*Pacific Rim Property Research Journal*, 2015
Vol. 21, No. 2, 91–113, http://dx.doi.org/10.1080/14445921.2015.1058031

# Determinants of house prices in Seoul: A quantile regression approach

Heeho Kim[a], Sae Woon Park[b]*, Sunhae Lee[b] and Xingqun Xue[c]

[a]*Kyungpook National University;* [b]*Changwon National University;* [c]*Dalian University of Technology*

This paper estimates house price determinants in the Korean housing market, focusing on Seoul and employing the method of a quantile regression of a hedonic price model. With this quantile regression approach, how implicit prices of housing characteristics vary in each quantile of house prices is investigated. The data sample for this paper comprises court auction data collected from district courts of Seoul between 2006 and 2012. The hedonic variables employed in this research include building age, size, floor height, and floor level, proximity to metro station and high school and scenic view. As dependent variables, house prices in three sub-regions of Seoul are considered. Those prices between before and after the 2008 financial crisis are compared to determine the impact of the crisis. The empirical analysis finds that school proximity has the largest effect on the prices among dummy variables and that the level of the effect is larger in lower quantiles (lower-priced houses). By contrast, scenic view has a larger effect in higher quantiles (higher-priced houses), while its effect is statistically insignificant in lower quantiles. The effects of both school proximity and scenic view are also found to decrease in magnitude after the crisis.

**Keywords:** house price; Korea housing market; hedonic price model; quantile regression

## Introduction

A house can be regarded 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 the house price is defined as a function of a bundle of inherent attributes (e.g. flat size, age, and floor level), neighbourhood characteristics (e.g. scenic view), accessibility (e.g.: to metro station and school) and environmental quality (e.g. fresh air or natural beauty) that yield utility or satisfaction to homebuyers. In particular, a hedonic price model by ordinary least squares (OLS) has been utilized in several studies to model the relationship between a set of housing attributes and price (Can, 1992; Can & Megbolugbe, 1997; Chau & Choy, 2011; Cheshire & Sheppard, 1995; Epple, 1987).

Traditional OLS linear regression is a statistical tool used to estimate the hedonic model in which the hedonic characteristics of a house constantly influence house prices. It estimates the mean value of house prices for given levels of the explanatory

*Corresponding author. Email: assw@changwon.ac.kr

variables. That is, the OLS model estimates how, on average, these housing characteristics affect the price. The "scenic view," for example, compares the effect of having a scenic view on the price with that of not having a scenic view. If a house has a mountain or a river view, it is normally considered to have a higher price than one without any scenic view. While this model can address the question of whether a scenic view matters in the price determination of a house, it cannot answer other important questions, such as, "does the level of the effect of a scenic view differ from quantile to quantile?" and "if so, how much is the difference?." These are among the key matters that the traditional OLS model cannot address.

To address this problem, a quantile regression method is adopted that models the relation between a set of explanatory variables and each quantile of house prices. By estimating the changes in a specific quantile produced by a one-unit change in an explanatory variable, the quantile regression can give a more comprehensive picture of the effect of explanatory variables on house prices and the difference in the level of the effect at the same time. This enables comparison of the level of the effect of the hedonic characteristics on house prices between quantiles or percentiles. This is reflected in the changes in the magnitude of the regression coefficients. Heckman (1979) suggests that the statistical issues associated with truncation could possibly be avoided with quantile regression since it makes use of the entire data sample rather than truncated data with the mean value of the house prices. This will eliminate the biased estimation problem created when the traditional OLS estimation is applied to house price sub-samples (Newsome & Zietz, 1992).

This paper empirically estimates how specific quantiles of house prices in Seoul respond differently to a one-unit change in the hedonic characteristics. This allows for a comparison of how specific quantiles of housing prices may be more affected by certain properties' characteristics than other quantiles. A hedonic house price model is estimated using court auction data and the quantile regression method used to determine whether there are any differences in the hedonic effects between the quantiles of house prices. House prices in three sub-regions of Seoul are considered, namely, Kangnam, Songpa, and Nowon, comparing prices before and after the 2008 financial crisis. The number of housing transactions in Seoul was 64,582 annually for two years from 2006 to 2008, and after the financial crisis, the number decreased to 58,526 on average for four years from 2009 to 2012. It may be noted that the average annual decrease of house prices was 0.3% after the crisis compared to 9.7% average annual increase before the crisis.

Using three steps, the hypothesis that specific quantiles of house prices in Seoul respond differently to a one-unit change in the hedonic characteristics is tested. First, an analysis of the full-period court auction data from the three counties in Seoul is conducted. Second, to check the robustness of the test results on the hedonic effects and the impact of the 2008 financial crisis on house prices at different price levels, the study period is divided into two sub-sample periods: before and after September 2008, being the date of Lehman Brothers' bankruptcy. Last, the sample of court auction data is separated by the three regional counties to determine whether there are any different effects of hedonic attributes between different regions.

Although there have been a number of recent studies of the determination of hedonic house prices, hedonic price models of housing valuation still remain as a popular research tool. Housing market studies of Korean cities have been limited most likely due to the difficulties of data collection; only recently did Korea's house transaction data become available. Houses and other real estate properties in Korea are in general traded through real estate agents who act independently as small businesses, so it is difficult if not impossible to obtain sufficient transaction records for a study of this level.

For this reason, the district court auction data is adopted instead of market transaction data for three counties in Seoul from January 2006 to December 2012. In total, 3459 sample data for housing transactions were obtained from the court in the three counties: 1110 from Kangnam, 943 from Songpa, and 1406 from Nowon. The house prices of the three counties are compared to determine whether the common hedonic characteristics have different effects on house prices in the three regions. Kangnam and Songpa are generally known to have higher-priced houses compared to Nowon.

It was difficult to obtain the data for hedonic characteristics such as scenic view and accessibility to metro stations and schools because those hedonic attributes required identification for each house using the geographical functions of Google and Daum. The sample data use all the hedonic attributes as well as apartment prices, excluding detached houses, nonresidential housing, offices, shops and warehouses. Although apartments seem to have fewer hedonic characteristics than single-family houses, since they have a standardized system of heating, security, maintenance, and management they are the most popular housing type in Korea (Cho, Kim, & Shilling, 2007). Apartments account for 59.0% of all housing stock according to the 2010 Housing Survey by Korea's National Statistical Office. Accordingly, apartments were selected instead of single-family houses for analysis. The homeownership rate of 53.8% in Korea in 2012 is somewhat lower than that of Australia (67.0% in 2011) and United Kingdom (66.7% in 2012) (Korea's National Statistical Office and WIKIPEDIA, http://en.wikipedia.org/ accessed January 17, 2015). The Korean government began building public housing in 1989, which is relatively late in comparison to European countries with the public housing rate being 5% in Korea in 2010 (Jang & Kim, 2013).

## Literature review

The quantile regression model introduced by Koenker and Bassett (1978) is more flexible than OLS. Quantile regression allows examination of more comprehensive pictures of different house price levels. The quantile regression is based on the minimization of weighted absolute deviations for estimating conditional quantile (percentile) functions (Koenker & 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 on the distribution of the dependent variable. For hedonic price functions, quantile regression makes it possible to statistically examine the extent to which housing characteristics are valued differently across the distribution of house prices. Although it may be argued that the same goal can 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 is much higher than that estimated by Gyourko and Linneman (1993) using 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 for Changsha, an emerging Chinese city. 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 and a number of rooms tend to increase house prices. This suggests that the major factors explaining house prices vary across the regions and cities in a country because of their different properties.

Lee, Chung, and Kim (2005) study the effects of house age on house prices but are constrained by empirical data problems associated with using house price data projected from real estate agents instead of using real-transaction data. Ong, Lusht, and Mak (2005) investigate the effects of market conditions, auction date, number of bidders and building location as determinants of house prices in Singapore using auction data for residential houses from January 1995 to December 2000. Investigating the effects of scenic view on house prices from auction data for 1475 cases in Hong Kong during 2005 to 2006, Jim and Chen (2009) find that an ocean view increased house prices by 2%–3%.

A hedonic model by Lee et al. (2005) differentiated the effects of building age on house prices into two categories: the depreciation effect and the redevelopment effect. The authors found that apartment prices tended to fall because of the age effect until buildings were 15–19 years old and then began to rise because of the expected profits from the redevelopment of the old apartments. Cho (2011) uses a transaction cost approach to analyze the process of the redevelopment of houses, where buyers and sellers compete to obtain interactive strategies using the uncertain probability of redevelopment and its costs. Fesselmeyer, Le, and Seah (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 the differences in the housing characteristics of white- and black-owned houses.

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

Kang and Liu (2014) investigate the impact of the 2008 financial crisis on house prices at different price levels in China and Taiwan. They find that in Taiwan house prices were more affected by the financial crisis when the price of real estate was high, while in China house prices were less affected by the crisis when prices were high.

In this context of the literature, this study uses a quantile regression and auction data from the district court auctions of Seoul for January 2006 to December 2012 to examine how the implicit prices of housing attributes vary across the house price distribution of three counties in Seoul. It is contended that this paper is one of the few to use the quantile regression technique in a Korean housing study based on housing auction data for Seoul.

Seoul presents an interesting case. First, it is a densely populated city, with the majority of its citizens residing in apartment units instead of residential stand-alone houses. The frequent auction transactions of residential properties within even a single apartment complex (typically with 10–20 blocks of apartment buildings) over time provide researchers with sufficient observations (from a sample of similar location-specific characteristics) to employ the quantile regression technique.

**Model specification**

The hedonic pricing model of a house takes the following form:

$$P_i = f(H_i, N_i, \alpha, \beta) \tag{1}$$

where:
$P_i$ is the auction price of house $i$
$H_i$ is a vector of physical housing attributes associated with an apartment
$N_i$ is a vector of neighbourhood and accessibility variables
α and β are the estimated parameters associated with the exogenous variables

In line with Koenker and Hallock's (2001) method, this paper adopts a quantile regression that 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 (2):

$$\min_{\xi \epsilon R} \sum p\tau(y_i - \xi) \tag{2}$$

where the function $p\tau(\cdot)$ 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 $\{y_1, y_2, \ldots, y_n\}$, it may be solved:

$$\min_{\mu \in R} \sum_{i=1}^{n} (y_i - \mu)^2 \tag{3}$$

Then, the sample mean and an estimate of the unconditional population mean, $EY$, can be obtained. If the scalar $\mu$ is replaced with a parametric function $\mu(x, \beta)$ and solved:

$$\min_{\beta \in R_\rho} \sum_{i=1}^{n} (y_i - \mu(x_i, \beta))^2 \tag{4}$$

an estimate of the conditional expectation function $E(Y|x)$ can be obtained.

For quantile regression, an estimate of the conditional median function may be obtained simply by replacing the scalar $\xi$ in Equation (2) with the parametric function $\xi(x_i, \beta)$ and setting $\tau$ to 1/2. To obtain estimates of the other conditional quantile functions, the absolute values with $p\tau(\cdot)$ may be replaced and solved:

$$\min_{\beta \in R_\rho} \sum \rho_t(y_i - \xi(x_i, \beta)) \tag{5}$$

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

In this study, the bootstrap method illustrated in Buchinsky (1995) is used to obtain estimates of the standard errors for the coefficients in a quantile regression. This type of analysis is of particular importance because it is a consistent and robust estimation method, particularly when the error term is heteroscedastic and non-normally distributed. To convey a sense of the relationships among the explanatory variables across the conditional house price distribution, the results for the 5th, 10th, 25th, 50th, 75th, 90th, and 95th quantiles are reported. In addition, the study period is divided into two sub-periods, 2006:1–2008:8 and 2008:9–2012:12, to investigate the effect of the 2008 financial crisis on housing prices. Lehman Brothers' bankruptcy in September 2008 is the demarcation between the pre- and post-financial crisis periods.

Equation (6) 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 meters. AGE represents the age of a house in years, which can be measured by the difference between the date of issue of the occupation permit after construction and the date of the auction transaction. TFL represents the number of total floor levels of the apartment building in which a specific unit exists. That is, if an apartment unit is on the third floor in a 15-story apartment building, its LFL is 3, and its TFL is 15. TFL is included as an explanatory variable because it is regarded as an important factor in price determination in Korea. LFL represents the living floor level of a house.

Apartment age and size are included as quadratic effects in the hedonic price equation to test the non-linear effect on prices. SOUTH represents the direction a property is facing, equalling 1 if a property is facing south and 0 otherwise. The reason why SOUTH is considered as an explanatory variable in this paper is that if a building faces south without being bothered by other buildings blocking the sunlight, it has plentiful sunlight. METRO represents the distance from a property to the nearest metro station, equalling 1 if it is possible to walk to the nearest metro station in 10 minutes and 0 otherwise. SCHOOL represents the distance from a property to the nearest high school, equalling 1 if it is possible to walk to the nearest high school in 10 minutes and 0 otherwise. VIEW represents a scenic view, equalling 1 if a property faces a river or a mountain and 0 otherwise.

$$P = \beta_0 + \beta_1 AGE + \beta_2 AGE^2 + \beta_3 SIZE + \beta_4 SIZE^2 + \beta_5 TFL + \beta_6 LFL + \beta_7 SOUTH + \beta_8 METRO + \beta_9 SCHOOL + \beta_{10} VIEW + \varepsilon \tag{6}$$

## Data

For this study, three counties in Seoul were selected: Kangnam, Songpa, and Nowon. The reason for choosing these counties for this study is that Kangnam is a top premium submarket in Seoul, Songpa is generally considered to be the second, while Nowon is a moderate and relatively cold submarket. Therefore, adopting these three counties as a sample is considered to be adequate and appropriate in representing various aspects of the Seoul housing market. In fact, Seoul, the capital city of Korea, is divided into two areas by the Han River, which runs from east to west through the middle of the city. These two areas include Kangnam (south of the river) and Kangbuk (north of the river). Both are located in the Seoul metropolitan area: Kangnam is a relatively new region consisting of 11 counties characterized by better living conditions including superior housing interiors, amenities, and, in particular, a favorable educational environment, while Kangbuk is older, with moderately changing house price behaviour. The former contains the most expensive housing areas in Korea. Kangnam and Songpa Counties are located in Kangnam area and Nowon is a part of the Kangbuk area. The Han River is the dark meandering line running through the middle of the map (see Figure 1).

By simply compiling data regarding these three counties, sufficient data is obtained for a quantile regression that enables us to analyze the effect of hedonic characteristics on each price level, namely, quantile.

Housing transactions in Korea are normally conducted through real estate agents, who act independently, unlike in other countries. While real estate agents usually work for a company in the United States, Australia and Japan, most Korean real estate agents work independently and are self-employed. Thus, it is extremely difficult to obtain adequately reported trading data from agents in Korea. In 2006, the Korean government implemented a law requiring the reporting of real estate transaction prices and only since then has the data been available to the public. Even so, detailed data for apartment units are not accessible, but for a few pieces of information – such as the name of the complex to which the specific apartment unit belongs, floor level, size, and price – being available.

A typical Korean apartment complex consists of more than 10 building blocks and each building contains, on average, 60 units. Each unit has different hedonic characteristics in terms of size, floor level, direction and scenic view (which may include a mountain, a river, a street, or a building view). In other words, even if they look similar, there are no identical units in terms of scenic view and distance from urban infrastructure (e.g. the nearest high school or metro station). That is, if two units on the same floor level belong to different building blocks, they are not identical in terms of


Figure 1. Map of Seoul.
Source: Korean Government.

scenic view and the distance from the nearest high school or metro station can also differ from unit to unit.

The public data reported by the Korean government only indicate floor level, size, and complex name and are thus insufficient for this kind of hedonic price modelling study. In contrast, however, court auction data are available to the public providing all the necessary information associated with the auction data of houses, although court auctions generally deal with distressed properties.

The real estate auction market clearly reveals all the market information and it thus leads the housing market to efficiency. Many studies on auction markets for houses focus on the auction price determinations. Mayer (1994, 1998) and Allen and Swisher (2000) empirically find that the auction prices of houses tend to be discounted from their normal market prices, while Lusht (1996), Quan (2002) and Qu and Liu (2012) find that auction prices are higher than market prices. Frino, Peat, and Wright (2011) find no significant statistical difference between the auction prices and market prices of houses. Although the literature shows that there can be some difference between auction prices and market prices, auction prices are adopted as only this data source is accessible for the Korean real estate market.

Data were collected manually from private domains as access was not possible to any readily available dataset for the Seoul housing market. Information on individual properties was obtained from the auction results from the Seoul District Court compiled by a private auction information provider (www.goodauction.com) for January 2006 through December 2012. This information provider's website provided essential information on auction price, size, age, floor level, number of total floors and address since January 2006.

For more details regarding the hedonic characteristics of each house, longitude and latitude was identified using maps from Google and Daum. The geographic coordinates allow users to calculate the distance from each property to the nearest metro station and high school. Data was collected on the direction and scenic view of each property with the help of property agents and verified by field work and Google and Daum map analysis. Observations were deleted with missing data for any of the variables. A sample of 3459 housing transactions (1110 apartment units in Kangnam, 943 in Songpa, and 1406 in Nowon) was obtained. The house prices for Kangnam, Songpa, and Nowon in Seoul are compared with each other to determine whether the common hedonic characteristics have different effects on house prices in the three regions with particular attention to higher-priced houses in Kangnam and Songpa versus lower-priced houses in Nowon.

Table 1 shows the descriptive statistics for house price, age, size, the number of total floors and living floor level in the three counties. The average house price in Kangnam County was 0.89 billion Korean won, and the highest price was 4.91 billion won. The average age of houses in the same county was 14.1 years, and the average size was 111.5sqm. The average number of total floors was 15 and the average living floor was the seventh. House prices and sizes in Songpa were lower and smaller than those in Kangnam and the other characteristics of Songpa were similar to those of Kangnam. The average house price in Songpa was 0.68 billion Korean won and its highest price was 3.35 billion won. The average age of houses in Songpa was 15.1 years, and the average size was 105sqmwhich was smaller than the average size of houses in Kangnam.

Meanwhile, the house prices and size in Nowon County were much lower and smaller than those in the Kangnam and Songpa Counties and the other

Table 1. Descriptive statistics.

| | Price (thousand won) | AGE | SIZE($m^2$) | Total FL | Living FL |
|---|---|---|---|---|---|
| **Panel A: Kangnam** | | | | | |
| 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 | 1110 | 1110 | 1110 | 1110 | 1110 |
| Watson's U2 | 4.367 | 6.744 | 2.239 | 11.409 | 6.857 |
| | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| **Panel B: Songpa** | | | | | |
| 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's U2 | 3.661 | 2.451 | 4.081 | 5.832 | 3.441 |
| | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| **Panel C: Nowon** | | | | | |
| 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 | 7570 | 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 | 1406 | 1406 | 1406 | 1406 | 1406 |
| Watson's U2 | 3.076 | 1.223 | 5.185 | 29.744 | 3.046 |
| | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |
| **Panel D: Total Samples** | | | | | |
| Mean | 575,667 | 14.658 | 93.606 | 15.215 | 7.736 |
| Median | 445,232 | 14 | 84.850 | 15 | 6 |
| Maximum | 4,911,300 | 38 | 270.250 | 69 | 54 |
| Minimum | 7570 | 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 | 3459 | 3459 | 3459 | 3459 | 3459 |
| Watson's U2 | 19.187 | 5.120 | 11.627 | 36.515 | 11.090 |
| | <0.001 | <0.001 | <0.001 | <0.001 | <0.001 |

Source: Authors.

characteristics of Nowon were similar to those in Kangnam and Songpa. 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, and the average size was 71sqm which was much smaller than the average size of houses in Kangnam and Songpa.

Table 2. OLS regression coefficient estimates.

| | Kangnam | | Songpa | | Nowon | | Total samples | |
|---|---|---|---|---|---|---|---|---|
| | **Coefficient** | **t-statistics** | **Coefficient** | **t-statistics** | **coefficient** | **t-statistics** | **coefficient** | **t-statistics** |
| **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 statistical significance at the 5-percent confidence level.
**For dummy variables, the impacts are based on ($e^{coefficient}$– 1).
Source: Authors.

## Empirical results

The empirical analysis is conducted by estimating Equation (6) with seven quantiles, the 5th, 10th, 25th, 50th, 75th, 90th, and 95th. This allows examination of the impact of the explanatory variables at different points of the housing price distribution. Table 2 presents the empirical results obtained by the hedonic pricing model using the traditional OLS method. Panel A in Table 3 presents the estimation results of the quantile regressions, goodness of fit measure and their diagnostic statistics. The slope equality test and symmetric quantile test results in Table 3 show that coefficients differ across quantile values and that the conditional quantiles are not identical.

To check the robustness of the estimation results and the impact of the 2008 financial crisis, the study period is divided into two sub-periods, being before and after September 2008 (Lehman Brothers' bankruptcy) as the demarcation between the pre- and post-financial crisis periods. Panel B of Table 3 shows the results for before the crisis, 2006:1–2008:8, and panel C shows the results for after the crisis, 2008:9–2012:12. As can be seen, there is no significant difference between the results for these separate sub-periods and those for the total period (the two sub-periods combined).

Compared to the pre-crisis period, the effect of proximity to school and scenic view declined slightly in magnitude after the crisis. While the effects of proximity to school and scenic view were 42.83% and 10.71%, respectively, before the crisis, they declined to 24.39% and 8.45%, respectively, after the crisis. From these results, it can be inferred that the impact of these variables on prices decreased because of the depressed economic conditions after the crisis.

According to the empirical results using data for the total period (two sub-periods combined) as panel A of Table 3 shows, most variables (except for SOUTH) are statistically significant at conventional levels and appear to have the expected signs. However, the coefficient of SOUTH is negative or statistically insignificant in some quantiles. There may be some reasons for this: the high cost of the land in Seoul has resulted in a vertical city where most people live in high-density high-rise apartments. So many buildings facing south may actually face another building or roads in front that may block the sunshine or cause noise and air pollution, while south frontage is generally considered an important price determinant in Korea housing market. From this result, we may infer that south frontage in itself may not be as important as the scenic view as defined in this study.

For the purpose of comparison, OLS estimates are reported in the first columns of Table 3. Most of the OLS and quantile coefficients bear the same sign, as shown in Panel A of Table 3, but the METRO variable shows negative signs or is statistically insignificant both in the OLS regression and in the coefficients of most quantiles except the coefficient of the 5th quantile which shows a statistically significant positive sign. This may be because residents of low-priced apartments favour the metro (one of the most popular means of public transportation) rather than private cars due to their limited income; thus, metro proximity would be a very important determinant in their home-buying decisions. Except in this quantile, METRO shows statistically insignificant or negative effects on prices in all other quantiles. In fact, Seoul has a well-organized metro system that serves almost every part of the city except for a few remote areas. Seoul's bus system is also extensive and efficient: the distance from one bus stop to the next on a bus line is around 10 minutes' walk. Buses run every 15 minutes, with a good transit system between the metro and buses around the city. As a result, locations may not matter in terms of access to transit. This may be why METRO

Table 3. Quantile regression coefficient estimates.

| | OLS | 5th | 10th | 25th | 50th | 75th | 90th | 95th |
|---|---|---|---|---|---|---|---|---|
| **Panel A: (full period) sample size = 3,459** | | | | | | | | |
| **Constant** | 17.483* | 16.5935* | 16.6631* | 16.8958* | 17.1809* | 17.6848* | 18.7313* | 19.0425* |
| | (235.04) | (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% |
| **Adjusted$R^2$** | 0.7753 | 0.5554 | 0.5690 | 0.5734 | 0.5524 | 0.5151 | 0.5022 | 0.5053 |
| **Quantile Slope Equality Test** | | | | 726.95 | | | <0.0001 | |
| **Symmetric Quantiles Test** | | | | 183.01 | | | <0.0001 | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Panel B: (sub-period 2006:1–2008:8) sample size = 1048** | | | | | | | | |
| **Constant** | 16.750* | 16.251* | 16.387* | 16.347* | 16.445* | 16.709* | 17.185* | 17.599* |
| | (181.67) | (73.522) | (113.58) | (139.03) | (153.11) | (147.84) | (111.59) | (80.604) |
| **AGE** | -0.0125 | -0.0200 | -0.0181 | -0.0170* | -0.024* | -0.0031 | 0.0191 | 0.0162 |
| | (-1.859) | (-1.8072) | (-1.8370) | (-2.4111) | (-2.994) | (-0.355) | (1.3209) | (0.8541) |
| **$AGE^2$** | 0.0012* | 0.0013* | 0.0013* | 0.0012* | 0.0015* | 0.0008* | 0.0003 | 0.0008 |
| | (5.2257) | (3.5118) | (4.7308) | (5.1206) | (4.9921) | (2.5662) | (0.5282) | (1.0611) |
| **SIZE** | 0.0355* | 0.0371* | 0.0353* | 0.0369* | 0.0381* | 0.0362* | 0.0312* | 0.0271* |
| | (32.061) | (10.327) | (18.663) | (26.486) | (24.407) | (21.124) | (11.057) | (5.7707) |
| **$SIZE^2$** | -9.47E* | -0.0001* | -9.59E-* | -0.0001* | -0.000* | -9.34E-* | -7.70E-* | -6.42E-* |
| | (-20.14) | (-5.4550) | (-11.002) | (-16.657) | (-13.94) | (-14.06) | (-7.3724) | (-3.8593) |
| **TFL** | 0.1416* | 0.1959* | 0.2008* | 0.2292* | 0.2454* | 0.1888* | 0.1294* | 0.0916 |
| | (4.6296) | (3.8703) | (4.2654) | (6.4844) | (6.8336) | (5.2391) | (2.8806) | (1.5788) |
| **LFL** | 0.0519* | 0.0542* | 0.0489* | 0.0416* | 0.0277 | 0.0319 | 0.0503 | 0.0930* |
| | (3.6511) | (2.6879) | (3.3878) | (2.6970) | (1.8913) | (1.6427) | (1.7918) | (2.1533) |
| **SOUTH** | 0.0438 | -0.0078* | -0.0236 | 0.0262 | 0.0458 | 0.0852* | 0.1137* | 0.1538* |
| | (1.6792) | (-0.2302) | (-0.9436) | (1.0758) | (1.8545) | (2.5887) | (2.4923) | (2.4085) |
| **Impact**** | 4.48% | -0.78% | -2.34% | 2.66% | 4.70% | 8.90% | 12.05% | 16.63% |
| **METRO** | 0.0261 | 0.0451 | 0.0484* | 0.0375 | 0.0326 | 0.0444 | 0.0027 | -0.0247 |
| | (1.1238) | (1.3211) | (1.9869) | (1.6078) | (1.3681) | (1.3014) | (0.0568) | (-0.3867) |
| **Impact**** | 2.65% | 4.62% | 4.96% | 3.83% | 3.32% | 4.55% | 0.27% | -2.44% |
| **SCHOOL** | 0.3564* | 0.2755* | 0.2516* | 0.3490* | 0.3806* | 0.3315* | 0.3721* | 0.3230* |
| | (12.013) | (5.0636) | (5.100) | (8.9602) | (12.125) | (8.473) | (6.054) | (4.7975) |
| **Impact**** | 42.83% | 31.73% | 28.62% | 41.77% | 46.32% | 39.32% | 45.08% | 38.14% |
| **VIEW** | 0.1017* | -0.039 | 0.0018 | 0.0050 | 0.1079 | 0.1371* | 0.1424 | 0.0781 |
| | (2.2105) | (-0.4623) | (0.044) | (0.1013) | (1.9000) | (2.6059) | (1.622) | (0.6726) |
| **Impact**** | 10.71% | -3.86% | 0.19% | 0.51% | 11.40% | 14.71% | 15.31% | 8.13% |
| **Adjusted R²** | 0.7892 | 0.5445 | 0.5797 | 0.6040 | 0.5954 | 0.5596 | 0.5159 | 0.498493 |
| **Quantile Slope Equality test** | | | | 222.2476 | | <0.0001 | | |
| **Symmetric Quantiles test** | | | | 100.3487 | | <0.0001 | | |

(*Continued*)

Table 3. (*Continued*).

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Panel C:(sub-period 2008:8–2012:12) sample size =2410** | | | | | | | | |
| **Constant** | 18.186 | 17.111* | 17.260* | 17.601* | 17.972* | 18.742* | 19.226* | 19.257 |
| | (314.12) | (116.96) | (137.15) | (228.7) | (210.3) | (180.9) | (190.06) | (192.36) |
| **AGE** | -0.0368* | -0.0190* | -0.0221* | -0.0308* | -0.036* | -0.0453* | -0.0461* | -0.0467* |
| | (-10.552) | (-2.9778) | (-3.1345) | (-6.3030) | (-6.911) | (-9.0012) | (-8.4316) | (-7.8064) |
| **AGE$^2$** | 0.0014* | 0.0009* | 0.0010* | 0.0013* | 0.0014* | 0.0016* | 0.0016* | 0.0017* |
| | (14.582) | (5.7843) | (5.4983) | (9.4989) | (9.6491) | (10.931) | (8.7958) | (8.5183) |
| **SIZE** | 0.0211* | 0.0244* | 0.0250* | 0.0255* | 0.0232* | 0.0186* | 0.0165* | 0.0172* |
| | (34.035) | (16.150) | (18.137) | (26.903) | (23.086) | (15.711) | (14.313) | (13.734) |
| **SIZE$^2$** | -4.39E-* | -6.03E-* | -6.23E-* | -6.33E-* | -5.28E* | -3.52E-* | -2.43E-* | -2.63E-* |
| | (-17.182) | (-7.8969) | (-9.2602) | (-13.52) | (-12.34) | (-7.1195) | (-6.5633) | (-6.6527) |
| **TFL** | 0.1166* | 0.2392* | 0.2137* | 0.1433* | 0.1527* | 0.0964* | 0.0348 | 0.0307 |
| | (0.1166) | (5.0647) | (7.0875) | (6.3851) | (6.8956) | (3.5939) | (1.0914) | (0.9904) |
| **LFL** | 0.0421* | 0.0284* | 0.0328* | 0.0426* | 0.0447* | 0.0293* | 0.0237* | 0.0241* |
| | (5.2183) | (2.4195) | (3.3432) | (4.9312) | (4.2843) | (2.4537) | (2.0157) | (2.1942) |
| **SOUTH** | -0.0249* | -0.0269* | -0.0226* | -0.0231* | -0.025* | -0.0283* | -0.0319* | -0.0293* |
| | (-12.898) | (-5.5041) | (-6.2872) | (-13.437) | (-13.32) | (-13.064) | (-12.010) | (-8.1964) |
| **Impact**** | -2.47% | -2.66% | -2.24% | -2.29% | -2.48% | -2.79% | -3.15% | -2.90% |
| **METRO** | -0.0046* | 0.0008 | -0.0019 | -0.0033* | -0.004* | -0.0060* | -0.0051* | -0.0061* |
| | (-3.5193) | (0.3919) | (-1.3849) | (-3.4539) | (-3.772) | (-4.1694) | (-2.7572) | (-2.6569) |
| **Impact**** | -0.47% | 0.09% | -0.20% | -0.33% | -0.41% | -0.60% | -0.51% | -0.61% |
| **SCHOOL** | 0.2182* | 0.2830* | 0.2794* | 0.2801* | 0.2068* | 0.1539* | 0.1719* | 0.1626* |
| | (14.307) | (6.1917) | (6.7156) | (13.776) | (10.293) | (7.5918) | (8.2498) | (8.5914) |
| **Impact**** | 24.39% | 32.71% | 32.25% | 32.34% | 22.98% | 16.65% | 18.77% | 17.66% |
| **VIEW** | 0.0810* | 0.0498 | 0.0161 | 0.0395 | 0.0945* | 0.1071* | 0.1049* | 0.0760* |
| | (3.3954) | (1.8393) | (0.5988) | (1.1895) | (3.2842) | (2.9529) | (3.0643) | (2.9937) |
| **Impact**** | 8.45% | 5.12% | 1.63% | 4.03% | 9.91% | 11.31% | 11.07% | 7.91% |
| **Adjusted R²** | 0.7892 | 0.5445 | 0.5797 | 0.6040 | 0.5954 | 0.5596 | 0.5159 | 0.4984 |
| **Quantile Slope Equality test** | | | | 525.2304 | | <0.0001 | | |
| **Symmetric Quantiles test** | | | | 66.59056 | | <0.0001 | | |

*Indicates statistical significance at the 5-percent confidence level.**For dummy variables, the impacts are based on 0 and 1($e^{coefficient}$– 1).
Source: Authors.

affects the price negatively in all quantiles except the lowest. This is also shown in Panel A of Figure 2. Likewise, the results of the study by Bae, Jun, and Park (2003) on the effect of proximity to Metro Line 5 on house prices in Seoul shows that proximity to the metro does not have a statistically significant effect on prices.

AGE and SIZE are quadratic effects in the model because their impacts might have non-linear patterns on house prices. Table 4 presents the turning points of the non-linear patterns of these variables. According to the linear regression model, which employs full periods, AGE appears to decrease the price until 8.7 years after construction and increases the price afterward. In this respect, 8.7 years is used as a turning point in this study. In the estimation of the quantile regression, apartment age appears to have a statistically significant impact on house prices at the traditional level and the turning point appears to be shorter for the medium quantiles than for lower and higher

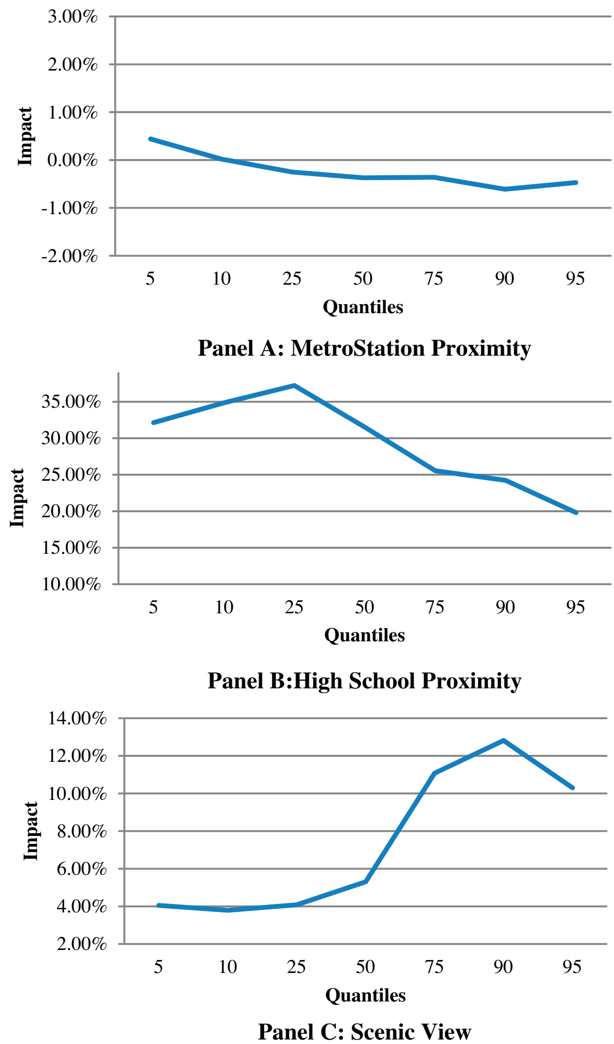


Figure 2. Trends of impacts on dummy variables.
Source: Authors.

Table 4. Turning point of housing characteristics.

| | OLS | 5th | 10th | 25th | 50th | 75th | 90th | 95th |
|---|---|---|---|---|---|---|---|---|
| **Panel A: (full period:2006:1–2012:12)** | | | | | | | | |
| 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 | 311.6 |
| **Panel B: (sub period: 2006:1–2008:8)** | | | | | | | | |
| AGE | 4.97 | 7.47 | 6.55 | 7.01 | 8.01 | 1.75 | -30.12 | -9.59 |
| SIZE | 187.94 | 177.01 | 184.11 | 181.33 | 180.07 | 193.88 | 203.06 | 211.14 |
| **Panel C: (sub period: 2008:9 –2012:12)** | | | | | | | | |
| AGE | 12.49 | 9.73 | 10.63 | 11.75 | 12.76 | 13.56 | 14.11 | 13.35 |
| SIZE | 240.85 | 202.75 | 200.90 | 201.93 | 219.94 | 265.24 | 341.19 | 327.39 |

Source: Authors.

quantiles. The house prices of these medium quantiles begin to increase after constantly falling for 7–8 years. This time period or turning point is relatively short compared to the 15–19 found in Lee et al.'s (2005) analysis.

Apartment aging not only leads to depreciation but also increases the possibility of and expectations for redevelopment. In Korea, redevelopment is normally accompanied by an increase in structural density and improvements in living conditions, all of which result in price increases. More specifically, an increase in structural density means an increased number of apartment units, which will in turn contribute to the original homeowners' capital gains. Improved living conditions from redevelopment will also increase demand, resulting in price appreciation. Therefore, expectation for redevelopment in the near future has a strong positive impact on the current price of housing. This redevelopment effect on house prices is statistically more significant after the financial crisis. Comparing AGE and AGE$^2$ in Panels B and C of Table 3, not all quantiles in Panel B are statistically significant, while, in Panel C, most are statistically significant. This may be because after the 2008 financial crisis, the housing market in general began to submerge and so houses expected to be redeveloped in the near future were preferred because of their investment value.

According to the linear regression model, apartment prices increase as size does up to 134.5m$^2$ which is considered the most popular size and decline afterward. In short, it seems that there exist turning points in size.

Figure 2 shows the impact of dummy variables (metro, school proximity, and scenic view) on house prices over a whole period sample and whose estimation results are shown in Table 3. In Panel B of Figure 2, the impact of high school proximity on house prices in lower quantiles is larger than that in higher quantiles, which implies that homebuyers in lower quantiles are more concerned with high school proximity. High school proximity tends to increase the prices up to 37.24% at the 25th quantile. They may prefer a shorter distance to high school because they might want their children to walk to and from school rather than using public or personal transportation. This may have been reflected in the prices.

However, the studies of Fack and Grenet (2010), Hahn, Kim, and Kim (2012) and Feng and Lu (2013) show that proximity to better schools also raises house prices. An analysis of the proximity of high schools with better student performance records was conducted using a sample of better high schools. However, the result was statistically insignificant and not reported in this paper, being possibly attributable to the effects of

Table 5. Quantile regression coefficient estimates by region.

| | OLS | 5th | 10th | 25th | 50th | 75th | 90th | 95th |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Kangnam sample size: 1110** | | | | | | | | |
| **Const.** | 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 | -0.00005 | 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* | -0.00002* | 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% |
| **Adjusted $R^2$** | 0.7536 | 0.5829 | 0.5717 | 0.5468 | 0.5076 | 0.4783 | 0.4789 | 0.4856 |
| **Quantile Slope Equality Test** | | 415.18 | | <0.0001 | | | | |
| **Symmetric Quantiles Test** | | 100.09 | | <0.0001 | | | | |

(*Continued*)

Table 5. (*Continued*).

| | OLS | 5th | 10th | 25th | 50th | 75th | 90th | 95th |
|---|---|---|---|---|---|---|---|---|
| **Panel B: Songpa sample size: 943** | | | | | | | | |
| **Const.** | 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% |
| **Adjusted $R^2$** | 0.6829 | 0.4893 | 0.5038 | 0.4959 | 0.4784 | 0.4506 | 0.4299 | 0.4231 |
| **Quantile Slope Equality Test** | | | 439.84 | <0.0001 | | | | |
| **Symmetric Quantiles Test** | | | 103.87 | <0.0001 | | | | |

**Panel C: Nowon sample size: 1406**

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| **Const.** | 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) | (-1.881) | (-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% |
| **Adjusted R²** | 0.7984 | 0.5492 | 0.5669 | 0.5808 | 0.5817 | 0.5861 | 0.5800 | 0.5717 |
| **Quantile Slope Equality Test** | | | 478.45 | <0.0001 | | | | |
| **Symmetric Quantiles Test** | | | 75.67 | <0.0001 | | | | |

*Indicates statistical significance at the 5-percent confidence level. **For dummy variables, the impacts are based on 0 and 1($e^{coefficient}$– 1).
Source: Authors.

the equalization policy perceived and attested by homebuyers. Nevertheless, the analysis of high school proximity with the sample of all high schools shows a significantly positive effect. The proximity to ordinary high schools is adopted as a variable in this paper (rather than to "better" schools), and it has the greatest effect on prices compared to other dummy variables such as view and metro proximity. This result is in contrast to the case of the United States, where students can use school buses. Most high schools in Korea currently do not operate a school bus system. The results of larger effects in the lower quantiles than in the higher quantiles may indicate that the proximity to school is more important to the parents in the lower quantiles for their not being able to give rides to their children vis-a-vis the wealthier parents who are able to do.

Floor level is also statistically positive at a 5% significance level. In a highly dense city, high floor height would increase the house price because of greater sunshine, improved view and less noise and air pollution from the roads. This result is consistent with empirical findings from Hong Kong (Jim & Chen, 2009) and Guangzhou, China (Jim & Chen, 2006). In contrast, in Western countries such as the Netherlands (Bengochea-Morancho, 2003), floor height may not have a significant effect on house prices. For widely dispersed single-family houses in Western countries, floor height would be less important.

As seen in Panel C of Figure 2, the impact of scenic view on house prices shows an increasing trend from the 25th to 90th quantiles, which implies that buyers of higher-priced properties opt for a house with a river or a mountain view more than do buyers of lower-priced properties. A mountain or a river view can increase the house price up to 12.8% at the 90th quantile. This phenomenon is represented by higher positive estimated coefficients of the VIEW variable at higher quantiles than at lower quantiles. These findings correspond to the empirical result from Hong Kong (Mak et al., 2010).

Table 5 shows the estimation results of the OLS and quantile regressions on house prices in Kangnam, Songpa, and Nowon. As evidenced in the previous estimation results, the determinants of house prices in the three counties are similar except for the environmental factor such as scenic view. However, the quantile regression analysis with the three counties combined verifies that hedonic attributes have different effects on prices from quantile to quantile. Of the hedonic attributes, VIEW has the most varied effects on house prices between Kangnam, Songpa, and Nowon. VIEW is statistically significant and positive in sign in determining house prices in all quantiles of Kangnam, while Songpa and Nowon (except for only one quantile of Songpa) have statistically insignificant coefficients. In other words, house prices in Kangnam tend to be higher with better views. It can be inferred that scenic view matters more vis-à-vis other factors for the well-to-do when it comes to home buying decision.

## Conclusions

This paper empirically estimates how specific quantiles of house prices in Seoul respond differently to a one-unit change in the hedonic characteristics of the house. An analysis of each county is conducted and the effects of the hedonic attributes on house prices compared between three regions of Seoul. A total data sample of 3459 court auction cases traded from 2006 to 2012 in three different counties of Seoul is used, Kangnam, Songpa and Nowon. To check the robustness of the estimation results and to analyze the impact of the 2008 financial crisis on the housing market, the study period is divided into two sub-periods, being before and after the crisis.

The results of our empirical analysis show that the effect of hedonic characteristics on house prices differs from quantile to quantile. This means homebuyers' preferences for specific housing attributes vary greatly across different quantiles of the conditional distribution of house prices. Specifically, while metro proximity is statistically significant only for the 5th quantile of house prices, it is statistically insignificant or negative for the other quantiles. In other words, with the exception of only the lowest quantile, metro proximity may not be an important factor in home buying decisions. This finding may attest to the facts that Seoul has a well-organized metro system that enables people to travel almost everywhere in the city and, in addition, the transit system between the metro and buses is also well arranged throughout Seoul. Thus, location may not matter as much in home purchase decisions.

High school proximity, however, appears to have a larger positive effect in lower quantiles than in higher quantiles. This may offer another implication that homebuyers in the lower quantiles prefer not to use any form of transportation, including public transportation, to save the commuting cost.

In contrast to these variables such as metro proximity and school proximity addressed above, scenic view has a larger positive effect in higher quantiles. In particular, in Kangnam County where the average house price is the highest of the three counties in the study (and probably the highest in Korea), scenic view has a statistically significantly positive effect in all quantiles.

The key findings of this study are that, first, of all the dummy variables, high school proximity has the greatest effect on prices. While most previous studies have dealt with the effect of the quality of education on house prices, this paper focuses on the proximity to the nearest high school which proves to have a greater effect than the quality of education. This result can be attributed to the fact that most students in Korea commute to school by walking or by public or personal transport because school buses are not widely used, as they are in other countries such as the United States. The quality of the nearest high school does not have a statistically significant effect on prices, as most high schools in Korea do not differ in terms of school quality most likely due to the high school equalization policy.

Second, both school proximity and scenic view have smaller effects on house prices after the financial crisis than before it. The reason behind this can be that due to the financial crisis and subsequent economic recession, the value of amenities such as school proximity and scenic view may have decreased.

Third, the building age and squared age variables, which represent expectations of redevelopment, have statistically significant effects in more quantiles after the crisis than before it. This may be because in a downturn market, people prefer older and potentially profitable housing (from expectations of redevelopment) to new, convenient, and less profitable housing.

## Notes on contributors

Heeho Kim is a professor of Economics at Kyungpook National University, Korea. Daehak Ro 80, Bukgu, Daegu, S. Korea 702-701. email: kimhh@knu.ac.kr, phone: 82-(0)53-950-5438 (o).

SaeWoon park is a professor of the Department of Business and Managment at Changwon National University (CNU). email: assw@changwon.ac.kr

Sunhae Lee is a lecturer teaching real estate management at Changwon National University (CNU). email: sueleesh@changwon.ac.kr

Xingqun Xue is a professor of Business at Dalian University of Technology. No.2 Linggong Road, Ganjingzi District, Dalian City, Liaoning Province, P. R. C., 116024. email: xuexingqun@naver.com

## Acknowledgement

This research was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2015S1A5A2A01009575).

## References

Allen, M., & Swisher, J. (2000). An analysis of the price formation process at a HUD auction. *Journal of Real Estate Research, 20*, 279–298.

Bae, C.-H. C., Jun, M.-J., & Park, H. (2003). The impact of Seoul's subway line 5 on residential property values. *Transport Policy, 10*, 85–94.

Bengochea-Morancho, A. (2003). A hedonic valuation of urbane green spaces. *Landscape Urban Plan, 66*, 35–41.

Buchinsky, M. (1995). Estimating the asymptotic covariance matrix for quantile regression models: A Monte Carlo study. *Journal of Econometrics, 68*(2), 303–338.

Can, A. (1992). Specification and estimation of hedonic housing price model. *Regional Science and Urban Economics, 22*, 453–474.

Can, A., & Megbolube, I. (1997). Spatial dependence and house price index construction. *Journal of Real Estate Finance and Economics, 14*, 203–222.

Chau, W. K., & Choy, L. H. T. (2011). Let the buyer or seller beware: Measuring lemons in the housing market under different doctrines of law governing transactions and information. *Journal of Law and Economics, 54*(4), 347–365.

Cheshire, P., & Sheppard, S. (1995). On the price of land and the value of amenities. *Economica, 62*, 247–267.

Cho, C.-J. (2011). An analysis of the housing redevelopment of process in Korea through the lens of the transaction cost framework. *Urban Studies, 48*(7), 1477–1501.

Cho, H., Kim, K., & Shilling, J. (2007). *Are house prices and trading volume related? Evidence from the Seoul housing market*. Working Paper.

Ebru, C., & Eban, A. (2011). Determinants of house prices in Istanbul: A quantile regression approach. *QualQuant, 45*(2), 305–317.

Epple, D. (1987). Hedonic prices and implicit markets: Estimating demand and supply functions for differentiated goods. *Journal of Political Economy, 95*(1), 58–80.

Fack, G., & Grenet, J. (2010). When do better schools raise housing prices? Evidence from Paris public and private schools. *Journal of Public Economics, 94*, 59–77.

Feng, H., & Lu, M. (2013). School quality and housing prices: Empirical evidence from a natural experiment in Shanghai, China. *Journal of Housing Economics, 22*, 291–307.

Fesselmeyer, E., Le, K. T., & Seah, K. Y. (2013). Change in the white-black house value distribution gap form 1997 to 2005. *Regional Science and Urban Economics, 43*, 132–141.

Frino, A., Peat, M., & Wright, D. (2011). The Impact of auctions on residential property prices. *Accounting & Finance, 52*(3), 815–830.

Gyourko, J., & Tracy, J. (1999, September). A Look at real housing prices and incomes: Some implications for housing affordability and quality. *FRBNY Economic Policy Review*, *5*(3), 63–77.

Gyourko, J. & Linnerman, P. D. (1993). The affordability of the American dream: An examination of the last thirty years. *Journal of Housing Research, 4*(1), 39–72.

Hahn, S., Kim, T.-H., & Kim, M. (2012). The influence of school quality on housing prices in Korea. *Applied Economics, 44*, 1021–1023.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica, 47*, 153–161.

Jang, Y. H., & Kim, S.-H. (2013). New experiments in public housing supply in Seoul, South Korea: The possibilities and limits. Chapter 8, In J. Chen, M. Stephens, & Y. Man (Eds.), *The future of public housing*. Berlin/Heidelberg: Springer 123–142.

Jim, C. Y., & Chen, W. Y. (2006). Impact of urban environmental elements on residential housing prices in Guangzhou (China). *Landscape and Urban Planning, 78*, 422–434.

Jim, C. Y., & Chen, W. Y. (2009). Value of scenic views: Hedonic assessment of private housing in Hong Kong. *Landscape and Urban Planning, 91*, 226–234.

Kang, H. H., & Liu, S.-B. (2014). The impact of the 2008 financial crisis on housing prices in China and Taiwan: A quantile regression analysis. *Economic Modelling, 42*, 356–362.

Koenker, R., & Bassett Jr., G. (1978, January). Regression Quantiles, *Econometrica, 46*(1), 33–50.

Koenker, R., & Hallock, K. (2001). Quantile regression: An introduction. *Journal of Economic Perspectives, 15*, 143–156.

Lee, B. S., Chung, E.-C., & Kim, Y. H. (2005). Dwelling age, redevelopment, and housing prices: The case of apartment complexes in Seoul. *Journal of Real Estate Finance and Economics, 30*(1), 55–80.

Liao, W.-C., & Wang, X. (2012). Hedonic house prices and spatial quantile regression. *Journal of Housing Economics, 21*, 16–27.

Lusht, K. (1996). A comparison of prices brought by English auction and private negotiations. *Real Estate Economics, 24*, 517–530.

Mak, S., Choy, L., & Ho, W. (2010). Quantile regression estimates of Hong Kong real estate prices. *Urban Studies, 47*(11), 2461–2472.

Mayer, C. J. (1998). Assessing the performance of real estate auctions. *Real Estate Economics, 26*(1), 41–66.

Mayer, C. J. (1994). A model of negotiated sale applied to real estate auctions. *Journal of Urban Economics, 38*(1), 1–22.

Newsome, B., & Zietz, J. (1992). Adjusting comparable sales using MRA: The need for segmentation. *Appraisal Journal, 6*, 129–135.

Ong, S. E., Lusht, K. M., & Mak, C. Y. (2005). Factors influencing auction outcomes: Bidder turnout, auction houses and market conditions. *Journal of Real Estate Research, 27*(2), 177–192.

Qu, W., & Liu, X. (2012). Assessing the performance of Chinese land lease auctions: Evidence from Beijing. *Journal of Real Estate Research, 34*(3), 291–310.

Quan, D. C. (2002). Market mechanism choice and real estate disposition: Search versus auction. *Real Estate Economics, 30*, 365–384.

Zietz, J., Zietz, E., & Sirmand, G. (2008). Determinants of housing prices: A quantile regression approach. *Journal of Real Estate Finance and Economics, 37*(4), 317–333.