to an estimation of the conditional mean hedonic prices pertaining to apartment characteristics. This method is not relevant when there are outliers in the dataset, when the distribution of data is skewed or when the goal is to construct reference ranges for an outcome. The quantile regression method, more particularly the median one, may be used instead in such situations.

Table 8 reports the mean and the median OLS results obtained with both full and cleansed samples. The mean and median results are globally the same and dropping outliers does not change the results[9]. This underlines the robustness of the latter. Explanatory performance (R-Squared) exceeds 90% in either case while predictive performance (Root MSE) stands at 22%. Moreover, nearly all the parameters are very well estimated (the *p*-values are less than 0.0001%, as indicated by two stars**). As for the parameters with lower significance levels (*p*-values higher than 1%), they are quite identical for both the mean and the median methods ("6 rooms", "9 rooms", "4 service rooms", "3 or more bathrooms", "Mezzanine", "Piece of furniture" and the street types: "Hamlet", "Dead end" and "Passage". As well, the cross-tab variables interacting "0 bathroom" with more than four room units are not quite relevant in any model, which is even more pronounced in the median regression.

As shown by the trend (price index) variable, apartment prices in Paris have experienced a 71% rise over the 2000-2006 period, which corresponds to a 9.4% yearly increase. Such a trend mirrors the sustained demand and relatively limited supply of housing goods in Paris during the pre-crisis era. As displayed in Figure 2, prices went through a severe correction in 2008, then resumed their ascent and have stabilized since 2011.

Considering that the logged sale price is used as the dependent variable – as opposed to, say, the logged unit price (price/sq. meter) -, the "Surface" parameter is an estimation of the price/surface elasticity. Findings suggest that it is significantly different from one and that, for any one unit (*i.e.* square meter) increase in living area, apartment prices rise by roughly 4%. As for the coefficients associated with the number of room variables, they are to be interpreted conditionally to the surface (as it is an exogenous variable). They represent, for a given living area, the percentage market premium assigned to more than one room

[9] There are few exceptions: i) the number of rooms variables, where the OLS estimations with all the observations are always significantly higher than the parameters in the three other regressions, ii) the street type 'Alley' has a lower negative impact for the OLS estimations with the full sample.

apartments, with single room units being used as the reference ("base" value reflected in the intercept). Thus, under the median estimation model, two and three room apartments command 0.7% and 0.9% premiums, respectively, as compared with the reference whereas four and five room units sell for 1.6% more.

The presence of "service rooms" increases the price significantly, with the market premium attached to a three service room unit standing at 11%, as opposed to only 5% and 7% for one and two service rooms, respectively. Considering that service rooms are most often independent from the main apartment, they are frequently leased at a very high level of rent to students or young people due to the lack of housing, which may explain the high demand for more service rooms. Findings also suggest that a duplex or a triplex is more than 10% more expensive than a standard apartment, which probably reflects the enhanced privacy such a housing type involves.

The Hausmannian period (1850-1913) is set as the reference construction period. This variable has a non-linear relationship with price. For buildings built between 1914 and 1947, prices are lower by some 1.8% (median estimation model) when compared with the Hausmannian ones and by more than 2.5% for those built from 1948 to 1969, that is during the reconstruction period following World War II (WWII). As for the most recent buildings - those built after 1991 according to modern standards -, they command a 13% premium over Hausmannian ones. Finally, pre-1850 buildings are also assigned a "historic good" premium of roughly 1% over Haussmannian ones. Two, as opposed to one (the reference), bathroom apartments command a 2% price premium under the mean estimation model, which is down to 1.4% under the median method. Units without a bathroom sell at a 5% to 10% discount, depending on the number of rooms.

With respect to the floor 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. Thus, the market premium stands at around 5% for the first floor, 8% for the second floor and raises to between 11% and 12% for upper floors (6^{th} to 9th) which offer a panoramic view on Paris[10] and on its famous roofs named "mansardes". The absence of a lift leads to a price discount of 2% or 3% compared to the same apartment with a lift[11].

[10] One may assume that a panoramic view on Paris is priceless. Wrong! It's worth 12%, on average...
[11] As for the bathroom variable, the presence of a lift is not very well documented in the dataset. Hence, we are not able to interpret too precisely such effects.

To park in Paris is quite a problem as underlined by the valorization of the presence of car parks included in the price. A premium of over 6% is induced by the existence of one parking place[12], which rises to more than 12% for two. While the presence of a balcony slightly increases the price (by 1% or 2%), but the impact of a mezzanine (+12%) or a garden (+15%) is much more substantial.

Compared to a 'street' (the street type reference), a 'Boulevard' (-4%) or an 'Alley' (-14%) location has a negative impact on prices. In the former case, the price discount stems from the noise thereby generated while, in latter case, it can be attributed to the narrowness of alleys which makes car access to home entry difficult – if not impossible – while also greatly reducing indoor luminosity[13]. On the contrary, a 'Place' (+5%) or a 'Quay' (+9%), two highly fashionable locations, increases significantly the value of an apartment.

Finally, the 'district' parameters are ordered from the poorest quarters to the more upper-class ones. Regression findings are displayed in Figure 3. As can be seen, apartments located in the 17th, 18th and 19th "arrondissements" (quarters 71 to 78) are found at the lower end of the spectrum while those belonging to the 5th through 8th "arrondissements" (quarters 20 to 29) are grouped in its upper end.

4.2 Applying Quantile regression

Quantile regression findings are reported in Table 9. It should be noted here that, while all series of explanatory variables have been included in the model for parameter estimation, district coefficients have been deliberately excluded from Table 9 for conciseness purposes. Furthermore, while all estimations – and graphs - have been made based on centiles, results are reported on a decile basis. Finally, QR is applied to the full sample (159,074 cases).

As can be seen, pseudo R-Squared statistics are much lower than those obtained with the OLS model, with the median decile R^2 standing at 0.736. Model explanatory power also rises with the price category, from 0.662 (1st decile) to 0.762 (9th decile). As for decile regression coefficients, most of them emerge as being statistically significant at the 0.01 or 0.001 level, although parameter estimates pertaining to the number-of-rooms variable as well as to its interactive version (bathroom missing) often are not. Miscellaneous features and location

[12] For the purpose of this study, a parking place is defined as private car box owned in an underground parking, either in the building where the apartment is or in an adjacent building.

[13] Luminosity has probably a significant impact on values but unfortunately the dataset does not contain this information and it cannot be measured.

attributes also yield nonsignificant implicit prices for some – if not across (Hamlet; Passage) – deciles.

Starting with the price index, it is worth noting that while Paris apartments have experienced an overall appreciation of 71% between 2000 and 2006, price increases are not uniform among deciles but are clearly inversely related to value. Thus, while total price appreciation stands at 76% (*i.e.* a 9.8% annual growth rate) for lower-priced properties, it progressively lessens thereafter and is down to 67% for luxury apartments. Such a trend is consistent with theoretical expectations and reflects 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. Consequently, the latter are assigned a higher potential for price appreciation over time.

Turning to size-related variables, parameter estimates pertaining to the surface variable tend to confirm the existence of clearly distinct submarkets in the Paris apartment market as well as the relevance of resorting to quantile regression for estimating the hedonic prices of housing attributes. Quite interestingly, and in line with past research (Liao and Wang, 2010), the higher the price category, the lower the price-elasticity of demand with respect to unit size. Thus, while the elasticity coefficient reaches 1.07 for the lowest decile, it is down to less than 1.03 for upper-end units. Such findings corroborate the fact that size increments command a substantially higher willingness-to-pay for smaller, cheaper units whereas, for more expensive apartments, indoor as well as outdoor quality features tend to outweigh mere quantitative dimensions. Results are reported in appendix in Graph 1.

With regard to the number of rooms (Graph 2), findings suggest that a second room only adds to value (+0.6%) for the cheapest units; for upper deciles, adding a second room impacts negatively on prices with the discount rising with apartment prices. While positive, the coefficients assigned to the three to five room units are, except for a few ones, not significant; the same is true for the nine room units. Where most significant (six to eight room apartments), regression coefficients exhibit a negative sign across deciles. A possible explanation for this may be that buyers – often couples without children or single-person households – have a clear preference for open-plan layouts.

As for the presence of service rooms, findings suggest that, as with the OLS approach, it commands a price premium which remains quite stable among deciles: while the latter tends to grow with price levels for one and two service rooms where it stands, roughly, between 4% and 7% of value, it rises to between 12% and 14% where three or more service rooms are added – although buyers' willingness-to-pay drops substantially for upper deciles.

With regard to the type of housing unit, the marginal contribution assigned to a duplex tends to rise progressively with price deciles, from around 9% (1st decile) to more than 15% (9th decile). It is the reverse for a triplex which commands a 13% premium for units in the lower end of the price range, as opposed to only 6% at the upper end of the spectrum. It may be explained by the kind of brand the duplex represents, especially for luxury apartments. At the opposite, a triplex rather conveys the image of an extended apartment, but without the prestige side.

Findings obtained for construction period variables (Graph 3) are in line with those derived from OLS regressions, with hedonics prices displaying little variations across deciles. Thus, apartments located in new buildings sell at a premium of 13% to 14% above Haussmannian prices while those dated from the interwar (1914-1947) and post-WWII (1948-1969) periods sell at a discount of 1.8% in the former case and within the 2-3% range in the latter. Here again, pre-1850 units do benefit from a price increment of 1% to 2% compared with the reference. The premium for the most recent apartments may be easily explained by the level of comfort, a greater functionality in line with the modern way of life and higher construction standards. On the contrary, apartments built between the two world wars and after WWII are penalized by a lower quality of construction and, quite often, by a smaller room size.

The marginal contribution of additional bathrooms (Graph 4) tends to increase with the price of the housing unit: it reaches between 1% and 3% for a second bathroom while three or more bathrooms will drive up the price by some 3-4%, but only for upper decile apartments (6 to 9). In contrast, units at the lower end of the price spectrum experience a price drop of some 2%, probably because a third bathroom reduces the already limited space available. Considering though that the coefficients pertaining to the two first deciles are not statistically significant at the 0.01 level, we have to remain cautious in our interpretation of these results.

As expected, the absence of a full bathroom has a detrimental effect on market values across deciles, but the negative impact is much more pronounced for the cheapest among smaller units (one and two rooms) where it exceeds 17%. This can be explained by the fact that, while well-off apartment buyers may take advantage of such a feature for making major improvements upon purchase, this is not the case for households with a tighter budget for whom the lack of bathroom is a serious limitation to the enjoyment of the premises. Finally, while the presence of a private toilet commands a premium which ranges from a high of 7% (1^{st} decile) to a low of 1% (9^{th} decile), apartments with a shared toilet experience a price drop which decreases with price, from 6% (1^{st} decile) to 1.6% (9^{th} decile).

The interpretation of floor variables should be done based on a ground floor unit in a lift-equipped building, which serves as the reference. On such grounds, regression findings suggest (**i**) that almost any apartment unit above the ground floor will sell at a premium (except for the "Entresol"), (**ii**) that the higher the unit the larger the relative (percentage) premium assigned – although the progression is not linear -, (**iii**) that the higher the price category the lower the premium and finally (**iv**) that for a similar location (same floor), an apartment unit will sell at a discount compared with the reference if it is located in a building without a lift. For instance, based on the middle decile (*i.e.* the median), an apartment located on the sixth floor will command an 11% market premium compared with a ground floor location but will sell at a 1.6% discount if the building has no lift.

The relative price of a parking place (Graph 5) goes up as the apartment value increases. This reflects buyers' motorization rate, with more expensive units going to households that may have two or more cars. Thus, while the premium paid for one parking space ranges from roughly 5% (lower deciles) to over 9% (upper decile), it reaches between 7% and 17% for two parking places. Such findings suggest that the incremental value of a second parking place stands at around 2.5% of apartment value for the cheapest units but reaches 7% of value for upper-class apartments.

Turning to miscellaneous features (Graph 6), findings suggest that, while some attributes may display strong variations across deciles (so is it for attics and pieces of furniture which are substantially more valorized by low-decile purchasers[14]), hedonic relative prices pertaining to a roofspace, a balcony, a mezzanine or a garden remain quite stable throughout the value spectrum. In particular, the market premium attached to a mezzanine varies between 12% and 15% and, for a garden, between 13% and 15%. Here again, some of these findings should be taken with caution considering their low level of statistical significance.

[14] While it is not possible, with the current database, to identify the aim of the purchase, it may be assumed that a substantial proportion of small, relatively cheap apartments are acquired for investment purposes. In that perspective, furnished apartments offer an advantage that is no more relevant for more expensive, owner-occupied housing units, thereby causing prices to drop for upper decile apartments, as is obvious from Graph 6.

Finally, neighborhood attribute coefficients shed some light on Paris homebuyers' behavior with regard to location features. When compared to a standard street location, used as the reference, locating on an alley or, to a lesser extent, a boulevard translates into a price reduction that, in the former case, rises with apartment value and can reach as much as 19% for upper-scale units (9^{th} decile) considering the drawbacks involved (car accessibility and luminosity issues). For the same reasons, dead ends and passages[15] also command a price discount but of a much smaller amplitude. By and large, locating on an avenue seems to provide buyers with some advantages which grow with decile, probably in line with landscaping features (tree planting, flower arrangements, etc.), but also with the social image the address conveys. A courtyard location adds between 2% and 4% to prices due to the quietness and privacy it conveys. Notwithstanding the fact that the variable parameters all emerge as being nonsignificant, findings suggest that buying on a hamlet, which comes with a view on the city (*e.g.* Montmartre), has a substantial impact on values (median premium at 16%), particularly for lower price decile units. Place, square and quay locations also translate into significantly higher prices, with the high premium attached to the latter (between 8% and 9% across deciles) stemming from the view on the River Seine it brings about.

5. Discussion

A first conclusion that can be drawn from this study is that, in line with past and recent research dealing with quite diverse residential market settings, it provides strong evidence that the QR method allows to bring out marked variations in the magnitude, and even direction, of housing attribute influences on price depending on the price range, which the standard OLS regression method does not. While not all price determinant implicit prices are found to vary along the value spectrum, several do: this is notably the case, in this research at least, for the price index, apartment size, number of rooms, service rooms and bathrooms, type of housing unit, floor level, parking place and some location attributes.

Secondly, considering that hedonic prices are a reliable estimate of the marginal utility derived from a given housing attribute, as expressed through homebuyers' willingness-to-pay, they are context-sensitive and should therefore be expected to differ substantially with respect to both their mean value (OLS) and degree of variability (QR). North American, European and Asian cities may differ with regard to which residential attributes are valued, to what extent they are and by whom; hence the discrepancies found in the literature between

[15] Coefficients for a « passage » location are, for most of them, not significant.

studies regarding QR findings. As a major European metropolis and international hub, Paris hosts households characterized by a great diversity of socio-economic profiles and cultural backgrounds. For that reason, its house price setting process is all the more complex and results from the combination of a multitude of submarkets, some overlapping with others, with each one reflecting a preference map for a given housing attribute bundle.

Whatever the urban context though, specific submarkets may be targeted for commercial marketing, public policy or mortgage lending purposes, in which case a reliable assessment of property values turns out to be of paramount importance. This is where the QR approach, which lends itself to a variety of methodological adaptations, has a clear advantage over the standard OLS method, although it should be viewed as a complement, rather than a substitute, to the latter.

6. Summary and conclusion

In this paper, the heterogeneity of the Paris apartment market is addressed through assessing the differences in the hedonic price of housing attributes over the 2000-2006 period for various price, hence income, segments of the housing market. For that purpose, quantile regression is applied to the 20 Paris "arrondissements" as well as to the 80 neighborhoods, called "quartiers" – or quarters - (each "arrondissement" is composed of four quarters), with market segmentation being based on price deciles (deciles 1 to 9). The database includes some 159,000 sales spread over a seven year period (2000 – 2006). Housing descriptors include, among other things, a price index, building age, apartment size, number of rooms and bathrooms, unit floor level, the presence of a lift and of a garage, the type of street and access to building (boulevard, square, alley, etc.) as well as a series of location dummy variables standing for both the "arrondissements" and the quarters.

In line with the literature on the subject, findings clearly 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 size variable, which stands at 1.07 for the first price decile (cheapest units), is down to 1.03 for units belonging to the ninth one (dearest units). The number of rooms, of service rooms, of bathrooms as well as the housing types all exhibit strong implicit price fluctuations among deciles while it is less so for the building period that affect prices in a more uniform way. As for apartment prices, they do not evolve at the same pace along the value range, with lower-priced properties experiencing an annual growth rate of 9.8% over the six year period, as opposed to only 8.9% for luxury apartments.

With respect to location within the building, all units located above the ground floor are assigned a market premium which rises with floor level but lessens as apartment prices increase. Apartments not served by a lift all sell at a discount. As expected, the willingness-to-pay for a parking place is higher in the upper segments of the market than it is for lower-priced properties. The discrepancy is even more pronounced for a second parking slot. Miscellaneous features yield quite stable hedonic prices throughout the value spectrum, with the presence of a mezzanine and of a garden commanding premiums ranging between 12% and 15% of base apartment price.

Finally, the pricing of some location attributes in the form of a market premium (-) or a price discount (+) may vary widely across their conditional distribution, following either an upward (alley-, avenue+) or downward (hamlet+) trend.

To conclude, the use of QR in real estate is at its early stage and further research is needed in order to shed some light in the way housing submarkets form, interact and compete with each other.

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Appendices: Map, Tables and Figures

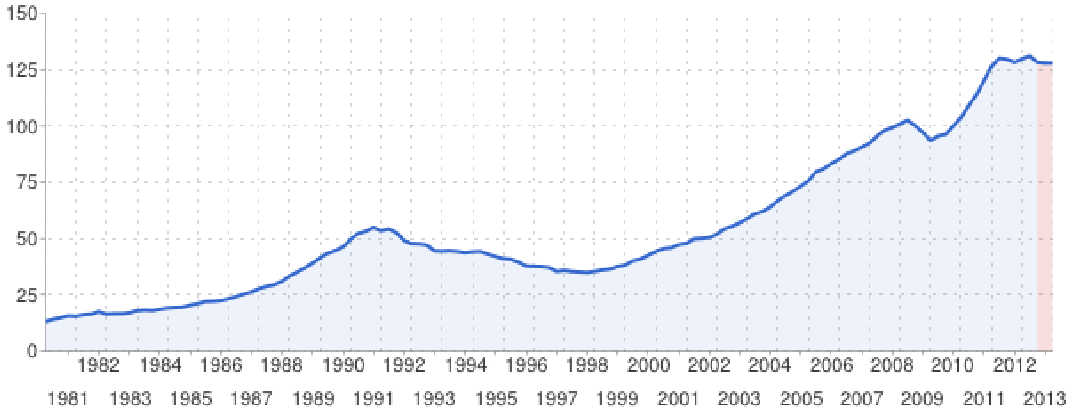


Figure 1 : Notaries index of apartments prices since 1980

Source: meilleursagents.com

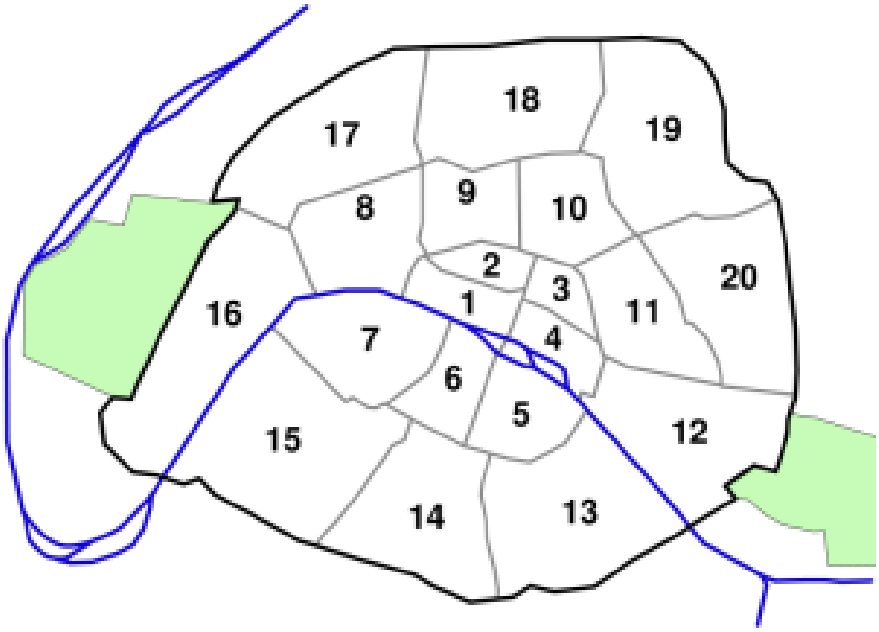


Figure 2 : Map of the "arrondissements" of Paris

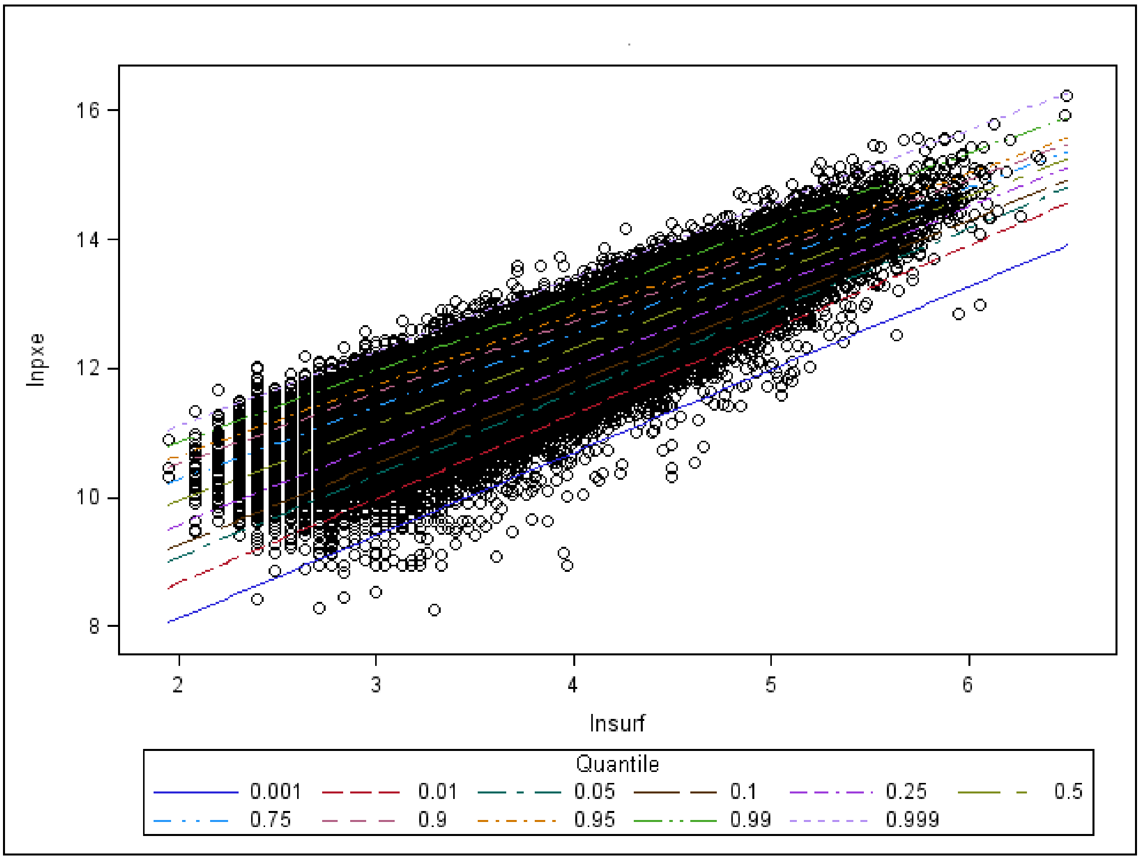


Figure 3: Quantile adjustment estimates for Ln of Sale Price

Construction date	Frequency	Percentage	Cumulative frequency	Cumulative Percentage
Before 1850	7,984	5.66	9,375	6.65
From 1850 to 1913	60,645	43.01	70,020	49.65
From 1914 to 1947	25,495	18.08	95,515	67.73
From 1948 to 1969	21,674	15.37	117,189	83.10
From 1970 to 1980	17,350	12.30	134,539	95.41
From 1981 to 1991	3,587	2.54	138,126	97.95
From 1992 to 2000	2,890	2.05	141,016	99 .01
From 2001	1,391	0.99	142,407	100.00

Table 1: Descriptive statistics – Construction period

Number of rooms	Frequency	Percentage	Cumulative frequency	Cumulative percentage
Studio	38,482	24.68	38,482	24.68
2 rooms	56,131	36.00	94,613	60.68
3 rooms	33,782	21.66	128,395	82.34
4 rooms	16,485	10.57	144,880	92.91
5 rooms	7,273	4.66	152,153	97.57
6 rooms	2,383	1.53	154,536	99.10
7 rooms	933	0.60	155,469	99.70
8 rooms	328	0.21	155,797	99.91
9 rooms	90	0.06	155,887	99.97
10 rooms and more	52	0.03	155,939	100.00

Table 2: Descriptive statistics – Number of rooms

Floor	Frequency	Percentage	Cumulative frequency	Cumulative percentage
Ground floor	13,869	9.00	13,869	9.00
Mezzanine	507	0.33	14,376	9.33
1st floor	25,073	16.27	39,449	25.60
2nd floor	25,791	16.73	65,240	42.33
3rd floor	24,763	16.07	90,003	58.40
4th floor	22,592	14.66	112,595	73.06
5th floor	18,812	12.21	131,407	85.27
6th floor	13,435	8.72	144,842	93.99
7th floor	4,859	3.15	149,701	97.14
8th floor	2,208	1.43	151,909	98.57
9th floor	1,192	0.77	153,101	99.34
10th floor	778	0.50	153,879	99.84
Basement 1	235	0.15	154,114	99.99
Basement 2	17	0.01	154,131	100.00
Basement 3	**2**	**0.00**	**154,133**	**100.00**

Table 3: Descriptive statistics – Distribution by floor

Lift	Frequency	Percentage	Cumulative frequency	Cumulative percentage
No	14,501	28.50	14,501	28.50
Yes	36,383	71.50	50,884	100.00

Table 4: Descriptive statistics – Presence of lift

« Arrondissement »	Frequency	Percentage	Cumulative frequency	Cumulative percentage
1	1,388	0.87	1,388	0.87
2	2,345	1.47	3,733	2.34
3	3,807	2.39	7,540	4.73
4	2,584	1.62	10,124	6.35
5	3,934	2.47	14,058	8.82
6	3,270	2.05	17,328	10.87
7	4,245	2.66	21,573	13.53
8	3,356	2.10	24,929	15.63
9	5,641	3.54	30,570	19 .17
10	8,039	5.04	38,609	24 .21
11	14,322	8.98	52,931	33 .19
12	8,949	5.61	61,880	38 .80
13	7,733	4.85	69,613	43.65
14	8,411	5.27	78,024	48.92
15	16,410	10.29	94,434	59.21
16	13,065	8.19	107,499	67.40
17	14,243	8.93	121,742	76.33
18	16,629	10.42	138,371	86.75
19	9,677	6.07	148,048	92.82
20	11,473	7.18	159,521	100.00

Table 5: Descriptive statistics – Distribution by “arrondissement”

Presence of a lift	Number of rooms	Number of apartments	Mean Sale Price (€)	Standard deviation	Minimum (€)	Maximum (€)
No	Studio	29,872	85,243.08	47,379.49	100,000	588,500
	2 rooms	45,487	140,070.81	77,918.00	100,000	1,496,638
	3 rooms	25,160	239,540.64	125,499.71	100,000	2,135,000
	4 rooms	10,881	395,317.14	198,346.73	30,489	3,744,899
	5 rooms	4,778	604,442.31	313,663.92	68,602	4,320,000
	6 rooms	1,650	849,608.53	446,327.18	83,846	5,699,999
	7 rooms	668	1,109,438.19	607,918.54	121,959	9,604,288
	8 rooms	233	1,385,910.09	663,055.70	219,000	4,421,021
	9 rooms	67	1,873,081.66	959,954.40	221,051	5,325,770
	10 rooms and more	35	2,247,229.09	1,847,091.70	516,000	11,145,000
Yes	Studio	8,610	108,312.42	51,768.35	4,725	560,000
	2 rooms	10,644	186,690.89	89,613.11	13,720	1,082,998
	3 rooms	8,622	290,313.97	139,206.22	28,702	1,683,038
	4 rooms	5,604	420,435.17	218,098.96	82,322	3,735,000
	5 rooms	2,495	623,634.93	312,831.93	106,714	3,085,000
	6 rooms	733	856,565.65	441,218.23	152,449	4,117,000
	7 rooms	265	1,172,784.78	568,376.51	289,653	5,685,266
	8 rooms	95	1,452,897.62	930,900.07	354,145	5,829,240
	9 rooms	23	1,776,734.96	718,863.26	640,285	3,048,980
	10 rooms and more	17	3,025,697.18	2,030,453.98	661,700	8,200,000

Table 6: Descriptive statistics – Apartment prices (€) according to the number of rooms crossed with presence (or not) of a lift

Presence of a lift	Number of rooms	Number of apartments	Mean Surface (in sq.m.)	Standard deviation	Minimum	Maximum
No	Studio	29,872	22.5977169	7.6286436	7	99
	2 rooms	45,487	36.9833359	10.7496416	10	154
	3 rooms	25,160	58.3416137	15.5342487	19	280
	4 rooms	10,881	86.0938333	21.7029943	30	286
	5 rooms	4,778	119.5089996	30.2214218	30	381
	6 rooms	1,650	158.7739394	41.0018908	59	339
	7 rooms	668	198.6871257	53.1426133	93	465
	8 rooms	233	243.3948498	63.1714168	99	451
	9 rooms	67	306.2238806	78.9617899	121	460
	10 rooms and more	35	340.8857143	108.7624966	144	664
Yes	Studio	8,610	26.6114983	7.5336043	8	90
	2 rooms	10,644	44.6517287	10.6590316	11	161
	3 rooms	8,622	66.4897936	14.1487475	25	170
	4 rooms	5,604	90.3451106	19.4426653	33	249
	5 rooms	2,495	119.3366733	28.0439796	54	348
	6 rooms	733	155.4106412	38.1046409	76	326
	7 rooms	265	200.5773585	48.2954396	104	358
	8 rooms	95	234.3684211	66.6848818	84	392
	9 rooms	23	260.9565217	67.2447891	144	415
	10 rooms and more	17	377.6470588	125.2132886	188	658

Table 7: Descriptive statistics – Number of rooms crossed with the surface and presence (or not) of a lift

Model	Without Cook	Cook 1%
# Obs.	159,074	157,484
R Squ.	91.46%	92.49%
Root MSE	0.2364	0.2184

	Mean estimation (OLS)		Median estimation (LS)	
Variable	With all the observations	Without 1% of the observations (selected with the Cook's distance)	With all the observations	Without 1% of the observations (selected with the Cook's distance)
Dependent Variable : Natural logarithm of sale price				
Intercept	7.4027**	7.3973**	7.4447**	7.4455
Year of transaction				
Year 2000	Reference			
Year 2001	0.0944**	0.0919**	0.0918**	0.0909**
Year 2002	0.1848**	0.1839**	0.1830**	0.1824**
Year 2003	0.3193**	0.3184**	0.3149**	0.3147**
Year 2004	0.4557**	0.4549**	0.4524**	0.4520**
Year 2005	0.5999**	0.5994**	0.5886**	0.5887**
Year 2006	0.7231**	0.7227**	0.7109**	0.7108**
Surface (in log)				
Surface (elasticity price/surface)	1.0430**	1.0467**	1.0394**	1.0396**
Number of rooms				
1 room	Reference			
2 rooms	-0.0042	-0.0078**	-0.0071*	-0.0075**
3 rooms	0.0137**	0.0082*	0.0092*	0.0086*
4 rooms	0.0197**	0.0139**	0.0164**	0.0157**
5 rooms	0.0217**	0.0128*	0.0158*	0.0149*
6 rooms	-0.0042	-0.0130	-0.0138	-0.0142
7 rooms	-0.0352*	-0.0505**	-0.0497**	-0.0552**
8 rooms	-0.0484	-0.0629**	-0.0733**	-0.0766**
9 rooms	0.0147	-0.0220	-0.0273	-0.0275
Service Rooms				
0 Service room	Reference			
1 Service room	0.0566**	0.0547**	0.0539**	0.0530**
2 Service rooms	0.0714**	0.0706**	0.0670**	0.0662**
3 Service rooms	0.1140**	0.1142**	0.1197**	0.1210**
4 Service rooms	0.1062*	0.0919	0.1686*	0.0987
5 Service rooms and more	0.2734**	0.2662*	0.1549	0.2539
Apartment type				
Normal (on one floor)	Reference			
Duplex	0.1109**	0.1152**	0.1039**	0.1048**
Triplex	0.1277**	0.1493**	0.1365**	0.1417**
Construction Period				
Built after 1991	0.1376**	0.1454**	0.1323**	0.1337**
From 1981 to 1991	0.0288**	0.0257**	0.0265**	0.0264**
From 1970 to 1980	-0.0043	-0.0076*	-0.0092**	-0.0097**
From 1948 to 1969	-0.0190**	-0.0219**	-0.0266**	-0.0270**
From 1914 and 1947	-0.0152**	-0.0169**	-0.0180**	-0.0183**
From 1850 to 1913 (Haussmannian period)	Reference			
Before 1850	0.0210**	0.0162**	0.0117**	0.0099*
Building construction missing	-0.0136**	-0.0158**	-0.0173**	-0.0179**

Bathrooms				
1 bathroom	Reference			
2 bathrooms	0.0213**	0.0187**	0.0137**	0.0132**
3 or more bathrooms	0.0267	0.0170	0.0185	0.0163
0 bathroom and 1 room	-0.0999**	-0.0921**	-0.0817**	-0.0784**
0 bathroom and 2 rooms	-0.1066**	-0.0989**	-0.0819**	-0.0798**
0 bathroom and 3 rooms	-0.0648**	-0.0586**	-0.0479**	-0.0465**
0 bathroom and 4 rooms	-0.0283**	-0.0195*	-0.0145	-0.0125
0 bathroom and 5 room	-0.0277*	-0.0242	-0.0240	-0.0236
0 bathroom and 6 rooms	-0.0387	-0.0330	-0.0334	-0.0358
0 bathroom and 7 rooms	-0.0354	-0.0410	-0.0226	-0.0215
0 bathroom and 8 rooms	-0.0293	-0.0254	-0.0069	-0.0120
0 bathroom and 9 rooms	-0.0069	-0.0463	-0.0398	-0.0391
Toilets				
0 toilet	Reference			
Shared toilet	-0.0378**	-0.0340**	-0.0339**	-0.0333**
Toilet (half bath.)	0.0328*	0.0392**	0.0234*	0.0273*
Floor				
Ground floor (building with lift)	Reference			
Entresol (with lift)	0.0196	0.0015	0.0099	0.0067
1st Floor (with lift)	0.0479**	0.0464**	0.0522**	0.0516**
2d Floor (with lift)	0.0832**	0.0797**	0.0846**	0.0832**
3d Floor (with lift)	0.0877**	0.0841**	0.0861**	0.0852**
4th Floor (with lift)	0.0938**	0.0901**	0.0946**	0.0936**
5th Floor (with lift)	0.1033**	0.0998**	0.1069**	0.1061**
6th Floor (with lift)	0.1095**	0.1082**	0.1111**	0.1105**
7th Floor (with lift)	0.1099**	0.1118**	0.1125**	0.1129**
8th Floor (with lift)	0.1145**	0.1130**	0.1177**	0.1168**
9th Floor (with lift)	0.1195**	0.1181**	0.1174**	0.1171**
10th Floor (with lift)	0.0687**	0.0720**	0.0724**	0.0724**
Ground floor (without lift)	-0.0506**	-0.0491**	-0.0379**	-0.0381**
Entresol (without lift)	-0.0145	0.0117	-0.0061	0.0027
1st Floor (without lift)	-0.0299**	-0.0301**	-0.0219**	-0.0220**
2d Floor (without lift)	-0.0280**	-0.0287**	-0.0219**	-0.0217**
3d Floor (without lift)	-0.0242**	-0.0234**	-0.0143**	-0.0145*
4th Floor (without lift)	-0.0241**	-0.0234**	-0.0177**	-0.0174**
5th Floor (without lift)	-0.0215**	-0.0200**	-0.0216**	-0.0219**
6th Floor (without lift)	-0.0191**	-0.0182**	-0.0154*	-0.0153*
Floor missing	0.0380**	0.0395**	0.0583**	0.0579**
Basement				
No basement	Reference			
1 basement or more	0.0140**	0.0123**	0.0105**	0.0102**
Parking place				
No parking	Reference			
1 parking place	0.0689**	0.0686**	0.0611**	0.0609**
2 parking places	0.1259**	0.1219**	0.1233**	0.1214**
3 or more parking places	0.1394**	0.1296*	0.1495*	0.1227**
Miscellaneous				
Roofspace (Combles)	0.0542**	0.0650**	0.0645**	0.0637**
Attic (Grenier)	0.0638**	0.0584**	0.0453*	0.0435*
1 or more balcony	0.0166*	0.0197**	0.0229**	0.0241**
Garden	0.1578**	0.1589**	0.1543**	0.1544**
Piece of furniture	-0.0228	0.0153	0.0215	0.0209
Mezzanine	0.1228**	0.1301**	0.1228**	0.1237**
Street type				
Street	Reference			
Alley	-0.1061**	-0.1379**	-0.1475**	-0.1503**
Avenue	0.0127**	0.0113**	0.0096**	0.0089**
Boulevard	-0.0410**	-0.0407**	-0.0433**	-0.0432**
Courtyard (Cour)	0.0350*	0.0429*	0.0386*	0.0422*

Hamlet (Hameau)	0.1198	0.1470	0.1519	0.1560
Dead end (Impasse)	-0.0237*	-0.0076	-0.0159	-0.0113
Passage	-0.0081	0.0014	-0.0048	-0.0030
Place	0.0593**	0.0477**	0.0529**	0.0473**
Quay	0.0965**	0.0932**	0.0913**	0.0887**
Square	0.0237*	0.0343**	0.0309*	0.0338*
« Quartier » (district)				
1 St-Germain-l'Auxerrois	0.4602**	0.4678**	0.4451**	0.4432**
2 Les Halles	0.3850**	0.3932**	0.3807**	0.3867**
3 Palais-Royal	0.4874**	0.5065**	0.4875**	0.4925**
4 Place Vendôme	0.5391**	0.5379**	0.5319**	0.5296**
5 Gaillon	0.4072**	0.4393**	0.4175**	0.4358**
6 Vivienne	0.3408**	0.3562**	0.3271**	0.3331**
7 Mail	0.2992**	0.3200**	0.3111**	0.3181**
8 Bonne-Nouvelle	0.2246**	0.2433**	0.2418**	0.2482**
9 Arts-et-Métiers	0.2781**	0.2869**	0.2882**	0.2904**
10 Enfants-Rouges	0.3619**	0.3763**	0.3658**	0.3696**
11 Archives	0.4970**	0.5122**	0.4970**	0.4995**
12 Sainte-Avoye	0.3694**	0.3846**	0.3781**	0.3801**
13 Saint-Merri	0.4580**	0.4727**	0.4506**	0.4550**
14 Saint-Gervais	0.5036**	0.5195**	0.5045**	0.5083**
15 Arsenal	0.4966**	0.5070**	0.4809**	0.4826**
16 Notre-Dame	0.8220**	0.8169**	0.7980**	0.7963**
17 Saint-Victor	0.5732**	0.5817**	0.5635**	0.5672**
18 Jardin des Plantes	0.4956**	0.4999**	0.4919**	0.4930**
19 Val-de-Grâce	0.5617**	0.5691**	0.5552**	0.5559**
20 Sorbonne	0.6040**	0.6165**	0.5971**	0.5997**
21 Monnaie	0.7143**	0.7339**	0.7227**	0.7264**
22 Odéon	0.7496**	0.7515**	0.7314**	0.7311**
23 Notre-Dame-des-Champs	0.6404**	0.6454**	0.6372**	0.6376**
24 St-Germain-des-Prés	0.8218**	0.8068**	0.7887**	0.7856**
25 St.-Thomas-d'Aquin	0.7318**	0.7395**	0.7180**	0.7182**
26 Les Invalides	0.6841**	0.6868**	0.6602**	0.6598**
27 Ecole-Militaire	0.5714**	0.5801**	0.5612**	0.5613**
28 Gros-Caillou	0.5766**	0.5725**	0.5586**	0.5567**
29 Champs-Elysées	0.6839**	0.6785**	0.6479**	0.6440**
30 Faubourg du Roule	0.4452**	0.4549**	0.4422**	0.4454**
31 La Madeleine	0.4827**	0.4779**	0.4709**	0.4684**
32 Europe	0.3891**	0.3924**	0.3795**	0.3796**
33 Saint-Georges	0.2390**	0.2423**	0.2397**	0.2401**
34 Chaussée-d'Anlin	0.2669**	0.2774**	0.2597**	0.2637**
35 Faubourg Montmartre	0.1847**	0.1959**	0.1913**	0.1951**
36 Rochechouart	0.1998**	0.2049**	0.2070**	0.2082**
37 St.-Vincent-de-Paul	0.0005	0.0056	-0.0008	0.0016
38 Porte Saint-Denis	0.0640**	0.0722**	0.0787**	0.0803**
39 Porte Saint-Martin	0.0895**	0.0957**	0.1014**	0.1030**
40 Hopital St.-Louis	-0.0195*	-0.0119	-0.0033	-0.0018
41 Folie-Méricourt	0.1114**	0.1148**	0.1210**	0.1217**
42 Saint-Ambroise	0.1860**	0.1912**	0.1897**	0.1903**
43 La Roquette	0.1961**	0.1967**	0.1956**	0.1950**
44 Sainte-Marguerite	0.1677**	0.1727**	0.1744**	0.1751**
45 Bel-Air	0.1742**	0.1786**	0.1774**	0.1797**
46 Picpus	0.1646**	0.1699**	0.1681**	0.1688**
47 Bercy	0.1097**	0.1198**	0.1122**	0.1145**
48 Quinze-Vingts	0.2033**	0.2072**	0.2019**	0.2016**
49 Salpétrière	0.2852**	0.2972**	0.2942**	0.2960**
50 Gare	0.0494**	0.0517**	0.0525**	0.0529**
51 Maison-Blanche	0.1689**	0.1703**	0.1735**	0.1738**
52 Croulebarbe	0.3533**	0.3574**	0.3485**	0.3507**
53 Montparnasse	0.4457**	0.4514**	0.4392**	0.4399**
54 Parc Montsouris	0.2791**	0.2809**	0.2735**	0.2740**
55 Petit Montrouge	0.2993**	0.2999**	0.2899**	0.2901**
56 Plaisance	0.2718**	0.2729**	0.2652**	0.2649**
57 Saint-Lambert	0.2705**	0.2709**	0.2631**	0.2630**
58 Necker	0.3560**	0.3589**	0.3450**	0.3453**
59 Grenelle	0.3758**	0.3752**	0.3604**	0.3597**
60 Javel	0.2960**	0.2975**	0.2925**	0.2928**
61 Auteuil	0.3528**	0.3543**	0.3353**	0.3352**
62 La Muette	0.4754**	0.4758**	0.4559**	0.4559**
63 Porte Dauphine	0.4693**	0.4713**	0.4616**	0.4620**
64 Chaillot	0.4690**	0.4685**	0.4508**	0.4507**

65 Ternes	0.3764**	0.3811**	0.3715**	0.3723**
66 Plaine Monceau	0.3715**	0.3762**	0.3724**	0.3734**
67 Batignolles	0.2418**	0.2434**	0.2456**	0.2457**
68 Epinettes	*0.0133*	*0.0141**	*0.0132**	*0.0135**
69 Grandes-Carrières	0.1214**	0.1220**	0.1182**	0.1175**
70 Clignancourt	0.0601**	0.0602**	0.0527**	0.0526**
71 La Goutte-d'Or	-0.2453**	-0.2407**	-0.2362**	-0.2364**
72 La Chapelle	-0.2120**	-0.2092**	-0.2252**	-0.2254**
73 La Villette	-0.1859**	-0.1753**	-0.1777**	-0.1753**
74 Pont de Flandre	-0.1571**	-0.1444**	-0.1642**	-0.1594**
75 Amérique	-0.0847**	-0.0830**	-0.0946**	-0.0938**
76 Combat	-0.0009	0.0037	0.0004	0.0019
77 Belleville	-0.0564**	-0.0472**	-0.0518**	-0.0506**
78 Saint-Fargeau	-0.0243**	-0.0239**	-0.0316**	-0.0327**
79 Père-Lachaise	0.0435**	0.0462**	0.0474**	0.0478**
80 Charonne		**Reference**		

*: p-value less than 1%; **: p-value less than 0.01%

Table 8: Regression results – OLS procedure

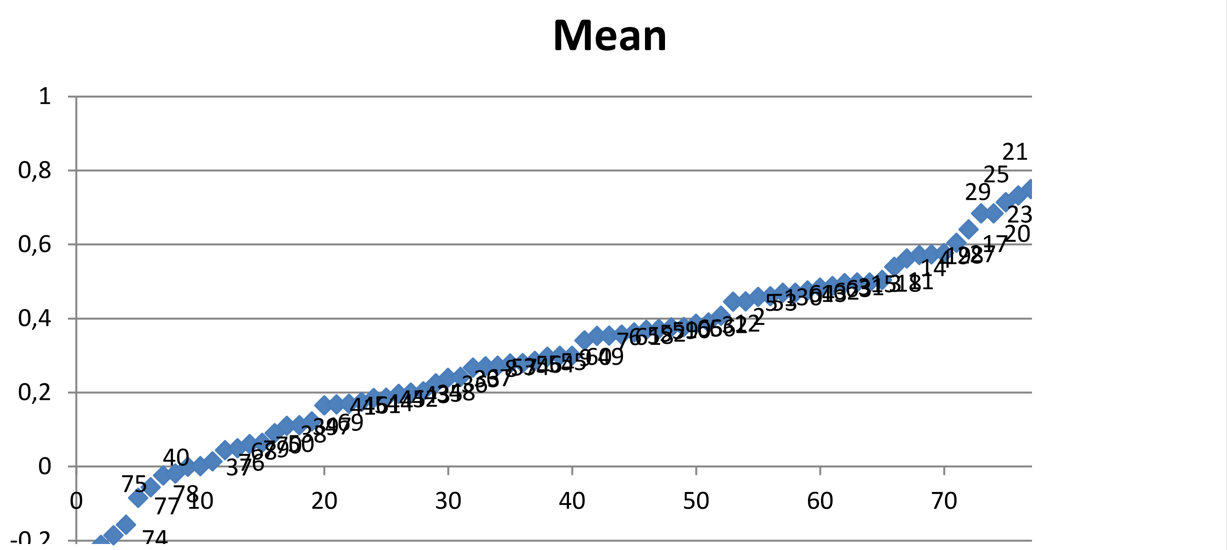


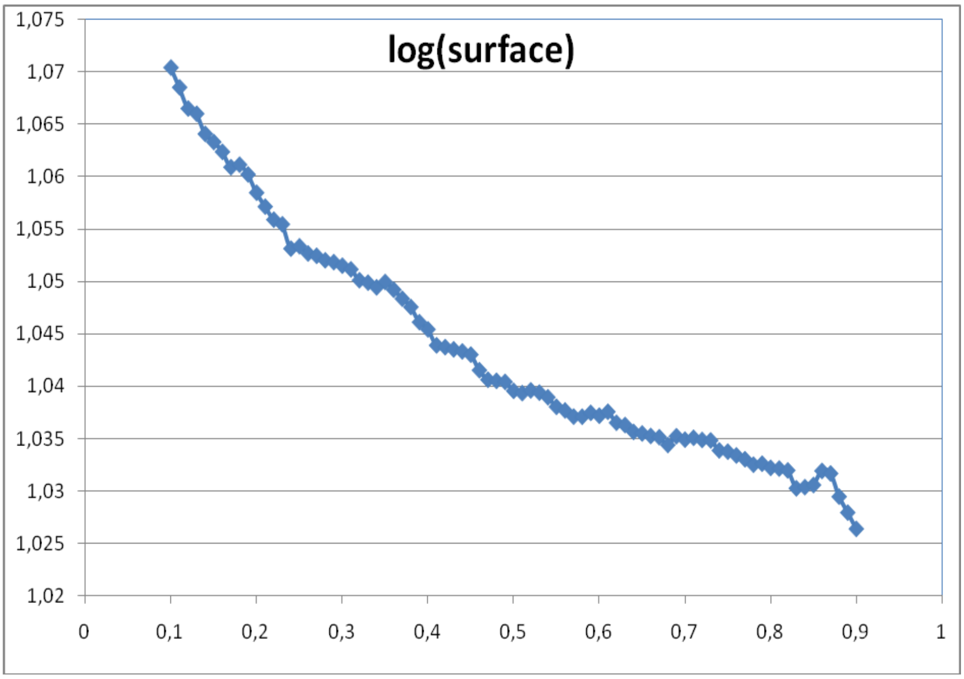
Figure 3: Mean location premium by Paris quarter

Parameters	0.1 quantile	0.2 quantile	0.3 quantile	0.4 quantile	0.5 quantile	0.6 quantile	0.7 quantile	0.8 quantile	0.9 quantile
Pseudo R2	**0.662**	**0.694**	**0.712**	**0.725**	**0.736**	**0.741**	**0.758**	**0.757**	**0.762**
Dependent Variable : Natural logarithm of sale price									
Intercept	6.9497**	7.1372**	7.2515**	7.3493**	7.4459**	7.5246**	7.6029**	7.6906**	7.8211**
Surface (in log)	1.0704**	1.0585**	1.0515**	1.0455**	1.0395**	1.0372**	1.0349**	1.0322**	1.0264**
Number of rooms									
Year 2000 (reference)									
Year 2001	0.1069**	0.1030**	0.0979**	0.0942**	0.0918**	0.0863**	0.0841**	0.0824**	0.0791**
Year 2002	0.2106**	0.2022**	0.1948**	0.1885**	0.1830**	0.1757**	0.1701**	0.1642**	0.1576**
Year 2003	0.3460**	0.3374**	0.3302**	0.3232**	0.3149**	0.3066**	0.2992**	0.2918**	0.2810**
Year 2004	0.4836**	0.4776**	0.4676**	0.4602**	0.4524**	0.4431**	0.4353**	0.4237**	0.4130**
Year 2005	0.6278**	0.6171**	0.6048**	0.5967**	0.5886**	0.5785**	0.5707**	0.5631**	0.5513**
Year 2006	0.7566**	0.7437**	0.7289**	0.7185**	0.7109**	0.7008**	0.6885**	0.6791**	0.6667**
Number of rooms									
1 room (Reference)									
2 rooms	0.0063**	-0.0031**	-0.0027**	-0.0058**	-0.0075**	-0.0099**	-0.0146**	-0.0166**	-0.0194**
3 rooms	0.0200*	0.0154	0.0124	0.0104	0.0086*	0.0049*	0.0003**	-0.0024**	-0.0059**
4 rooms	0.0257*	0.0166	0.0166	0.0150	0.0157	0.0128	0.0099	0.0074*	0.0056*
5 rooms	0.0198**	0.0160	0.0118	0.0128	0.0152	0.0115	0.0078	0.0060	0.0057
6 rooms	-0.0020	-0.0159	-0.0150**	-0.0169**	-0.0131**	-0.0189**	-0.0209**	-0.0180**	-0.0067*
7 rooms	-0.0433*	-0.0469**	-0.0524**	-0.0515**	-0.0530**	-0.0550**	-0.0568**	-0.0469**	-0.0468*
8 rooms	-0.0128	-0.0630**	-0.0721**	-0.0676*	-0.0760**	-0.0746**	-0.0706*	-0.0666*	-0.0729
9 rooms	0.0749	0.0312	0.0245	-0.0023	-0.0289	-0.0564	-0.0625	-0.0722	-0.0943
Number of service rooms									
0 service room (reference)									
1 service room	0.0407**	0.0382**	0.0417**	0.0437**	0.0530**	0.0588**	0.0619**	0.0649**	0.0655**
2 service rooms	0.0576**	0.0590**	0.0574**	0.0693**	0.0658**	0.0728**	0.0763**	0.0662**	0.0654**
3 or more service rooms	0.1275	0.1220	0.1380*	0.1306**	0.1245**	0.1161**	0.1298**	0.0970**	0.0616*
Apartment type									
Normal (on one floor – Reference)									
Duplex	0.0913**	0.0930**	0.0958**	0.0979**	0.1049**	0.1117**	0.1193**	0.1308**	0.1506**
Triplex	0.1644*	0.1437**	0.1468**	0.1477**	0.1416**	0.1488**	0.1368**	0.1398**	0.1283**
Construction Period									
Built after 1991	0.1510**	0.1418**	0.1393**	0.1372**	0.1336**	0.1324**	0.1358**	0.1344**	0.1412**
Between 1981 and 1991	0.0382**	0.0340**	0.0353**	0.0325**	0.0263**	0.0205**	0.0223	0.0189*	0.0116*
Between 1970 and 1980	0.0288**	0.0130	0.0037	-0.0025*	-0.0097**	-0.0142**	-0.0185**	-0.0236**	-0.0318**

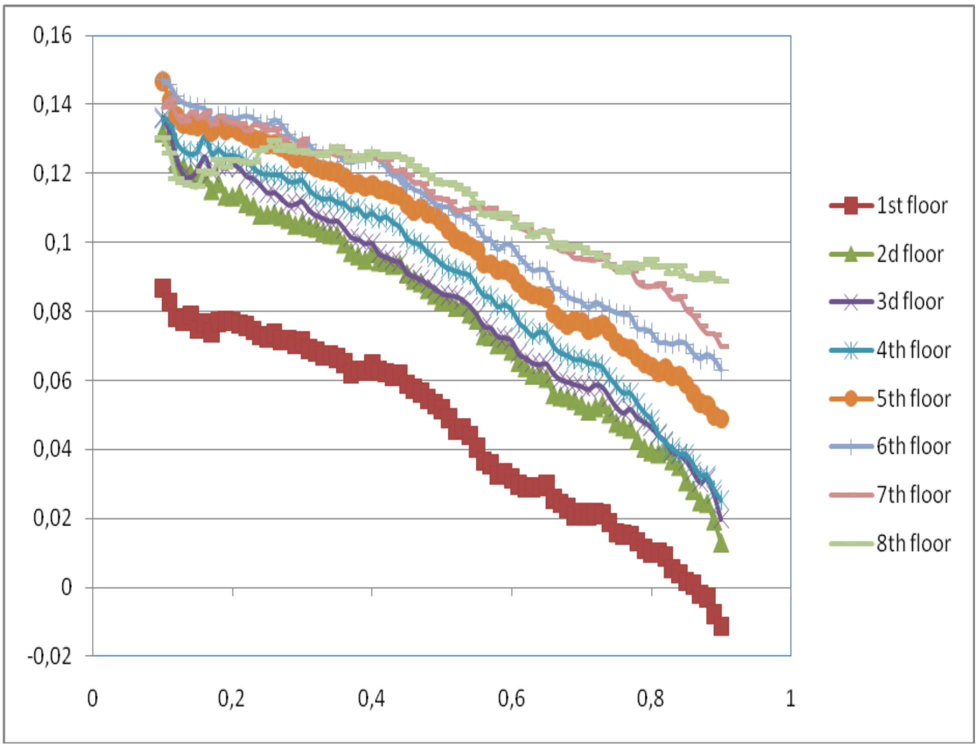
Between 1948 and 1969	-0.0074	-0.0159**	-0.0222**	-0.0267**	-0.0270**	-0.0301**	-0.0306**	-0.0312**	-0.0298**
Built between 1914 and 1947	-0.0101	-0.0145**	-0.0178**	-0.0190**	-0.0183**	-0.0185**	-0.0181**	-0.0175**	-0.0183**
Between 1850 and 1913 (Haussmannian period - Reference)									
Before 1850	0.0134**	0.0112**	0.0112**	0.0123**	0.0099**	0.0128**	0.0139**	0.0164**	0.0245**
Period missing	-0.0240**	-0.0227**	-0.0209**	-0.0176**	-0.0178**	-0.0149*	-0.0116	-0.0063	-0.0007
Bathrooms									
1 bathroom (Reference)									
2 bathrooms	0.0084	0.0110*	0.0132**	0.0127**	0.0131**	0.0125**	0.0192**	0.0260**	0.0306**
3 or more bathrooms	-0.0221	-0.0126	0.0025*	0.0115*	0.0151*	0.0275**	0.0350**	0.0407**	0.0378**
Bath. missing and 1 room	-0.1738**	-0.1342**	-0.1124**	-0.0927**	-0.0784**	-0.0661**	-0.0576**	-0.0460**	-0.0429**
Bath. missing and 2 rooms	-0.1707**	-0.1311**	-0.1080**	-0.0909**	-0.0797**	-0.0714**	-0.0629**	-0.0578**	-0.0523**
Bath. missing and 3 rooms	-0.1044**	-0.0776**	-0.0645**	-0.0533**	-0.0457**	-0.0388**	-0.0348**	-0.0323**	-0.0328**
Bath. missing and 4 rooms	-0.0545*	-0.0270	-0.0226*	-0.0144	-0.0126	-0.0117	-0.0139	-0.0066	-0.0021
Bath. missing and 5 rooms	-0.0318	-0.0183	-0.0213	-0.0230	-0.0240	-0.0252*	-0.0277	-0.0097	-0.0190
Bath. missing and 6 rooms	-0.0196	-0.0169*	-0.0375	-0.0282	-0.0344	-0.0234	-0.0193	-0.0317	-0.0551
Bath. missing and 7 rooms	0.0613	-0.0107	-0.0145	-0.0167	-0.0235	-0.0532	-0.0875	-0.1230	-0.0935
Bath. missing and 8 rooms	0.0399	0.0835	0.0256	0.0061	-0.0122	-0.0585	-0.1095	-0.1136	-0.1602
Bath. missing and 9 rooms	0.0822	0.0464	-0.0064	-0.0197	-0.0374	-0.0468	-0.0866	-0.1370	-0.1945
Toilets									
0 toilet (Reference)									
Shared toilet	-0.0613**	-0.0469**	-0.0423**	-0.0337**	-0.0333**	-0.0288**	-0.0234**	-0.0217**	-0.0157*
Toilet	0.0712**	0.0523*	0.0334**	0.0276**	0.0275*	0.0255*	0.0190*	0.0119	0.0122
Floor									
Ground floor (building with lift) – Reference									
Entresol	0.0988	0.0726	0.0286	0.0257	0.0065	-0.0326	-0.0703	-0.0631	-0.1008
1st Floor with lift	0.0867**	0.0771**	0.0712**	0.0646**	0.0516**	0.0314**	0.0214**	0.0099*	-0.0112
2d Floor with lift	0.1319**	0.1133**	0.1060**	0.0969**	0.0831**	0.0686**	0.0528**	0.0394**	0.0129**
3d Floor with lift	0.1364**	0.1227**	0.1119**	0.0999**	0.0853**	0.0716**	0.0583**	0.0465**	0.0198**
4th Floor with lift	0.1357**	0.1254**	0.1181**	0.1086**	0.0937**	0.0805**	0.0660**	0.0486**	0.0253**
5th Floor with lift	0.1466**	0.1332**	0.1248**	0.1165**	0.1060**	0.0910**	0.0767**	0.0641**	0.0487**
6th Floor with lift	0.1471**	0.1358**	0.1294**	0.1252**	0.1103**	0.0990**	0.0827**	0.0738**	0.0630**
7th Floor with lift	0.1392**	0.1348**	0.1298**	0.1250**	0.1124**	0.1073**	0.0952**	0.0871**	0.0696**
8th Floor with lift	0.1305**	0.1239**	0.1266**	0.1263**	0.1162**	0.1069**	0.0983**	0.0950**	0.0887**
9th Floor with lift	0.1676**	0.1360**	0.1254**	0.1240**	0.1175**	0.1076**	0.0938**	0.0863**	0.0930**
10th Floor with lift	0.0978**	0.0863**	0.0766**	0.0754**	0.0729**	0.0677**	0.0670**	0.0676	0.0487**
Ground floor without lift	-0.0559**	-0.0427*	-0.0430*	-0.0356*	-0.0381**	-0.0451**	-0.0493**	-0.0542**	-0.0607**
Entresol without lift	-0.0394	-0.0295	0.0047	-0.0110	0.0029	0.0211	0.0572	0.0453	0.0485
1st Floor without lift	-0.0287**	-0.0267**	-0.0277**	-0.0252**	-0.0221**	-0.0171**	-0.0190**	-0.0232**	-0.0239**
2d Floor without lift	-0.0318**	-0.0199**	-0.0211**	-0.0204**	-0.0210**	-0.0236**	-0.0201**	-0.0251**	-0.0218**
3d Floor without lift	-0.0154*	-0.0175*	-0.0170**	-0.0134**	-0.0146**	-0.0174**	-0.0207**	-0.0259**	-0.0250**

4th Floor without lift	-0.0100*	-0.0126*	-0.0157**	-0.0168**	-0.0178**	-0.0207**	-0.0228**	-0.0216**	-0.0246**
5th Floor without lift	-0.0101	-0.0067**	-0.0120**	-0.0152**	-0.0217**	-0.0209**	-0.0204**	-0.0210**	-0.0317**
6th Floor without lift	-0.0217	-0.0160*	-0.0151**	-0.0169**	-0.0156*	-0.0152*	-0.0081	-0.0117*	-0.0170*
7th Floor without lift	-0.0176	-0.0099	-0.0032	-0.0035	-0.0050	-0.0114	-0.0072	-0.0034	-0.0007
Floor missing	0.0543**	0.0576**	0.0615**	0.0628**	0.0576**	0.0450**	0.0307**	0.0196	0.0162
Basement									
No basement (reference)									
1 basement or more	0.0369**	0.0250**	0.0182**	0.0138**	0.0105*	0.0056*	0.0014	-0.0021	-0.0081*
Garage									
No parking (Reference)									
1 parking place	0.0458**	0.0516**	0.0525**	0.0564**	0.0606**	0.0669**	0.0718**	0.0788**	0.0921**
2 parking places	0.0698**	0.0854**	0.0980**	0.1106**	0.1211**	0.1298**	0.1406**	0.1471**	0.1684**
3 or more parking places	0.2261	0.1651	0.1338	0.1200	0.1233	0.1106*	0.1083**	0.0799**	0.0536*
Miscellaneous									
Roofspace (Combles)	0.0761	0.0733	0.0808	0.0822*	0.0755**	0.0842**	0.0824**	0.0855**	0.0706**
Attic (Grenier)	0.0524*	0.0300	0.0140	0.0138	0.0285	0.0222*	0.0341**	0.0500*	0.0226**
1 or more balcony	0.0443	0.0400	0.0355*	0.0325**	0.0316*	0.0274*	0.0248*	0.0229	0.0200
Garden	0.1517**	0.1481**	0.1448**	0.1430**	0.1431**	0.1387**	0.1417**	0.1364**	0.1325**
Piece of furniture	0.1392	0.1034	0.1102	0.1015	0.0948	0.0676	0.0457	0.0098	0.0342
Mezzanine	0.1550**	0.1339**	0.1467**	0.1401**	0.1326**	0.1182**	0.1253**	0.1232**	0.1267**
Street type									
Street (Reference)									
Alley	-0.0467	-0.0847	-0.1139**	-0.1363**	-0.1506**	-0.1706**	-0.1680**	-0.1815**	-0.1910*
Avenue	-0.0063	-0.0012	0.0054	0.0070*	0.0086**	0.0122**	0.0174**	0.0200**	0.0284**
Boulevard	-0.0545**	-0.0542**	-0.0515**	-0.0461**	-0.0437**	-0.0374**	-0.0299**	-0.0208**	-0.0136
Courtyard (Cour)	0.0396	0.0283	0.0202	0.0338	0.0422*	0.0380*	0.0412*	0.0337**	0.0226*
Hamlet (Hameau)	0.2404	0.1621	0.2326	0.1967	0.1558	0.1233	0.0831	0.0626	-0.0267
Dead end (Impasse)	0.0049*	0.0002*	-0.0069*	-0.0067**	-0.0110*	-0.0051*	-0.0095*	-0.0061	0.0015
Passage	0.0010	-0.0017	-0.0021	-0.0011	-0.0031	-0.0055	0.0031	-0.0021	0.0164*
Place	0.0294*	0.0280**	0.0293**	0.0411**	0.0476**	0.0585**	0.0587**	0.0603**	0.0676**
Quay	0.0651**	0.0785**	0.0822**	0.0827**	0.0888**	0.0826**	0.0909**	0.0888**	0.0932**
Square	0.0233	0.0245*	0.0352**	0.0312**	0.0336**	0.0364**	0.0317**	0.0339*	0.0270*

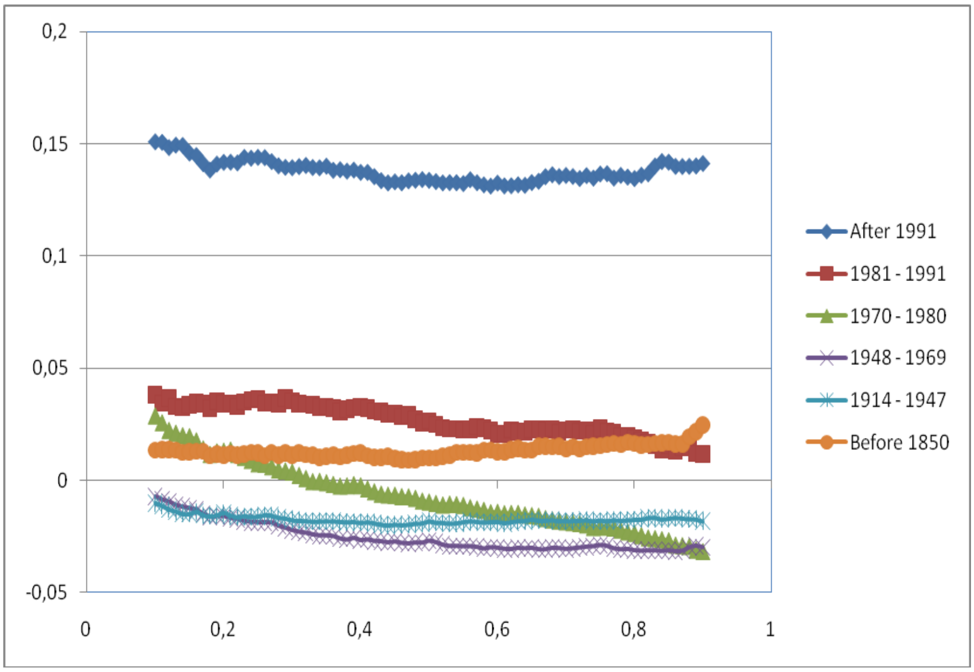
Table 9: Quantile regression results



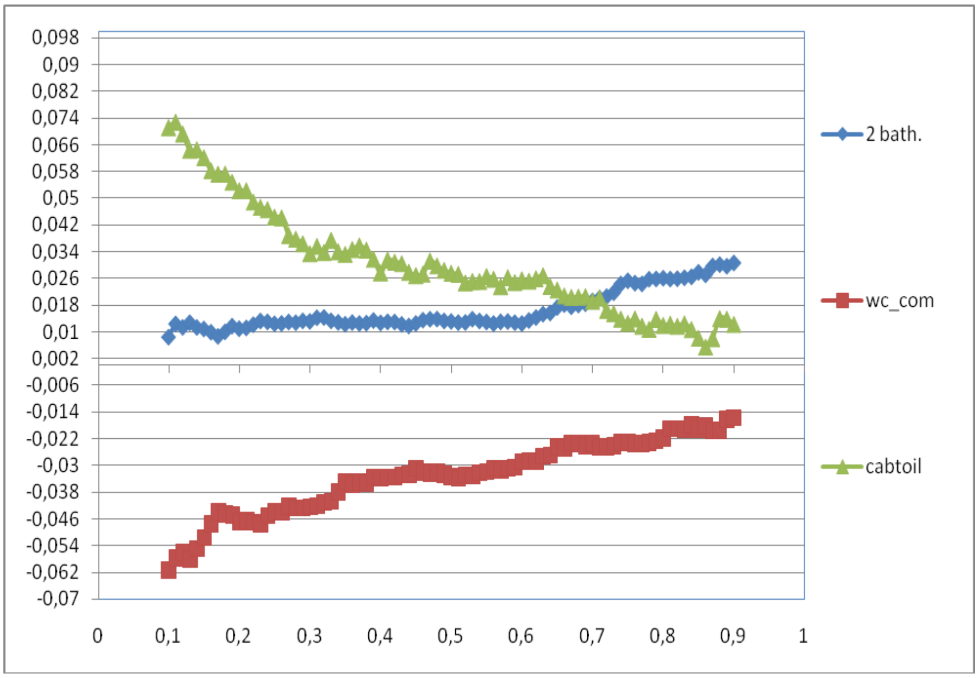
Graph 1: Price-elasticity coefficients for Surface



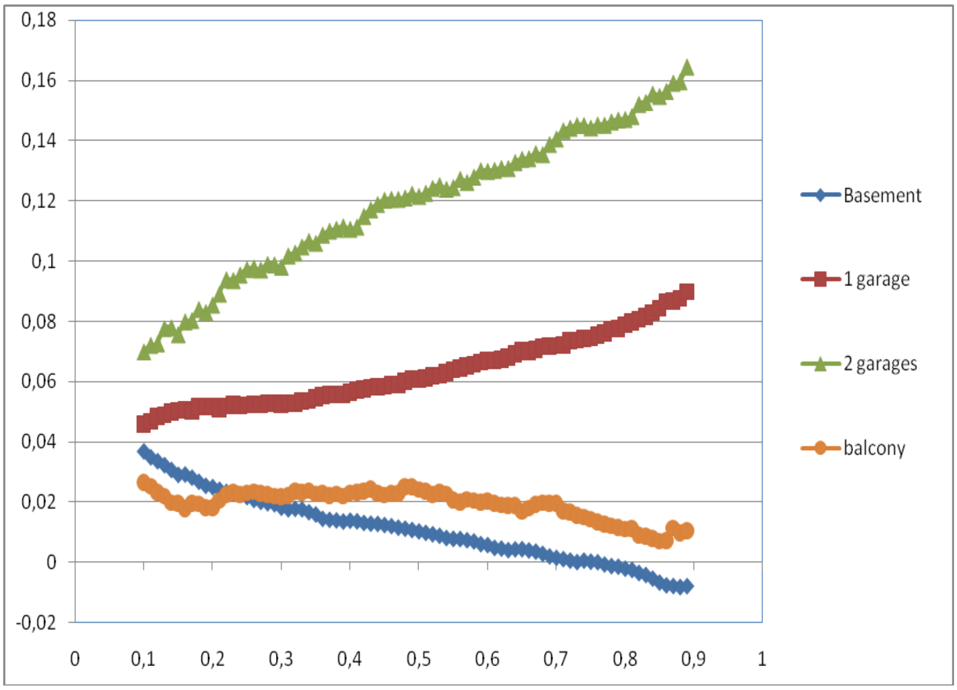
Graph 2 : Number of rooms (Ground floor as the reference)



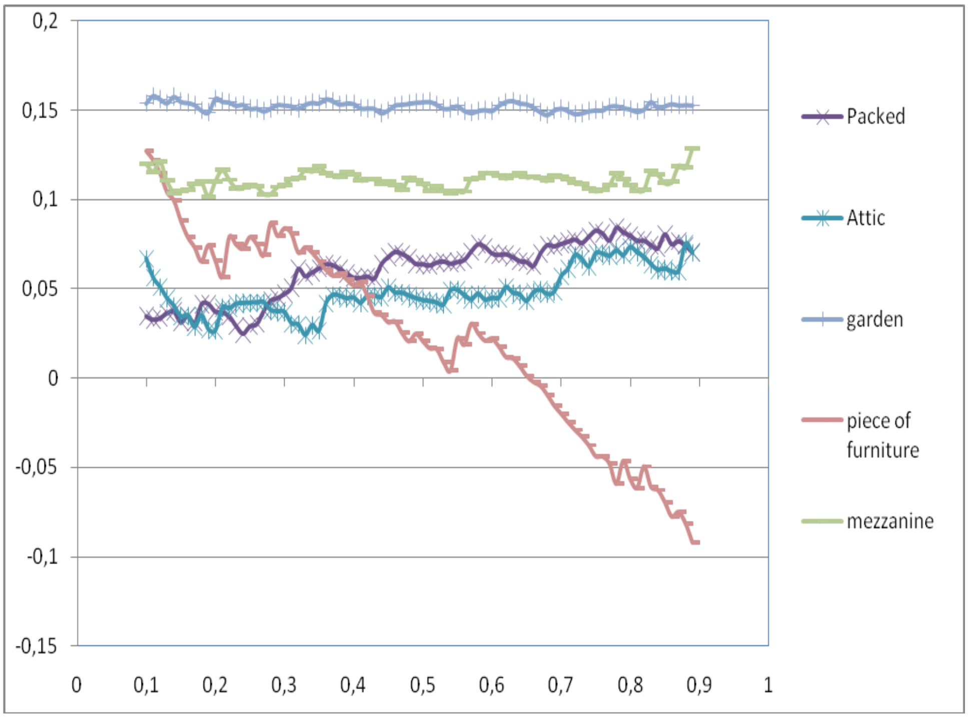
Graph 3 : Construction period (Haussmann as the reference)



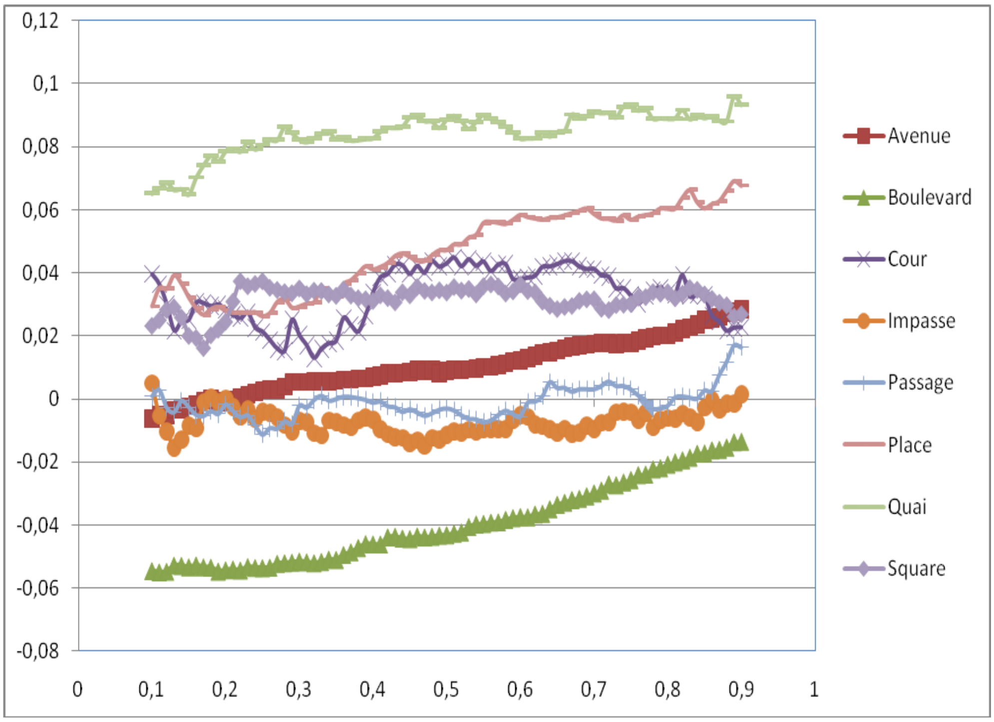
Graph 4: Bathroom and toilet (One bathroom as the reference)



Graph 5: Basement, Parking places and Balcony



Graph 6: Miscellaneous features



Graph 7: Location attributes