International Journal of Statistics and Economics;
[Formerly known as the "Bulletin of Statistics & Economics" (ISSN 0973-7022)];
ISSN 0975-556X; Year: 2017, Volume: 18, Issue Number: 4; Int. j. stat. econ.;

The Analysis of Istanbul Housing Prices by Hedonic Price Theory: Insights from Parametric and Semiparametric Models

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ABSTRACT

Most researchers use parametric models involving specific functional forms in estimating hedonic housing price functions although related literature emphasizes intrinsic nonlinearity in the relationship between housing prices and characteristics. The rigid structure of parametric models might cause to be misspecification errors arising from a wrong functional form and so, misleading inferences. In contrast to the shortcomings of the parametric model, semiparametric models offer significant advantages for hedonic price function estimation by providing functional form flexibility. This paper investigates that how semiparametric models can be used to assist in the specification of a hedonic house price function using a dataset of apartment flat sales in Istanbul for 2013 October–December. The findings based on semiparametric model demonstrate that all housing attributes in nonparametric form have a significant nonlinear impact on housing prices. Among all housing attributes considered, Bosphorus view has the strongest positive impact on housing prices in Istanbul.

Keywords: Hedonic analysis, Semiparametric model, Parametric model, Penalized Iteratively Reweighted Least Squares, Istanbul Housing Market

Mathematics Subject Classification:62P20, 91B24

Journal of Economic Literature (JEL)Classification: R32, R21, C12, C13, C14

1. INTRODUCTION

Hedonic housing price model assumes that the housing price reflects the value placed on a particular set of housing attributes. For instance, a house may be valued at a certain price based on quantitative characteristics such as the age of the house, the number of rooms, and garage space, and qualitative factors such as the geographical location, school districts, and environmental quality and so on. Therefore, the price of one house relative to another will differ with the amounts of various attributes inherent in one house relative to another (Bin 2004).

While hedonic price models have been routinely used to analyze the market price of housing, selecting an appropriate functional form has been a frequent concern in the literature (Cropper et al. 1988; Halvorsen and Pollakowski 1981). At least since Rosen's (1974) seminal paper developing the theory of hedonic price functions, empirical researchers have recognized that hedonic house price functions are likely to be nonlinear in structural characteristics and there is no reason to expect prices to be linear in continuous measures of locational variables such as distance from the city center.

The issue arises because there is little guidance from the economic theory about the proper functional relationship between housing price and its attributes(Butler 1982; Halvorsen - Pallakowski 1981; Caglayan - Arikan 2011). Recognizing the potentially serious consequences of functional misspecification, most researchers have attempted to estimate hedonic price models by specifying more flexible regression models (Bin 2004). Most of these attempts have concentrated on parametric specifications including the model introduced by Box and Cox (1964) and its variants. However, a considerably smaller set of authors has proposed semi and fully nonparametric specifications for hedonic price functions (Martins-Filho - Bin 2005).

Nonparametric models offer significant advantages for hedonic price function estimation. Functional form flexibility is a common feature of all nonparametric procedures (McMillen - Redfearn 2010). The nonparametric procedure is appropriate in the reasonable case in which the researcher does not have accurate prior knowledge of the true functional form. If the assumed functional form is incorrect, coefficient estimates and hypothesis tests are generally biased. Moreover, the researcher might conclude that there is no relationship between variables when they are strongly related. The best way will be proceeded to avoid from mentioned issues is to estimate the appropriate functional form from the data in the absence of strong theory for the functional form (Keele 2008).

While most of the literature has concentrated on the parametric specifications of the hedonic price model, some recent studies have assessed the advantages of some nonparametric and semi-parametric models. Comparative studies suggest that these latter methods fit the data better than parametric specifications (Anglin - Gencay 1996; Gencay - Xian 1996;Iwata et al. 2000; Bao - Wan 2004; Bin 2004; Bajari - Kahn 2005; Martins-Filho - Bin 2005; McMillen - Redfearn 2010; Bontemps et al. 2008).

The first main objective of this study is to determine the functional forms properly in the context of the hedonic pricing using a semiparametric model which is alternative to parametric model. The second is to make a hedonic analysis for Istanbul Housing Market using a model fitting perfectly the dataset in order to obtain the willingness to pay estimates for housing attributes.

The rest of the paper organised as follows: Sections 2, 3 and 4 introduce hedonic housing price model and literature, methodology and data used, respectively. Estimation results are presented and discussed in Section 5. The final section provides a conclusion.

2. HEDONIC HOUSING PRICE MODEL

Hedonic housing price model enables to construct a relationship between housing price and its characteristics. In such a case, hedonic housing price models are essential in order to determine how the price of a unit of housing varies with the set of attributes it possesses.

In general, the purchase price of a heterogeneous housing goods could be expressed by a hedonic pricing model which embraces a bundle of housing characteristics in parametric form:

$$Y = X\beta + \varepsilon$$

where, Y housing price vector, β coefficient matrix, X matrix of independent variables and ε, error term vector. Independent variables are the characteristics of the housing.

The partial derivatives of the price with the respect to housing characteristics provide information on the marginal willingness to pay for an additional unit ofeach characteristic (Palmquist 1991; Geoghegan et al. 1997; Malpezzi 2003; Caglayan -Arikan2011).

The hedonic price literature almost unanimously underlines the intrinsic nonlinearity in the relationship between housing prices and characteristics, though nothing is known a priori about a specific functional form (Anglin - Gencay 1996; Gencay - Yang 1996; Ekeland et al. 2002, 2004; Haupt et al. 2010; Núñez-Tabales et al. 2016). Nevertheless, while the literature suggests that the equilibrium price function is nonlinear, most empirical studies use flexible functional forms, such as Box-Cox functions (Goodman 1978; Halvorsen - Pollakowski 1981; Cassel - Mendelson 1985; Cropper et al.1988) or simple parametric models such as OLS (Ozus et al. 2007; Ottensmann et al. 2008; Alkay 2008; Keskin 2008; Adair et al. 2011; Koramaz - Dokmeci 2012)

According to Ekeland et al. (2004), the nature of the relationship between housing prices and the various associated attributes is complex and nonlinear in reality, so it would be better represented by nonparametric models rather than the classical parametric specifications.

More, in particular, Pace (1993,1995), Anglin and Gencay (1996), Gencay and Yang (1996) made an important contribution to this field by comparing the prediction performances of parametric and semiparametric models in their studies. In recent years, there is a growing number of studies have applied nonparametric or semiparametric regressions in estimating the hedonic price function (Pavlov 2000; Clapp 2003; Bao - Wan 2004; Bin 2004;Martins-Filho - Bin 2005; McMillen - Redfearn 2010;Sunding - Swoboda 2010; Karato et al.2015). The most of these studies suggested nonparametric and semi-parametric models fitting the data better than parametric models.

3.METHODOLOGY

Semiparametric model allows us to mix parametric terms with nonparametric terms in the same model and takes the following form

$$Y = \alpha + \beta' X + f(Z) + \varepsilon$$

In the above model, $\alpha + \beta' X$ represents the parametric component and f(Z) the non-parametric component. In other words, the relationship between Y and X is parametric, while that between Y and Z is nonparametric. The nonparametric variables in *Z*are assumed to have a nonlinear effect on Y and are fitted with nonparametric smoothers.

The parametric part of the model allows discrete covariates such as dummy variables and the nonparametric part of the model allows any continuous covariates.

Thus, the semiparametric model provides estimation ability related to a wide variety of functional forms. This advantage of the semiparametric model might prevent possible misspecification errors will arise by providing flexible estimations. For instance, assuming linearity when the relationship between two variables is actually nonlinear might conclude that there is no relationship between them when the two are strongly related. In this situation, instead of assuming that we know the functional form of a regression model, a better alternative is to estimate the appropriate functional form from the data. Semiparametric regression model estimates the functional form from the data and enables the best way to proceed in the absence of strong theory for the functional form (Keele, 2008).

On the other hand, nonparametric regression estimators are very flexible but their statistical precision decreases greatly if we include several explanatory variables in the model. This problem defined as *the curse of dimensionality* is the most serious problem of nonparametric estimations (Ahamada and Flachaire 2013). To overcome this problem, dimension reduction methods can be employed. Such methods usually combine features of parametric and nonparametric techniques. As a consequence, they are usually referred to as semiparametric methods (Härdle et al. 2004).

These models can be estimated using Penalized Iteratively Reweighted Least Squares (P-IRLS). This estimation problem can be solved by minimizing the following objective function:

$$\min\left\{\frac{1}{n}\sum_{i=1}^{n}(Y_i - f(Z_i) - \alpha - \beta' X)^2 + \lambda\int f''(Z)d(Z)\right\}$$

where f(Z) is a regression spline and f'' stands for the second derivative of f(Z). The roughness of f(Z) is captured by $\int f''(Z_i)d(Z)$ and n denotes the number of observations. This expression describes the trade-off between fitting perfectly the data (i.e. minimizing the squared residuals) and having the smoothest possible approximating function f. This trade-off is controlled by parameter λ.

The selection of the optimal smoothing parameter λ is integrated into this procedure using the Generalised Cross Validation (GCV) criterion. According to this criterion, the optimal λ minimizes the following expression:

$$GCV(\lambda) = \frac{RSS(\lambda)}{[1 - n - 1tr(S(\lambda))]^2}$$

where RSS(λ) = e'e is the sum of squared residuals of the estimated model for a given λ and tr(S(λ)) is the trace of the projection matrix S(λ) that satisfies $\hat{Q} = SQ$. For each of the models estimated, the corresponding minimized GCV scores are also reported (Ahamada - Flachaire 2013).

Furthermore, this methodology enables us to test the statistical significance of each non-parametric variable in the specified semi-parametric model. This is done via an F-test that compares the sum of squared residuals (RSS) of the semi-parametric model (unrestricted) with the RSS of the restricted model that excludes the non-parametric variable. The corresponding F statistic is given by:

$$F = \frac{(RSS_{restricted} - RSS_{unrestricted})/(tr(S) - 1)}{RSS_{unrestricted} / df_{res,unrestricted}}$$

where $df_{res} = n - tr(2S - SS')$. This statistic under the null hypothesis of equal RSS follows an F distribution with $df_{res,restricted}$-$df_{res,unrestricted}$ and $df_{res,unrestricted}$ degrees of freedom.

Likelihood Ratio (LR) test can be used to test whether the semi-parametric model has explanatory power superior to that of the parametric model:

$$LR = -2*(LogLikelihood_{restricted} - LogLikelihood_{unrestricted})$$

This test compares the log-likelihood of the fully parametric model (restricted) with the log likelihood of the semi-parametric model (unrestricted). The test statistic under the null hypothesis of equal likelihoods follows an approximate χ^2 distribution with degrees of freedom given by the difference in the number of parameters across the two models (Keele 2008).

4.DATA

The data set used to estimate the model, obtained through real estate agency surveys in 2013 (October–December). In this period, 113431 apartment flats presented for sale from 39 counties in Istanbul were determined. The stratified sampling method was used in the selection of sample size. In the selection of sample size, margin of error and sample error are considerably important since the sample size will represent much better the population when the errors are small. Therefore, the margin of error and sample error were determined as 2% and 5%, respectively. So, we used 2838 observations in this study. The sample size according to counties in Istanbul was exhibited in Figure 1.

Table 1: Sample Sizes for Counties

County		County		County		County		County	
Adalar	6	Besiktas	25	Eyup	95	Pendik	73	Umraniye	129
Arnavutkoy	11	Beykoz	6	Fatih	14	Sancaktepe	73	Uskudar	205
Atasehir	110	Beylikduzu	253	Gaziosmanpasa	35	Sarıyer	15	Zeytinburnu	136
Avcilar	50	Beyoglu	12	Gungoren	34	Silivri	7	**Total**	**2838**
Bagcilar	20	Buyukcekmece	12	Kadikoy	93	Sultanbeyli	3		
Bahcelievler	100	Catalca	3	Kagithane	30	Sultangazi	56		
Bakirkoy	26	Cekmekoy	58	Kartal	133	Sile	2		
Basaksehir	113	Esenler	18	Kucukcekmece	95	Sisli	20		
Bayrampasa	16	Esenyurt	563	Maltepe	177	Tuzla	11		

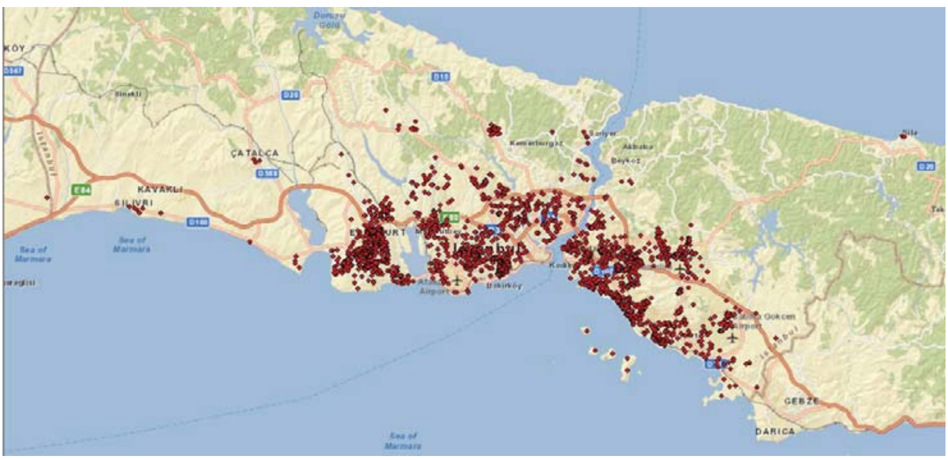

Figure 1. Distribution of Housings in Istanbul

After sample sizes representing Istanbul Real Estate Market and its sub-markets were determined, the relevant literature was examined especially for Istanbul Real Estate Market (Ozus et al. 2007; Keskin2008; Alkay2008; Caglayan -Arikan2009; Koramaz - Dokmeci2012) and a group of variables was selected, which was exhibited detailed in Table 2.

The geographic coordinates of housings, defined as “Coordinates” in Table 2, allow us to calculate the distance from each property to the target places such as central business district, the nearest shopping center using the Haversine formula of great-circle distance. All distance variables in the list were calculated by this formula.

Table 2: Description of the variables

Variable Name	Definition	Type	Name in the analysis
Housing Price	Asking price of housing, (Turkish Lira)	Continuous	Price
Bosphorus view	(1: if housing has Bosphorus view, 0: if not)	Discrete	Bosphorus _View
Sea view	(1: if housing has sea view, 0: if not)	Discrete	Sea_View
Side	(1: if housing is located in European side, 0: if not)	Discrete	Side
Convenience of credit	(1: if housing is good for mortgage, 0: if not)	Discrete	Credit_Convenience
Parking place	(1: if housing has a car park, 0: if not)	Discrete	Car_Park
Security system	(1: if housing has a security system, 0: if not)	Discrete	Security
Swimming pool	(1: if housing has a swimming pool, 0: if not)	Discrete	Swimming_Pool
Number of floors	(Number of floor in the building where the housing is located)	Continuous	Number_Floors
Ground floor	(1: if housing is located on the ground floor; 0: if not)	Discrete	Ground_Floor
Basement floor	(1: if housing is located at the basement floor; 0: if not)	Discrete	Basement
Vanity unit	(1: if housing has a vanity unit, 0: if not)	Discrete	Vanity_Unit
Jacuzzi	(1: if housing has a jacuzzi, 0: if not)	Discrete	Jacuzzi
Ground floor	(1: if housing is located on the ground floor; 0: if not)	Discrete	Ground_Floor
Basement floor	(1: if housing is located at the basement floor; 0: if not)	Discrete	Basement
Vanity unit	(1: if housing has a vanity unit, 0: if not)	Discrete	Vanity_Unit
Jacuzzi	(1: if housing has a jacuzzi, 0: if not)	Discrete	Jacuzzi
Coordinates	(The geographic coordinates, longitude and latitude,where the housing is located)	Continuous	
Distance to Central Business District	(Distance between Central Business District and housing, km)	Continuous	CBD
Distance to nearest shopping center	(Distance between nearest shopping center and housing, km)	Continuous	Shopping_Center
Distance to sea bus station	(Distance between sea bus station and housing, km)	Continuous	Sea_Bus
Distance to nearest metrobus stop	(Distance between nearest metrobus stop and housing, km)	Continuous	Metrobus
Size of a housing	(Size of a housing, in square meters)	Continuous	Square_Meter
Age of the building	(Current year minus the year that the building was built)	Continuous	Building_Age
Distance to nearest bus stop	(Distance between nearest bus stop and housing, km)	Continuous	Bus_Stop
Distance to city center	(Distance between city center and housing, km)	Continuous	City_Center
Life Quality Index	(Life Quality Index is calculated as average of 7 sub-scales such as Education, Health & Life, Economic Development, Transportation and Accessibility, Environmental Status, Social Life, Demographical Structure. Resource:Istanbul Chamber of Commerce, 2011)	Continuous	LQI

5. RESULTS

The relationships between housing prices and attributes were investigated by semiparametric regression models without any restrictive assumption about functional form in order to avoid misspecification problem. In order to make a comparison between the parametric and semiparametric model, the estimation results of the parametric model were also reported. While the parametric model was estimated by Ordinary Least Squares (OLS), the semiparametric model was estimated by Penalized Iteratively Reweighted Least Squares (P-IRLS).

Coefficients of the dummy variables in parametric and semiparametric models, in semi-logarithmic form, were interpreted based on the approach exhibited by Halvorsen and Palmquist (1980).

In the presence of heteroscedastic errors in the linear model, the OLS estimator of the parameters is consistent but its variance is no longer so. Any tests based on these estimates will thus no longer be valid. The same problem can arise in the parametric part of the semiparametric model. It is possible to calculate an estimate of the variance which is robust to heteroscedasticity, as proposed by White (1980) for both of models. For this reason, the standard errors of the parametric and semiparametric model were obtained as robust to heteroscedaticity in all estimations. Moreover, Ramsey's RESET test designed to detect if there are any neglected nonlinearities in the parametric models was used.

The empirical results of parametric and semi-parametric models are reported in Table 3.

Table 3: Estimation Results

Variable	Parametric (OLS Model)	Semiparametric Model
Intercept	5.071*** [244.756]	5.200*** [2269.51]
Bosphorus _View	0.231*** [6.264]	0.228*** [5.776]
Sea_View	0.046*** [3.681]	0.033*** [2.939]
Side	0.039*** [4.162]	0.047*** [3.013]
Credit_Convenience	0.087*** [6.119]	0.066*** [5.060]
Car_Park	0.048*** [6.015]	0.047*** [6.355]
Security	0.061*** [5.626]	0.086*** [8.498]
Swimming_Pool	0.140*** [11.685]	0.122*** [11.476]
Number_Floors	0.002* [1.768]	0.003*** [2.968]
Ground_Floor	-0.072*** [-9.937]	-0.060*** [-9.164]
Basement	-0.205*** [-7.964]	-0.169*** [-7.458]
Vanity_Unit	0.037*** [5.544]	0.022*** [3.443]
Jacuzzi	0.068*** [4.471]	0.079*** [5.755]
LQI	0.235*** [18.843]	See Fig 1. F-stat: 107.081***

CBD	-0.009*** [-19.006]	See Fig 1. F-stat: 269.431***
Shopping _Center	0.001 [0.319]	See Fig 1. F-stat: 4.902***
Sea _Bus	-0.006*** [-5.131]	See Fig 1. F-stat: 16.476***
Metro bus	0.006*** [7.076]	See Fig 1. F-stat: 7.068***
Square_Meter	0.003*** [31.341]	See Fig 1. F-stat: 288.389***
Building_Age	-0.0001 [-0.131]	See Fig 1. F-stat: 10.826***
Bus_Stop	-0.0001 [-0.011]	See Fig 1. F-stat: 4.162***
City_Center	-0.004*** [-4.270]	See Fig 1. F-stat: 269.431***
R^2 adjusted	0.80	0.85
logLik	1582.52	1986.933
LR test	808.826***	
Ramsey RESET test (power=2)	19.667***	
Ramsey RESET test (power=3)	14.778***	

***,**,* Coefficient is statistically significant at the 1% level, 5% level and 10% level, respectively.
F-stat reports the F-test statistic value for the statistical significance of each non-parametric term in the semi-parametric model.
The values in brackets are t-statistics.

The estimation results in Table 3 provided a remarkable inference related to the convenience of functional form. Hereunder, some explanatory variables in the parametric model (Shopping_Center, Building_Age, Bus_Stop) are not statistically significant while the same variables are significant in the semiparametric model. This situation might depend on the choice of wrong functional form. In other words, assuming linearity when the relationship between variables actually nonlinear can cause to be misspecification problem. In this case, it might be concluded that there is no relationship between variables when they are strongly related. Ramsey's RESET test shows also that there are neglected nonlinearities in the parametric model.

Furthermore, the semiparametric model explains substantially more variation in the housing prices than the parametric model, R^2=0.85 versus 0.80. The results of LR test support also these results and indicate that the explanatory power of the semiparametric model is better than the parametric model. For this reason, the coefficients of the semiparametric models will only be interpreted. The marginal effects of variables in the parametric portion of the semiparametric model will be computed by Halvorsen and Palmquist (1980) approach as mentioned before.

According to the semiparametric model results, Bosphorus _View is the most effective housing attribute has a positive influence on housing prices in Istanbul. Having a house in the neighborhoods by the Bosphorus adds more 25.60% to the price of the property.

The second most and positive effective housing attribute is the Swimming_Pool. Having the swimming pool facility in the property will increase the price of the property 12.97%.

The third most important factor to affect housing prices is Security. The presence of security system increases the price of the property 8.98%.

The Basement is the most effective housing attribute has a negative influence on housing prices. When the property is located on the basement floor, the price of the property decreases 18.41%.

The other significant variables might be ranked according to their importance as follows: Jacuzzi, Credit_Convenience, Ground_Floor, Car_Park, Side, Sea_View, Vanity_Unit, Number_Floors.

The partial impact of each nonlinearly related variable on housing price in the semiparametric model is depicted in Figure 1. The estimated coefficients of the variables added in nonparametric form into the semiparametric model are demonstrated by figures. Since each observation in the dataset is determined respectively as target observation in nonparametric estimation procedure, the number of models are estimated as much as the number of observations in the dataset. Consequently, the estimates are based on 2838 local semiparametric regressions, so that 2838 estimated coefficients were obtained for each explanatory variable in nonparametric form. Therefore, the estimated coefficients of the explanatory variables in nonparametric form were demonstrated by figures in Figure 2.

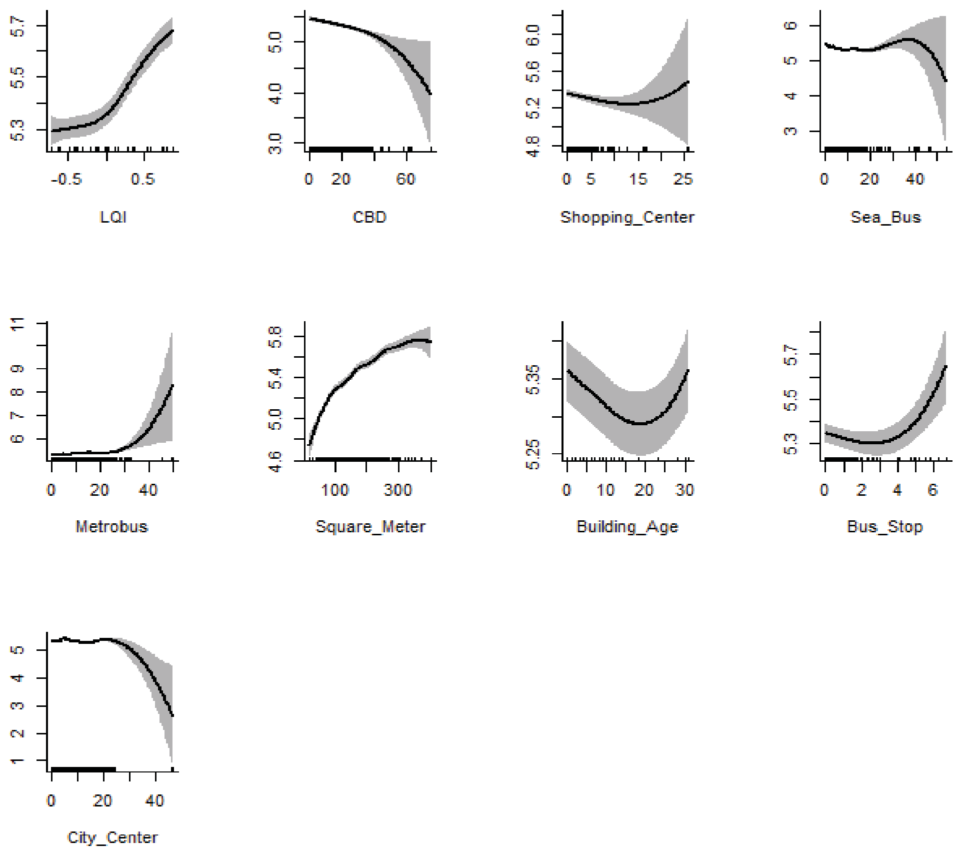

Figure 2. Nonparametric Relations

In Figure 2, it is observed clearly that the relationships between housing prices and their some attributes added in nonparametric form into the semiparametric model are nonlinear. The shaded regions in figures show the 95% confidence interval band for inference.

The upper left figure portrays the estimated relationship between the housing price and life quality index and shows that when the life quality increase, housing price is positively affected. However, an increase in positive values of life quality index rises the housing prices more than an increase in negative values of it. An ideal quality of life is an indicator of a person’s overall well-being; that is, an individual’s total utility (Blomquist 2006). Therefore, housing prices can be expected to be higher in areas with high quality of life, because people will pay a premium to live in these areas.

The second from upper left figure reveals that the distance to the central business district is non-linearly and negatively related to housing price. As the distance to the central business district more and more increase, housing price decrease considerably. This decline occurs, particularly after 40 km. A central business district is simply the site of all business. Wealthy people often live near the central businesses areas, even while nearby neighborhoods suffer from extreme levels of poverty, crime, and unemployment. This choice might arise from the sites closer to the central business district offer households lower commuting costs. In an attempt to avoid costly commutes, households are willing to pay a premium for sites closer to the central business district (Arnott – McMillen 2008).

The upper right figure reflects the effect of the change in the accessibility to sea bus on housing price. The housing price achieves the maximum level at a distance of 40 km but after this point, increasing distance to sea bus is causing a decrease in the housing price. The proximity to the sea bus is an increasing factor for housing prices in terms of accessibility and sea view, so increasing distance to sea bus can cause to be a decline in housing prices. On the other hand, housings very close to the sea bus might suffer from noise and pollution and this could cause a decreasing effect on housing prices.

The second from upper right figure illustrates that the effect of the change in the nearest distance to a shopping center on housing price could be decreasing or increasing in value. Increasing distance to shopping center reduces housing prices up to 15 km but housing prices start to increasing after 15 km. It is possible to explain the occasion of a nonlinear relationship between housing price and distance to shopping center. A large shopping center might provide a wide range of products and services. It creates great convenience to residents and thus enhances property value. The negative effect, on the other hand, is that a housing too close to the shopping center would suffer more from noise, lights, etc. (Wong et al. 2002).

The middle left figure points out that the distance to a metro bus is non-linearly and positively related to housing price. Increasing distance to the metro bus after 30 km is causing an increase in the housing price. The distance to the metro bus station that reflects accessibility induces changes in housing prices in a mostly nonlinear form (Srour etal. 2002). The closest distances gain high accessibility work as a positive amenity effect. However, the closest locations to the metro bus station suffer noise, visual and air pollution and localized traffic congestion, which may affect a decrease in housing price (Waddell etal. 1993). In spite of such negative effects, the effect of proximity to transportation on housing price differs across income groups (So etal. 1997). For instance, low-income households prefer to live in locations in which travel distance is relatively low in order to value their travel cost at their wage rate.

The second from middle left figure represents the nonlinear and positive relationship between housing price and square meters of the house and shows that increasing square meters of the house on sale increase the price of that property. The gross floor area of a housing directly determines the quantity of living space. It is clear that more living space a flat contains, the higher the total price of the flat (Wong et al. 2002). This does not, however, imply that the influence quantity of increasing size in square meters on the price of the property is not same everywhere. In other words, the effect of added per square footage to a house located in the city center compared to a house in a suburban area is different.

The middle right figure reflects the effect of the change in the accessibility to a bus stop on housing price. The nearest distance to the bus stop is nonlinearly associated with the property’s observed sale price. The housing price enhances also while the distance to nearest bus stop increases after 3 km. This is not an expectable finding since housings close to bus stops tend to have higher values than those away from the bus system. Some researchers speculated that the noise of buses and the spread of bus services in lower-income neighborhoods might contribute to this negative association (Bina et al.2006).

The second from middle right figure shows that the nonlinear relationship between housing price and age of the building. The price of housing declines while the age of building increases up to 10-year-old but housing price rallies when the age of building achieved the 20-year-old. Although it is expected that the age of the building variable should have a negative sign, a positive result is obtained due to the impact of renovated buildings in the old districts, and higher housing prices in the well-established neighborhoods than the new developing ones (Ozus et al. 2007).

The bottom left graph illustrates that changes in distance to city center is also non-linearly related to housing prices. The housing prices decrease as the distance to city center increases. In other words, as the household moves closer to the center of the city, it faces higher housing prices and lower commuting costs and consumes relatively fewer housing services. Otherwise, as the household moves farther from the city center it faces lower housing prices, higher commuting costs, and consumes relatively more housing services.

6. DISCUSSION AND CONCLUSION

The economic theory of hedonic pricing provides very little theoretical guidance on the appropriate functional relationship between housing prices and attributes in the hedonic price function. This is a considerable shortcoming for empirical studies since theoretical models are critical in determining well specified econometric models. To avoid the issues in the selection of functional form in the absence of strong theory, the models allow for flexible functional forms such as semiparametric or nonparametric model are suggested.

This study estimates a hedonic housing price function using a semi-parametric regression and compares with a conventional parametric model. The empirical profiles of relationships between housing prices and their attributes in nonparametric form indicate the nonlinearities in relationships. In addition, it was concluded that the semiparametric model structure is the most appropriate model to explain the relationships between housing prices and attributes. The results obtained based on the semiparametric model indicate that all housing attributes considered in the study are effective on housing prices while some of them are not significant in the parametric model. Probably this contrasting result from the assumption of wrong functional form in the parametric model.

Besides, the findings based on the semiparametric model show that the most important factors which affect positively housing prices are Bosphorus view, swimming pool and security. The world famous natural beauty of the Bosphorus shoreshas attracted affluent households throughout history and still is the most important factor on housing prices. Growing population in Istanbul may cause some problems like unemployment, irregular urbanization and increasing crime rates. For this reason, security is an important determining on the housing prices. Furthermore, after the 1999 Marmara Earthquake, householdspreferred to live in the buildings at the highly secured that have swimming pools and facilities.On the other hand, the prices of housings located on basement and ground floors affected considerably as negative.Basement and ground floors are generally not preferred for security reasons. Also, basement floor has a negative impact because of possibly related to endemic dampness problems.In conclusion, the results on the willingness to pay estimates for housing attributes seem reasonably in line with apriori expectations and the reasons causing nonlinearities in the relationships. The factors of housing prices may vary because of the properties of country, region or city. All these findings may give important information in the real estate market to consider determinants of housing prices.

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