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Determinants of House Prices in Seoul: The Quantile Regression Approach

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<Abstract>

Using auction data of district courts of Seoul, Korea from January 2006 to December 2012, this paper estimate quantile regression of hedonic price model for each quantile of the conditional distribution of house prices to investigate house price determinants.The quantile regression is to investigate how the implicit prices of housing characteristics vary across the quantiles of house prices. The hedonic variables employed in this research include building age, size, grand floor, floor level, location, scenic view, and proximity to subway and high schools. We consider three regions - Kangnam, Songpa and Nowon in Seoul and compare the estimation results with one another.

We find that determinants of house price in these three regions are similar except for environmental factors such as scenic view. Scenic view has statistically significant effect on house prices in Kangnam while it is not the case in Songpa and Nowon. The quantile analysis of these three regions shows each quantile has different effects of hedonic attributes to the determination of house prices. The size of houses affects the house prices in all regions and the degree of its effect seems to get higher toward the lower price quantile. Proximity to the subway is statistically insignificant. Good scenic view has quite significant impact on the house prices of medium and higher price quantiles. These results can provide a more precise price valuation tools for property taxation and for developers targeting different submarkets and customers.

Keywords: Korean House Prices, Hedonic Price Model, Quantile Regression

1. Introduction

House can be considered as a bundle of utility-bearing attributes that are valued by consumers. These attributes are characterized by their physical inflexibility, durability and spatial fixity such that different combinations of them can produce a heterogeneous good. In the real estate literature, housing price is defined as a function of a bundle of inherent attributes (i.e. flat size, age, floor level), neighborhood characteristics (i.e. scenic view), accessibility (i.e. metro transport station and school) and environmental quality (fresh air or natural beauty) that yield utility or satisfaction to homebuyers. Particularly, a hedonic price model by ordinary least squares (OLS) can be utilized to model the relation between a set of housing attributes and real estate price (Epple, 1987; Can, 1992; Cheshire and Sheppard, 1995; Can and Megbolugbe, 1997: Chau and Choy 2011).

Traditional OLS linear regression is a statistical tool used to estimate the hedonic model, in which each hedonic characteristics of a house constantly influence the housing price at average. It estimates the mean value of the housing price for given levels of the explanatory variables. That is, the OLS model estimates how, on average, these houses' characteristics impact on real estate prices. The "scenic view" as an explanatory variable compares the effect of having a scenic view on housing prices with not having a scenic view. While this model can address the question of whether or not a scenic view matters in the price determination of house, it cannot answer another important question: ''Does a scenic view influence the housing prices differently for lower-priced houses than for high-priced houses?''. One can obtain a more comprehensive picture of the effect of the view on the housing prices by using a quantile regression, which models the relation between a set of explanatory variables and the quantiles of the housing prices. It specifies changes in the quantiles of the housing prices. The quantile regression parameter estimates the change in a specified quantile of the housing price produced by a one-unit change in the explanatory variable. This allows for a comparison of how specific percentiles of housing prices may be more affected by certain houses' characteristics than other percentiles. This is reflected in the change in the magnitude of the regression coefficient.

The objective of this paper is to estimate empirically how specific quantiles of apartment prices in Seoul respond differently to a one-unit change in the hedonic characteristics of apartment. In a step forward, the quantile regression is to investigate how the implicit prices of housing characteristics vary across the quantiles of house prices.

Despite of its long history, hedonic pricing for housing valuation remains an active research area. However, housing studies regarding Korean cities are limited because the publication of market trading information such as prices and volumes of houses sold has a short history which began just in 2006. The housing dataset of prices and other variables are obtained from the auction results of real estates in each District Court of Seoul. The house prices from three counties of Kangnam, Songpa and Nowon in Seoul will be compared with each other to examine whether or there exist the different quantile effects of the common hedonic characteristics on the house prices between the three regions in Seoul during January 2006 through December 2012. Kangnam and Songpa counties in Seoul is well known to have high-priced houses in general, while the house prices in Nowon county are thought to be relatively low, compared to the other two counties. We used only the sample data of apartment houses, excluding detached houses, nonresidential housing, offices, shops, and warehouses. Apartment houses are the most popular housing type in Korea as Cho, Kim and Shilling(2007) point out.[1]In particular, since the apartment houses have the standardized systems of heating, security, and management, etc. in its nature, they seem to have less hedonic characteristics than stand-alone independent residential buildings or houses do.

Data of the house's hedonic characteristics such as scenic view, accessibility to metro transport station and schools are difficult to obtain since they are only available by handmade works to identify for each individual house, using the geographical functions of Google and Daum portals. The comparison between the quantile effects of different hedonic characteristics on the house prices will

[1]Apartment account for 59.0% of all housing stock according to the 2010 Housing Survey by Korea National Statistical Office.

provide a meaningful implication for a price valuation tools for government property taxation or for the real estate development markets. As an alternative to OLS regression, this study adopts the quantile regression to identify the implicit prices of housing characteristics for the different percentiles of the distribution of housing prices as well as to control spatial dependency. This explicitly allows the higher-priced apartments to have different implicit prices for a house's characteristic than the lower-priced apartments. Heckman (1979) suggests that the issues associated with truncation could possibly be avoided since the quantile regression makes use of the entire sample rather than the mean value of the house prices. This will eliminate the problem of biased estimates that is created when the OLS estimation is applied to the house price sub-samples. (Newsome and Zietz, 1992).

This paper is organized as follows. Section 2 briefly presents a literature review of the quantile regressions. Section 3 discusses the model specification adopted in this paper, while the data quality and sources will be presented in section 4. Section 5 presents and discusses the empirical results, utilizing housing auction data from the three counties, Kangnam, Songpa and Nowon in Seoul for the period between January 2006 and December 2012. The last section summarizes the major findings and policy implications.

2. Literature Review

The quantile regression model introduced by Koenker and Bassett(1978) is more flexible than OLS. Quantile regression allows us to examine more comprehensive pictures for different house prices.

The quantile regression is based on the minimization of weighted absolute deviations for estimating conditional quantile (percentile) functions (Koenker and Bassett, 1978; Koenker and Hallock, 2001). For the median (quantile = 0.5), symmetrical weights are used, while asymmetrical weights are employed for all other quantiles (0.1, 0.2, ..., 0.9). While the traditional OLS regression estimates conditional mean functions, quantile regression can be employed to explain the determinants of the dependent variable at any point of the distribution of the dependent variable. For hedonic price functions, quantile regression makes it possible to examine statistically the extent to which housing characteristics are valued differently across the distribution of housing prices. Although one may argue that the same goal may be accomplished by utilizing the price series sub-samples according to the unconditional distribution and then applying OLS to the sub-samples, Heckman (1979) argues that the truncation of the dependent variable may create biased parameter estimates and should be avoided if possible. Since quantile regression employs the full dataset, a sample selection problem does not arise in the first place.

Gyourko and Tracy(1999) suggest that constant- quality growth in high-quality homes using the quantile regression was much higher than what was estimated by Gyourko and Linneman(1993) using the OLS regression.

Mak, Choy and Ho(2010) suggest that homebuyers' tastes and preferences for specific housing attributes vary greatly across different quantiles in Hong Kong. Liao and Wang(2012) carry out an analysis using a dataset on an emerging Chinese city, Changsha. Their paper applies spatial quantile regression to investigate how the implicit prices of housing characteristics vary across the quantiles of house prices as well as to control for the effects of spatial dependence. Ebru and Eban(2011) examine the determination of house prices in Istanbul by a quantile regression, and find that age, cable TV, security, heating system, garage, kitchen area, numbers of room tend to increase the house prices. This suggests that the major factors explaining house prices can be changed over regions and cities in a country due to their different properties. Lee, Chung and Kim(2005) studied the effects of house age on the house prices, although they had empirically data problems associated with using house price data projected from brokers of real estate instead using real trading data in the estimation of the house prices. Ong, Lusht and Mak(2005) provide the effects of market conditions, auction date, number of bidders, building location as determinants of house prices, using auction data of residential houses from January 1995 to December 2000 in Singapore. Investigating the effects of scenic view on the house prices from auction data of 1,475 cases in Hong Kong during 2005 to 2006, Jim and Chen(2009) found that the ocean view increased the house prices by 2-3% higher. A hedonic model by Lee, Chung and Kim(2005) differentiated the effects of building age on the house prices into two categories; depreciation effect and redevelopment effect. It showed that the apartment house prices tended to fall due to the age effect at the initial ages of building until 15-19 year old, but begins to rise after then due to the expected profits from the redevelopment of the old house. Cho(2011) used a transaction cost approach to analyze the process of the re-development of houses, where buyers and sellers compete to get interactive strategies using uncertain probability of redevelopment and its costs.

Fesselmeyer et al(2013) estimate and decompose the changes in the white-black house value gap from 1997 to 2005 using quantile regression. They find that the racial gap in 1997 and 2005 is mostly explained by differences in housing characteristics of white- and black-owned houses.

There are various reasons for these diverse results on the relationship between the house prices and hedonic characteristics. The most obvious cause is that each result is specific to its market of study. Another reason for the difference in the house hedonic price estimates is that housing characteristics is valued differently at different points of conditional distribution of house prices, which is referred to quantile effects in this paper. Zietz, et al. (2008) using a spatial quantile regression, find that same housing attributes are valued quite differently across the conditional price distribution.

This study uses a quantile regression and real trading data of houses from the District court auctions of Seoul during January 2006 to December 2012 to examine how implicit prices of housing attributes vary across the quantiles of house prices. To the best of our knowledge, our paper is the first of its kind to use the quantile regression technique, based on housing auction data in Seoul, to investigate the implicit prices of housing characteristics in different quantiles of house prices across the threedifferent regions in Seoul. Seoul, for many reasons, presents an interesting case. First, it is a very densely populated territory, with the majority of its citizens residing in apartment houses instead of stand-alone residential buildings or houses. Frequent auction transactions of residential properties within even one single apartment complex (typically with 10–20 blocks of buildings) over time provide researchers with adequate observations (from a sample of similar location-specific characteristics) to employ the quantile regression technique to identify how differently housing prices respond to a change in one unit of housing characteristic at different quantiles of housing prices, without the need to account for spatial autocorrelation.

3. Model Specification

For the purpose of this study, the hedonic pricing model of residential real estate takes the following forms:

$$P_i = f(H_i, N_i, \alpha, \beta) \quad (2)$$

where, P_i is the house sales price of property i; H_i is a vector of physical housing attributes associated with an apartment; N_i is a vector of neighborhood, environment, locational variables; and αand β are the estimated parameters associated with the exogenous variables.

A variety of econometric issues arises from estimating hedonic models, including the model specification, function form, the problems associated with heteroscedasticity and spatial correlations. Ideally, model specification and function form should be determined by a theoretical framework. Unfortunately, there is little theoretical guidance regarding model specification and restrictions imposed on function form, with the exception of the guidance in respect of the expected signs of certain coefficients associated with the variables. On the one hand, model specification is largely determined by data availability and a priori beliefs about the type of location and structural amenities that are relevant to each household. On the other hand, the choice of functional form is largely evaluated by empirical evidence. A typical approach is to compare the goodness of fit, Akaike information criterion (AIC) or Bayesian information criterion (BIC) from alternative functional forms and then pick up the best-fitting model.

In the ordinary least square (OLS) estimation, one of the classical assumptions is that the endogenous and residual variables are homoscedastic. However, heteroscedasticity is often found to exist in cross-sectional or panel data due to the properties of the data. For example, larger or older houses tend to have a larger error term than those of smaller or relatively houses. To test for the assumption of homoscedasticity, White's (1980) test can be performed, which involves an auxiliary regression of the squared residuals on the original regressors and their squares to test for the null hypothesis of no heteroscedasticity against heteroscedasticity of some unknown general form. The test statistic is computed by an auxiliary regression, where the squared residuals are regressed on all possible (non-redundant) cross-products of the regressors.

Following Koenker and Hallock's (2001) methodology, an alternative methodology is the use of a quantile regression which generalizes the concept of an unconditional quantile to a quantile that is conditioned on one or more covariates. The quantile can be defined through a simple alternative expedient as an optimization problem. For example, the sample mean could be defined as the solution to the problem of minimizing a sum of square residuals and the median could be defined as the solution to the problem of minimizing a sum of absolute residuals. The symmetry of the piecewise linear absolute value function implies that the minimization of the sum of absolute residuals must equate with the number of positive and negative residuals. Hence, it ensures that there are the same numbers of positive and negative observations above and below the median. As the symmetry of the absolute value yields the median, minimizing a sum of asymmetrically weighted absolute residuals (i.e. simply giving differing weights to positive and negative residuals) would yield the quantiles. Solving equation (3),

$$\min_{\xi \epsilon R} \sum \rho_\tau(y_i - \xi) \quad (3)$$

where, the function $\rho_\tau(\cdot)$ is the tilted absolute value function that yields the sample quantile as its solution. Least squares regression offers a model for how to define conditional quantiles in an analogous fashion. If there is a random sample {y_1, y_2, …,y_n}, we can solve it

$$\min_{\mu \epsilon R} \sum_{i=1}^{n} (y_i - \mu)^2 \quad (4)$$

Then the sample mean and an estimate of the unconditional population mean, EY, can be obtained. If we replace the scalar $\mu$by a parametric function $\mu(x, \beta)$and solve

$$\min_{\beta \epsilon R_\rho} \sum_{i=1}^{n} (y_i - \mu(x_i, \beta))^2 \quad (5)$$

We can then obtain an estimate of the conditional expectation function E(Y|x).

For quantile regression, we can simply go further to obtain an estimate of the conditional median function by replacing the scalar ξ in equation (3) by the parametric function $\xi(x_i, \beta)$ and setting τ to1/2. To obtain estimates of the other conditional quantile functions, we can replace the absolute values by $\rho_\tau(\cdot)$ and solve

$$\min_{\beta \epsilon R_\rho} \sum \rho_\tau(y_i - \xi(x_i, \beta)) \quad (6)$$

When $\xi(x_i, \beta)$ is formulated as a linear function of parameters, the resulting minimisation problem can then be solved very efficiently by linear programming methods.

The standard errors and confidence limits for the coefficient estimates can be obtained with asymptotic and bootstrapping methods. Both methods provide robust results (Koenker and Hallock, 2001), with the bootstrap method considered more practical (Hao and Naiman, 2007).

4. Data Sources

For the purpose of this study, we choose the three counties of Kangnam, Songpa and Nowon in Seoul because apartment houses in each county have a relatively homogeneous design and standardized system of heating, and management, and composed of similar hedonic characteristics. It is a standard mass housing estate located in the Seoul with a high trading volume at all times. Since the current study casts a focus on only the three counties' apartment house complex, the accessibility characteristics (such as accessibility to metro transport, amenities and schools, etc.) and the external environment are more or less identical for all dwelling units of the complex.

Data of the three counties of Kangnam, Songpa and Nowon in Seoul on house prices, physical and location- specific characteristics are generated from the auction results in Seoul District Court during January 2006 through December 2012. Seoul, the capital city of Korea, is divided into two areas – Kangnam(the southern part of the river) and Kangbuk(its northern part) -by the Han river running from east to west through the middle of the city. Although in the same metropolitan city(Seoul), Kangbuk is the older part showing a moderate changing behavior of house price while Kangnam area is relatively a brand new region consisting of 11districts characterized by its well living conditions such as decent housing interior, amenities and favorable educational circumstances, in particular, thus rendering itself the most expensive housing area in Korea. Counties of Kangnam and Songpa are located in Kangnam area (the southern part of Seoul), while Nowon county belongs to Kangbuk area (the northern part). (See Fig 1).

(Fig. 1) Map of Seoul

The Han River is the dark meandering stripe through the middle of the map

The market information about the house prices and trading volumes were not available until 2006 since the publication of trading information and official register records on prices and volumes of houses sold have a short history which began just in 2006.The auction market of real estate functions to clearly reveal all the market information, and, thus, leads the housing markets to the efficiency. Lots of studies on the auction markets of houses focus on the auction price determinations. Mayer (1994,1998), and Allen and Swisher (2000) found out empirically that the auction prices of houses tend to be discounted, compared to their normal market prices, while Lust (1996), Quan (2002), and Qu and Liu (2012) showed the premium value of auction prices to the their market prices. Meanwhile, Frino, Peat and Wright (2011) indicated that there are no significant statistical difference between determinations of auction prices and market prices of houses.

The house prices of the three counties of Kangnam, Songpa and Nowon in Seoul will be compared with each other to examine whether or there exist the different quantile effects of the common hedonic characteristics on the house prices between the three regions in Seoul. The house's hedonic characteristics such as scenic view, accessibility to metro transport station, floors are investigated by handmade worksusing the geographical functions of Google and Daum portals. Kangnam and Songpa counties in Seoul is well known to have high-priced houses, while the housing prices in Nowon county are generally thought to be low, compared to the other two counties.

Table 1 shows the descriptive statistics of the house prices, total floors, age, size, etc.. in the three counties of Seoul. The average house price in Kangnam county is 0.89 billion Korean won, while the highest price was 4.9 billion won. The average age of houses in Kangnam was 14.1 years old, and its size was 111.5m^{2}on average. Total floor was 15 levels, and the living floor was 7thlevel at average. The house prices and size in Sonpa were very lower than these prices and sizes in the Kangnam, although the other characteristics of Sonpa were similar to the Kangnam region. The average house price in Sonpa was 0.68 billion Korean won, and its highest price was 3.35 billion won. The average age of houses in Sonpa was 15. 1 years old, and its size was 105m^2, which was smaller than the average size of houses in Kangnam.

Meanwhile, the house prices and size in Nowon were very lower than these prices and sizes in the Kangnam and Songpa, although the other characteristics of Nowon were similar to the Kangnam and Songpa region. The average house price in Nowon was 0.25 billion Korean won, and its highest price was 0.83 billion won. The average age of houses in Nowon was 14. 7 years old, and its size was 71m^2, which was smaller than the average size of houses in Kangnam and Songpa.

Table 1-1. Descriptive statistics of Kangnam

	Price (thousand)	AGE	SIZE(m^2)	Total FL	Living FL
Mean	897,250	14.147	111.521	14.722	7.679
Median	764,050	11	101.345	13	6
Maximum	4,911,300	38	270.250	69	54
Minimum	44,150	1	9.650	3	1

S.D.	556,198	9.930	47.056	10.361	7.078
Skewness	1.774	0.519	0.637	2.624	2.533
Kurtosis	8.324	1.839	3.096	11.181	12.709
Observation	1,110	1,110	1,110	1,110	1,110
Watson(U2)	4.367	6.744	2.239	11.409	6.857
	<0.001	<0.001	<0.001	<0.001	<0.001

Table 1-2. Descriptive statistics of Songpa

	Price (thousand)	AGE	SIZE(m^2)	Total FL	Living FL
Mean	679,344	15.100	105.902	15.920	8.350
Median	573,199	14	85.000	15	7
Maximum	3,355,500	35	253.590	46	46
Minimum	78,100	1	26.650	3	1
S.D.	386,074	8.810	40.620	8.215	6.614
Skewness	2.115	0.188	0.847	1.512	1.493
Kurtosis	11.770	1.826	3.495	5.687	6.184
Observation	943	943	943	943	943
Watson(U2)	3.661	2.451	4.081	5.832	3.441
	<0.001	<0.001	<0.001	<0.001	<0.001

Table 1-3. Descriptive statistics of Nowon

	Price (thousand)	AGE	SIZE(m^2)	Total FL	Living FL
Mean	252,249	14.766	71.215	15.132	7.370
Median	225,045	15	61.780	15	7
Maximum	830,000	31	194.690	28	27
Minimum	7,570	0	9.120	3	1
S.D.	136,462	6.230	26.685	3.863	4.937
Skewness	1.032	−0.148	0.718	0.268	0.644
Kurtosis	4.016	2.135	3.172	5.400	2.906
Observation	1,406	1,406	1,406	1,406	1,406
Watson(U2)	3.076	1.223	5.185	29.744	3.046
	<0.001	<0.001	<0.001	<0.001	<0.001

Table 1-4. Descriptive statistics of total samples

	Price (thousand)	AGE	SIZE(m^2)	Total FL	Living FL
Mean	575,667	14.658	93.606	15.215	7.736
Median	445,232	14	84.850	15	6
Maximum	911,300	38	270.250	69	54
Minimum	7,570	0	9.120	3	1

S.D.	475,435	8.287	42.391	7.687	6.168
Skewness	2.143	0.295	0.990	2.547	1.898
Kurtosis	10.612	2.084	3.928	13.671	9.920
Observation	3,459	3,459	3,459	3,459	3,459
Watson(U2)	19.187	5.120	11.627	36.515	11.090
	<0.001	<0.001	<0.001	<0.001	<0.001

Equation (7) indicates the hedonic pricing model. House prices, P; represent the log value of the inflation adjusted auction price (including other charges) of a house, in Korean Won. SIZE represents the total gross floor area of a house, which is measured in square meter. AGE represents the building age of a housein years, which can be measured by the difference between the date of issue of the occupation permit and the date of auction transaction. TFL represents the floor level of a house in a residential building block. LFL represents the living floor level of a house. Apartment size, age, floor level and living floor level are included as quadratic effects for the hedonic price equation to test the non-linear effect on prices. (See Table 1 for descriptive statistics.) SOUTH represents the direction a property is facing and equals 1 if a property is facing south, 0 otherwise. METRO represents the distance from a property to the nearest subway station and equals 1 if one can walk to the nearest subway station in 10 minutes, 0 otherwise. SCHOOL represents the distance from a property to the nearest high school and equals 1 if one can walk to the nearest high school in 10 minutes, 0 otherwise. View represents a property is facing a river or a mountain and equals 1 if a property is facing a river or a mountain, 0 otherwise.

$$\mathrm{P} = \beta_0 + \beta_1 AGE + \beta_2 AGE^2 + \beta_3 SIZE + \beta_4 SIZE^2 + \beta_5 TFL + \beta_6 LFL + \beta_7 SOUTH + \beta_8 METRO + \beta_9 SCHOOL + \beta_{10} VIEW + \varepsilon \quad (7)$$

5. Empirical Results

Most analysis using the hedonic pricingmodel has employed conventional least squares regressionmethods. However, it has been recognized that the resulting estimates of various effects on the conditional mean of real estate prices are not necessarily indicative of the size and nature of these effects on the lower tail of the price distribution. A more complete picture of covariate effects can be provided by estimating a family of conditional quantile functions. At any chosen quantile, one can ask how different are the corresponding real estate prices, given a specification of the other conditioning variables. Table 2 and 3 present a summary of the empirical results obtained by the traditional hedonic pricing model using OLS method and the quantile regression. The estimated coefficient estimates for the linear regression and the 5th, 10th, 25th, 50th, 75th, 90th and 95th quantile regression coefficient estimates for house prices (along with their t-statistics), goodness of fitness measures and diagnostic statistics are shown. To correct for the observed heteroscedasticity and correlations among observations in cross-sectional data, this study employs HAC covariance to estimate the implicit prices of the housing attributes in the OLS specification. Most variables are statistically significant at conventional levels and have the expected signs.

The apartment house AGE and SIZE enter the model as quadratic effects because their impacts might be non-linear patterns on house prices. According to the linea rregression model using total samples of all three counties, while AGE tends to decrease prices up to 8.7 years and, thereafter, increase prices beyond 8.7 years in total sample. SIZE tends to increase real estate prices up to the size of 134.5 square meter, and, then, turns to decrease prices beyond that size in total samples. Homebuyers generally do not favor properties that have a building or obstructive view; most prefer properties with a river view or a mountain view. Empirical results demonstrate that homebuyers ofhigher-priced properties are more concerned about the type of view their properties have and they are not willing to opt for properties with a building or obstructive view unless a bigger discount is offered to them than to the homebuyers of lower-priced properties. This phenomenon is represented by bigger and positive estimated coefficients of these two variables at higher quantiles than those of their mean values and the lower quantiles.

Table 2. OLS regression coefficient estimates(dependent variable: P)

	Kangnam-gu		Songpa-gu		Nowon-gu		Total sample	
	coefficient	t- value	coefficient	t- value	coefficient	t- value	coefficient	t- value
Constant	17.763*	(160.65)	18.042*	(161.84)	16.948*	(167.33)	17.483*	(235.04)
AGE	0.0309*	(5.7222)	-0.025*	(-4.605)	0.0084	(1.4543)	-0.0209*	(-4.98)
AGE^2	-0.0003*	(-2.212)	0.0013*	(7.6334)	0.00002	(0.114)	0.0012*	(9.3833)
SIZE	0.0205*	(14.121)	0.0125*	(8.9327)	0.0357*	(25.232)	0.0269*	(30.501)
$SIZE^2$	-0.00004*	(-7.969)	-0.00002*	(-3.529)	-0.0001*	(-14.25)	-0.0001*	(-17.20)
TFL	0.2242*	(9.889)	0.3179*	(10.911)	0.1045*	(3.8673)	0.1533*	(8.0549)
LTL	0.0248*	(2.0086)	0.0507*	(3.7393)	0.0342*	(3.983)	0.0474*	(5.898)
SOUTH	0.0463*	(1.9827)	0.0305	(1.3691)	-0.0029	(-1.834)	-0.0234*	(-13.988)
Impact**	4.74%		3.10%		-0.29%		-2.31%	
METRO	-0.0688*	(-3.243)	0.0724*	(3.6892)	-0.0029*	(-3.482)	-0.0038*	(-3.608)
Impact**	-6.65%		7.51%		-0.29%		-0.38%	
SCHOOL	0.0462*	(2.4833)	0.2836*	(5.2279)	0.1248*	(4.4774)	0.2698*	(15.848)
Impact**	4.73%		32.79%		13.29%		30.97%	
VIEW	0.1692*	(4.9469)	-0.0029	(-0.077)	0.0071	(0.3325)	0.0845*	(3.3019)
Impact**	18.44%		-0.29%		0.71%		8.82%	
Adjusted R^2	0.7559		0.6930		0.7999		0.7760	
Durbin-Watson	1.8344		1.8306		1.8105		1.8474	
AIC	0.4813		0.3675		-0.1612		0.7414	
HQC	0.5000		0.3890		-0.1458		0.7565	

*****indicates statistically significant at the 5 percent confident level.

**for dummy variables, the impacts based on 0 and 1($e^{coefficient} - 1$).

Table 3.Quantile regression coefficient estimates of total sample(dependent variable: P)

	OLS	5%	10%	25%	50%	75%	90%	95%
Constant	17.4832*	16.5935*	16.6631*	16.8958*	17.1809*	17.6848*	18.7313*	19.0425*
	(235.0415)	(143.4175)	(214.9116)	(248.6228)	(227.3295)	(191.3203)	(158.3502)	(179.6961)
AGE	-0.0209*	-0.0214*	-0.0203*	-0.0172*	-0.0167*	-0.0175*	-0.034*	-0.0366*
	(-4.98)	(-3.5277)	(-3.786)	(-4.7437)	(-3.7643)	(-3.0378)	(-5.3916)	(-5.581)
AGE^2	0.0012*	0.0011*	0.0011*	0.0011*	0.0011*	0.0011*	0.0015*	0.0016*

	(9.3833)	(7.0962)	(6.9368)	(9.9738)	(7.9499)		(6.0462)	(7.6445)	(7.3211)
SIZE	0.0269*	0.0316*	0.0314*	0.0309*	0.0294*		0.0262*	0.0196*	0.0182*
	(30.5011)	(17.615)	(29.5884)	(33.0998)	(26.7477)		(21.142)	(18.0747)	(14.7318)
$SIZE^2$	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.0001*		−0.0001*	−0.00003*	−0.00003*
	(−17.2013)	(−8.8781)	(−16.2302)	(−18.4762)	(−14.4305)		(−12.1)	(−8.7904)	(−7.6004)
TFL	0.1533*	0.2361*	0.238*	0.2096*	0.202*		0.1775*	0.0621	0.0455
	(8.0549)	(6.4481)	(9.869)	(9.7243)	(9.5292)		(8.5296)	(1.9197)	(1.3899)
LFL	0.0474*	0.0421*	0.0414*	0.0385*	0.0408*		0.0522*	0.0407*	0.0245*
	(5.898)	(3.6631)	(4.7012)	(4.5186)	(4.6126)		(4.7359)	(3.0565)	(2.2095)
SOUTH	−0.0234*	−0.0267*	−0.0232*	−0.0223*	−0.0227*		−0.0277*	−0.029*	−0.0321*
	(−13.9884)	(−5.6599)	(−6.9109)	(−10.4204)	(−10.991)		(−12.4819)	(−10.5684)	(−11.2031)
Impact**	−2.31%	−2.63%	−2.29%	−2.21%	−2.25%		−2.73%	−2.85%	−3.16%
METRO	−0.0038*	0.0044*	0.0002	−0.0025*	−0.0037*		−0.0036*	−0.0062*	−0.0047*
	(−3.6085)	(2.0871)	(0.0988)	(−1.9951)	(−3.0967)		(−2.5479)	(−3.3536)	(−2.4507)
Impact**	−0.37%	0.44%	0.02%	−0.25%	−0.37%		−0.36%	−0.61%	−0.47%
SCHOOL	0.2698*	0.2788*	0.2991*	0.3166*	0.2739*		0.2275*	0.217*	0.1807*
	(15.8485)	(7.2858)	(9.9495)	(16.6074)	(14.4231)		(12.1412)	(11.0225)	(9.9651)
Impact**	30.97%	32.15%	34.87%	37.24%	31.51%		25.55%	24.23%	19.81%
VIEW	0.0845*	0.0397	0.0372	0.04	0.0517		0.105*	0.1206*	0.098*
	(3.3019)	(1.3793)	(1.4379)	(1.5311)	(1.79)		(2.5512)	(4.0369)	(3.8773)
Impact**	8.82%	4.05%	3.79%	4.08%	5.31%		11.08%	12.82%	10.30%
Quantile Slope Equality test			726.95			<0.0001			
Symmetric Quantiles test			183.01			<0.0001			

*indicates statistically significant at the 5 percent confident level.

**for dummy variables, the impacts based on 0 and 1($e^{coefficient}$ – 1).

Table 4.Optimum estimates

	OLS	5%	10%	25%	50%	75%	90%	95%
AGE	8.71	9.73	9.23	7.82	7.59	7.95	11.33	11.44
SIZE	134.50	158.00	157.00	154.50	147.00	131.00	295.18	311.64

In the estimation of the quantile regression, the age of the apartments statistically significant on the house prices at the traditional level, and its optimal age tend to be shortened for the middle priced houses than in the case of the low-priced or high-priced houses. The price of the middle priced house converts to increasing after falling in 7-8 years. The size of apartment is statistically significant at a 5% significance level and positive, while its square size is negative in sign. This implies that the apartment house prices increases as its size gets larger at the first stage, and then, fall after 134.5 m2in the optimal size of house.

Accessibility to the metro transportation is not statistically significant at the conventional level, contrast to the expected result in theory. It is because all the three regions in Seoul are generally located in the well netted metro transport stations. The existence of good high schools nearby is significant on the house prices in all the three regions in Seoul, and its impact on the house prices in Kangnam and Songpa counties is similar in magnitude to that impact in Nowon area, which lower income residents do live. The most important difference of the effects of hedonic characteristics on the housie prices between Kangnam, Songpa and Nowon counties is "view" variable. The scenic view is statistically significant in determining the house prices in Kangnam county only, while it is not the case in Nowon area. The house prices in Kangnam tend to increase as the houses have a better view.

In sum, determinants of house price in the three regions prove to be similar except environmental factors such as view. The quantile analysis of these three regions combined shows each quantile has different effects of hedonic attributes. The size affects the house prices in all three regions and the degree of the effect seems to be greater for the higher price quantile. Proximity to the subway seems to show a positive coefficient at the lower 5% price quantile, which implies that public transportation has the importance in determining the hedonic characteristics of the low priced houses. In contrast, though, it has a negative effect on these characteristics of the high priced houses. Good view has quite significant impact on the prices of houses with medium and high price ranges.

6. Conclusion

This paper purposes to estimate empirically how specific quantiles of housing prices in Seoul respond differently to a one-unit change in the house's hedonic characteristics. The housing prices of the three counties of Kangnam, Songpa and Nowon in Seoul is compared with each other to examine whether or there exist the different quantile effects of the common characteristics of house on the housing prices between the three regions in Seoul during January 2006 through December 2012. Kangnam and Songpa counties in Seoul is well known to have high-priced houses, while the housing prices in Nowon county are generally thought to be low, compared to these housing prices in the other counties. The housing dataset are obtained from the auction results in Seoul District Court. The comparison between the quantile effects of different characteristics on the housing prices will provide a meaningful implication for housing development markets and real estate taxation. As an alternative to OLS regression, this study adopts the quantile regression to identify the implicit prices of housing characteristics for the different percentiles of the distribution of housing prices. This explicitly allows the higher-priced apartments to have different implicit prices for a house's characteristic than the lower-priced apartments.

In the estimation of the quantile regression for the relationship between housing prices and its hedonic characteristics, the apartment AGE and SIZE enter the model as quadratic effects. According to the linear regression model, while AGE tends to decrease prices up to 8.7 years and increase prices beyond 8.7 years in total sample. SIZE tends to increase real estate prices up to the size of 134.5 square meter, it tends to decrease prices beyond 134.5 square meter in total sample.

In the estimation of the quantile regression, the ages of the apartment house built is statistically significant on the house prices at the traditional level, and its optimal ages are shortened for the middle priced housing. The price of the middle priced house reverts to increase after a fall in their price in 8-9 years. The size of apartment also is statistically significant and positive, while its square of size is negative in sign. This implies that the apartment prices increases as its size gets larger at the first stage, and then, fall after 134.5suare meter in size of house.

Accessibility to the metro transportation is statistically significant and positive in sign only for the lower price quantile, while its impact is negative for the higher price quantile. The existence of good high school is significant on the housing prices in all the three regions in Seoul, and its impact on the housing prices in Kangnam and Songpa counties is similar to that impact in Nowon area. The most important difference of hedonic characteristics between Kangnam, Songpa and Nowon counties is "view" variable to the determination of the housing price. The view is statistically significant in the housing prices in Kangnam county, while it is not the case in Nowon area.

This paper is very meaningful in the implications in that it can provide an exact guide for determining the housing prices with the given data. These results can provide a more precise price valuation tools for property taxation and for developers targeting different submarkets and customers. However, this paper still has its limit to the research scope where the uncertain variables in determining the housing prices are not considered significantly. The uncertainty may be so important for determination of the auction and housing markets that the estimation model needs to involve these uncertain explanatory variables on the distribution of the housing prices.

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Appendix table 1-1. Quantile regression coefficient estimates of Kangnam(dependent variable: P)

	OLS	5%	10%	25%	50%	75%	90%	95%
Constant	17.7625*	16.6417*	17.0643*	17.42*	17.5086*	18.1024*	18.905*	19.1098*
	(160.6544)	(68.4685)	(100.3934)	(187.7351)	(168.5173)	(90.8465)	(117.3959)	(123.3929)
AGE	0.0309*	0.0159	0.0277*	0.036*	0.0397*	0.0262*	0.0175*	0.0079
	(5.7222)	(1.2213)	(2.5642)	(6.1364)	(6.5809)	(3.1191)	(2.2463)	(0.7817)
AGE^2	−0.0003*	0.0001	−0.0003	−0.0005*	−0.0006*	−0.0002	−0.0000479	0.0002
	(−2.2124)	(0.1349)	(−0.9525)	(−2.8123)	(−3.3339)	(−0.8861)	(−0.2072)	(0.5941)
SIZE	0.0205*	0.0336*	0.0288*	0.0238*	0.0225*	0.0156*	0.0086*	0.0095*
	(14.1211)	(9.6737)	(10.6788)	(18.1378)	(16.6443)	(5.9413)	(4.1425)	(4.4081)
$SIZE^2$	−0.0004*	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.000023*	0.0000	0.0000
	(−7.9689)	(−6.662)	(−7.5597)	(−10.5088)	(−9.8509)	(−2.224)	(−0.0787)	(−0.5334)
TFL	0.2242*	0.2296*	0.2085*	0.2251*	0.269*	0.2624*	0.213*	0.1702*
	(9.8886)	(4.0245)	(5.1892)	(7.2309)	(9.5718)	(7.0253)	(5.1337)	(3.465)
LFL	0.0248*	0.0468*	0.0452*	0.0322*	0.0302*	0.0203	0.0277	0.0448
	(2.0086)	(2.0744)	(2.2544)	(2.1574)	(2.3936)	(1.1292)	(1.4643)	(1.8144)
SOUTH	0.0463*	0.0116	0.0254	0.0214	0.0315	0.0685*	0.0945*	0.0424
	(1.9827)	(0.2635)	(0.7294)	(0.8378)	(1.5696)	(2.0757)	(2.3981)	(0.868)
Impact**	4.74%	1.17%	2.57%	2.17%	3.20%	7.09%	9.92%	4.33%
METRO	−0.0688*	0.0045	−0.0392	−0.057*	−0.0852*	−0.0527*	−0.0306	0.0189
	(−3.2436)	(0.0952)	(−1.2328)	(−2.1964)	(−4.3683)	(−2.016)	(−0.9573)	(0.549)
Impact**	−6.65%	0.45%	−3.85%	−5.54%	−8.16%	−5.14%	−3.01%	1.91%
SCHOOL	0.0462*	0.0461	0.048	0.0217	0.0419*	0.067*	0.063*	0.0902*
	(2.4833)	(1.1782)	(1.3731)	(1.1048)	(2.0733)	(2.3995)	(2.0583)	(2.4327)
Impact**	4.73%	4.72%	4.92%	2.19%	4.27%	6.93%	6.50%	9.44%
VIEW	0.1692*	0.2031*	0.1808*	0.121*	0.0819*	0.1023*	0.1175	0.1219
	(4.9469)	(3.5699)	(3.7031)	(3.3285)	(2.3943)	(2.1335)	(1.7485)	(1.4477)
Impact**	18.44%	22.52%	19.82%	12.86%	8.54%	10.77%	12.46%	12.97%
Quantile Slope Equality Test			415.18		<0.0001			
Symmetric Quantiles Test			100.09		<0.0001			

*indicates statistically significant at the 5 percent confident level.

**for dummy variables, the impacts based on 0 and 1($e^{coefficient} - 1$).

Table 1-1.Optimum estimates

	OLS	5%	10%	25%	50%	75%	90%	95%
AGE	51.50	−79.50	46.17	36.00	33.08	65.50	182.67	−19.75
SIZE	25.63	168.00	144.00	119.00	112.50	342.11	7557.12	1181.59

Appendix table 2-1. Quantile regression coefficient estimates of Songpa(dependent variable: P)

	OLS	5%	10%	25%	50%	75%	90%	95%
Constant	18.0417*	17.2164*	17.1528*	17.4004*	17.7815*	18.5315*	19.0305*	19.281*
	(161.8482)	(88.1011)	(139.6595)	(149.8255)	(114.1071)	(125.4128)	(77.9367)	(97.0071)
AGE	−0.0255*	−0.0243*	−0.0161*	−0.0181*	−0.0217*	−0.0437*	−0.0387*	−0.0275*
	(−4.6056)	(−3.2384)	(−2.6822)	(−3.4847)	(−3.9036)	(−5.5946)	(−3.311)	(−2.0769)
AGE^2	0.0013*	0.0012*	0.0009*	0.001*	0.0012*	0.0019*	0.0017*	0.0012*
	(7.6334)	(5.5928)	(5.2042)	(6.7859)	(6.7333)	(7.753)	(4.0912)	(2.5461)
SIZE	0.0125*	0.0183*	0.0192*	0.0178*	0.0155*	0.0107*	0.009*	0.0089*
	(8.9327)	(7.607)	(12.6566)	(10.8463)	(6.0973)	(4.298)	(4.4186)	(3.9391)
$SIZE^2$	−0.00002*	−0.00005*	−0.00005*	−0.00004*	−0.00003*	−8.9E−06	−1.4E−06	−2E−06
	(−3.5291)	(−4.466)	(−7.4299)	(−6.768)	(−2.8284)	(−0.875)	(−0.1863)	(−0.2645)
TFL	0.3179*	0.4064*	0.4117*	0.4043*	0.3531*	0.2671*	0.1866*	0.1085*
	(10.9114)	(8.1757)	(13.3587)	(12.1876)	(13.301)	(5.4472)	(3.1652)	(2.3005)
LFL	0.0507*	0.042	0.0554*	0.0361*	0.0425*	0.0347	0.0251	0.0285
	(3.7393)	(1.6212)	(3.5839)	(2.7858)	(3.5277)	(1.7579)	(1.0969)	(1.1955)
SOUTH	0.0305	0.021	0.0234	0.0193	0.0097	0.0271	−0.0039	0.0842
	(1.3691)	(0.4555)	(0.8244)	(0.7902)	(0.3994)	(0.754)	(−0.1076)	(1.8927)
Impact**	3.09%	2.12%	2.37%	1.95%	0.98%	2.75%	−0.38%	8.78%
METRO	0.0724*	0.0168	0.0365	0.0491	0.0605*	0.0825*	0.1017*	0.115*
	(3.6892)	(0.4416)	(1.4376)	(1.937)	(2.8976)	(3.6313)	(2.86)	(2.8193)
Impact**	7.51%	1.70%	3.72%	5.03%	6.24%	8.60%	10.70%	12.19%
SCHOOL	0.2836*	0.2511	0.3648*	0.3398*	0.2669*	0.2245*	0.0454	0.0162
	(5.2279)	(1.8659)	(2.7119)	(4.1473)	(4.1887)	(3.2516)	(0.6372)	(0.3101)
Impact**	32.79%	28.54%	44.03%	40.46%	30.59%	25.17%	4.64%	1.64%
VIEW	−0.0029	0.1398*	0.0941	0.0152	−0.0226	−0.043	−0.0863	−0.0788
	(−0.077)	(2.071)	(1.7223)	(0.4531)	(−0.4642)	(−0.6956)	(−1.0604)	(−0.6021)
Impact**	−0.29%	15.00%	9.86%	1.53%	−2.24%	−4.21%	−8.27%	−7.58%
Quantile Slope Equality Test			439.84		<0.0001			
Symmetric Quantiles Test			103.87		<0.0001			

*indicates statistically significant at the 5 percent confident level.

**for dummy variables, the impacts based on 0 and 1($e^{coefficient} - 1$).

Table 2-2.Optimum estimates

	OLS	5%	10%	25%	50%	75%	90%	95%
AGE	9.81	10.13	8.94	9.05	9.04	11.50	11.38	11.46
SIZE	312.50	197.62	194.33	203.66	243.71	600.45	3284.67	2247.47

Appendix table 3-1. Quantile regression coefficient estimates of Nowon(dependent variable: P)

	OLS	5%	10%	25%	50%	75%	90%	95%
Constant	16.9481*	16.2646*	16.3528*	16.538*	16.7996*	17.4232*	17.7957*	18.1788*
	(167.3341)	(88.2572)	(132.8255)	(176.6291)	(166.4617)	(122.0648)	(96.0624)	(71.2116)
AGE	0.0084	−0.0181	−0.0221*	−0.0115	0.0095	0.0119	0.0098	0.0064
	(1.4543)	(−1.4292)	(−2.3214)	(−1.9084)	(1.4908)	(1.55)	(1.7849)	(0.7341)
AGE^2	0.00002	0.0007	0.001*	0.0007*	−6.8E−06	−0.0002	−0.0002	−0.0001
	(0.114)	(1.6951)	(2.7623)	(3.4155)	(−0.0307)	(−0.91)	(−1.2881)	(−0.3825)
SIZE	0.0357*	0.0382*	0.037*	0.0365*	0.0353*	0.0358*	0.0347*	0.0325*
	(25.2321)	(11.11)	(18.9682)	(24.4964)	(22.1731)	(22.5134)	(15.5747)	(13.4586)
$SIZE^2$	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.0001*	−0.0001*
	(−14.2565)	(−6.6782)	(−11.2849)	(−13.2549)	(−13.0905)	(−12.1889)	(−7.7049)	(−6.01)
TFL	0.1045*	0.2904*	0.309*	0.2415*	0.1704*	−0.0208	−0.0782	−0.1623*
	(3.8673)	(4.6261)	(6.7094)	(7.7455)	(5.9608)	(−0.5637)	(−1.5772)	(−2.0606)
LFL	0.0342*	0.0316	0.0329*	0.0338*	0.0317*	0.0349*	0.0219	0.0177
	(3.983)	(1.7919)	(2.7687)	(3.8171)	(4.6129)	(3.4052)	(1.8681)	(1.3081)
SOUTH	−0.0029	0	−0.0015	−0.0037	−0.0011	−0.0019	−0.0035*	−0.0038
	(−1.834)	(0.0051)	(−0.6968)	(−1.1067)	(−0.4643)	(−0.9882)	(−2.2916)	(−1.6)
Impact**	−0.29%	0.00%	−0.15%	−0.37%	−0.11%	−0.19%	−0.35%	−0.38%
METRO	−0.0029*	0.0011	−0.0008	−0.0017	−0.0032*	−0.0036*	−0.0038*	−0.0041*
	(−3.4821)	(0.5096)	(−0.4936)	(−1.4112)	(−3.4411)	(−3.744)	(−3.9601)	(−2.5226)
Impact**	−0.29%	0.11%	−0.08%	−0.17%	−0.32%	−0.36%	−0.38%	−0.41%
SCHOOL	0.1248*	0.05	0.0886*	0.1208*	0.0956*	0.1158*	0.1115*	0.1157*
	(4.4774)	(1.0103)	(2.5803)	(1.9614)	(2.566)	(4.2658)	(5.7575)	(4.2295)
Impact**	13.29%	5.12%	9.27%	12.84%	10.04%	12.27%	11.80%	12.27%
VIEW	0.0071	−0.0512	−0.0157	−0.0084	0.0036	0.0233	0.0334	0.0168
	(0.3325)	(−0.9564)	(−0.4241)	(−0.3011)	(0.1313)	(0.7569)	(1.1695)	(0.3277)
Impact**	0.71%	−4.99%	−1.56%	−0.84%	0.36%	2.36%	3.40%	1.69%
Quantile Slope Equality Test			478.45		<0.0001			
Symmetric Quantiles Test			75.67		<0.0001			

*indicates statistically significant at the 5 percent confident level.

**for dummy variables, the impacts based on 0 and 1($e^{coefficient} - 1$).

Table 3-2.Optimum estimates

	OLS	5%	10%	25%	50%	75%	90%	95%
AGE	−210.00	12.93	11.05	8.21	695.46	29.75	24.50	32.00
SIZE	178.50	191.00	185.00	182.50	176.50	179.00	173.50	162.50