Paper for the 2005 ENHR Housing Conference in Reykjavík, Iceland,
29 June ~ 2 July 2005

The Asymmetric Price Effects of Brokerage Service Using Quantile Regressions

Liao, Chung-Jen * Chang, Chin-Oh **

* PhD Candidate, Department of Land Economics, National Chengchi University, Taipei, Taiwan. Email: liao.evan@msa.hinet.net.
** Professor, Department of Land Economics, National Chengchi University, Taipei, Taiwan. Email: jachang@nccu.edu.tw.

Abstract

A number of past and recent studies provided conflicting empirical answers to the effect of real estate brokerage service on housing price. Yavas and Colwell's search model indicates that there are two opposing impacts of pricing on the broker's search effort level: one is that a higher price means a higher commission fee in the event of a sale. Also, buyers overpay for the house to trade off their search cost. The other effect is that a higher price means a smaller probability that a buyer will purchase the house. Their model provides that there are asymmetric effects of brokerage service on higher-priced and lower-priced houses. To test the asymmetric effects of brokerage service, we employ quantile regression to capture the behavior at each quantile of conditional house price distribution. An important findings of this paper is that when selection bias is controlled, the price effects of real estate brokerage service are significant heterogeneous across the conditional price distribution. The contribution of this paper to the prior literature is to provide empirical evidence by showing that broker might have a positive, negative, or zero impact on the housing prices compared to Yavas and Colwell's numerical examples.

Keywords： Search Model, Quantile Regression, Brokerage Service, Self-Selection

1 Introduction

A home seller or buyer searches for the counterpart either on his own efforts or through brokerage service. Due to economics of scale of search behavior, brokers can match two traders quickly. Yinger（1981）was one of the first to use a search model in a formal analysis of real estate markets. He considered the impact of uncertainty on the behavior of real estate brokers and concludes that too many resources are devoted to broker's search activities. Yinger's analysis, however, does not include buyers' and sellers' search activities. Wu and Colwell（1986）extend Yinger's model and focus on the impact of a change in search cost on the price of housing and the broker's commission rate. Salant（1986）uses a dynamic search model to proves the seller's asking price declines but jumps up in the period when the broker is first enlisted. These search models assume that the seller posts an asking price that the buyer can either accept or reject. Yavas（1992） considered a bargaining process between the buyer and the seller and concluded that the seller receives a higher price when he employs a broker, but the increase in price is less than the commission fee.

A number of studies have examined whether a seller raises the price of his house to pass on a portion, if not all, of the broker's commission to the buyers when he chooses to sell his house through a real estate broker. However, the past empirical results provided seemingly conflicting answers to this question. Janssen and Jobson（1980）、Doiron et al.（1985）, Jud and Frew（1986）, and Frew and Jud（1987）found that a willingness of buyers to pay more for broker-listed house than those sold directly by owners. On the other hand, competition from for-sale-by-owner properties may prevent sellers from passing on commission costs to buyers in the form of higher prices （Zumpano, Elder, and Baryla, 1996）. In addition, the brokers also have an incentive to lower the pricing in order to sell houses faster and save their search costs if the sellers can not monitor their search effort level. The results of Kamath and Yantek (1982) and Zumpano, Elder, and Baryla (1996)[1] reveal that the prices of houses sold through brokers are lower than those sold directly by owners. The third results also stand in Jud (1983) and Elder, Zumpano and Baryla (2000). That is, there is no significant price differential whether the sellers use a broker or not.

To explain such prior contradictory empirical results, Yavas and Colwell (1995) extend one-period bilateral search model and consider broker's search intensity and pricing strategy. They report that when the seller lists the house with a broker, he has to consider the impact of his price choice on the broker's search effort level. An increase in the seller's price has two opposing effects on the broker's search intensity: one is that a higher price means a higher commission fee in the event of a sale. Hence, it gives more incentives to the broker to search harder. The other effect is that a higher price means a smaller probability that the buyer will purchase the house. As a result, it reduces the broker's incentive to search more. In other words, there are two forces to determine the pricing strategy for brokers, higher commission or quicker sale. Using numeric method they prove that an increase in the price of the house increase the broker's search intensity if the price is below the median, an increase in the price of the house decreases the broker's search intensity while the price is above the median. The contribution of Yavas and Colwell (1995) model provides a theoretical model to explain the conflicting empirical results, but they did not prove it through empirical study.

To date, all studies of price effect of brokerage service estimate the unknown parameters specified in the regression model using the method of ordinary least squares (OLS). It is well known that the regression model estimated by OLS in effect approximates the conditional mean

[1] Zumpano, Elder, and Baryla (1996) also consider self-selection bias problem about broker choice. See treatment effect of sample selection in Greene (2003) and Heij et. al (2004).

function of Y given X. This methodology is limited in the sense that it cannot fully characterize a conditional house price distribution, which may in turn lead researchers to conclude that structural effects of the price determinants remain constant along the price percentile (Reck, 2003). To properly identify the effects of house price determinants on price stratification, we employ "quantile regression" (QR) developed by Koenker and Bassett (1978) and Koenker and Hallock (2001). With this method, we are able to characterize the behavior at each quantile of the conditional price distribution and to test whether a particular coefficient of multiple price determinants, especially the role of broker, is homogeneous or heterogeneous. Therefore, quantile regression provides a chance to test the expectation of Yavas and Colwell model. The contribution of this paper to the literature is to compare the estimated results from OLS and quantile regression and also test for potential selectivity bias problems in the data by employing the two-stage estimation procedure described in Lee (1978).

The reminder of the paper is organized as follows. We first introduce the basic concept of quantile regression. We then present the econometric model and explain our rationale for model specifications. After a description of our data source and variables used, we report and discuss the empirical findings. And we finally end with a conclusion.

2 Quantile Regression, QR

Ordinary least square method (OLS) is based on the mean of conditional distribution of dependent variable and assumes no significant different impact of independent variables across the conditional distribution. However, the estimated results will make a big error if the assumption cannot be hold. To test the relation of conditional distribution of dependent variable and independent variables, some researchers segment the dependent variable into subsets according to its unconditional distribution and then doing least squares fitting on these subsets. Clearly, this form of “truncation on the dependent variable” would yield disastrous results (Koenker and Hallock, 2001) .

Quantile regression as introduced by Koenker and Bassett (1978) seeks to extend these ideas to the estimation of *conditional quantile functions* - models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates. The term quantile is synonymous with percentile. For instance, the sample median is taken as an estimator of the population median *m*, a quantity which splits the distribution F_Y into two halves in the sense that, if a random variable Y can be measured on the population, then $P(Y \le m) = P(Y \ge m) = 0.5$. Therefore, for $\theta \in (0,1)$, the θ-th quantile, denoted as $q(\theta)$, is such that $q(\theta) := \inf\{y : F_Y(y) \ge \theta\}$. Note that $q(\theta)$ solves the following objective function:

$$\min_{q} \theta \int_{y>q} |y-q| dF_Y(y) + (1-\theta) \int_{y<q} |y-q| dF_Y(y), \tag{1}$$

When Y has the conditional distribution $F_{Y|X}(y)$, the θ-th quantile function conditional on the vector of variables X , denoted as $Q(X;\theta)$, minimizes the objective function below:

$$\min_{Q(X)} \theta \int_{y>Q(X)} |y-Q(X)| dF_{Y|X}(y) + (1-\theta) \int_{y<Q(X)} |y-Q(X)| dF_{Y|X}(y), \tag{2}$$

Given the data $\{y_i, x_i\}_{i=1}^{n}$, we may specify a linear regression,

$$y_i = x_i^T \beta + e_{i,}$$

and use $x_i^T \beta$ to approximate the conditional quantile function $Q(X;\theta)$. The unknown parameter β can then be estimated by the average of weighted absolute errors with weight θ on positive errors and $(1-\theta)$ on negative errors:

$$\frac{1}{n}\left[\theta \sum_{i:y_i \geq x_i^T \beta} \left|y_i - x_i^T \beta\right| + (1-\theta) \sum_{i:y_i < x_i^T \beta} \left|y_i - x_i^T \beta\right|\right], \tag{3}$$

The resulting estimator of β, denoted as $\hat{\beta}(\theta)$, can then be solved from the first order condition of minimizing (3): [2]

$$\frac{1}{n}\sum_{i=1}^{n} x_i (\theta - 1_{\{y_i - x_i^T \beta < 0\}}) = 0, \tag{4}$$

Hence, unlike OLS can only describe the averaging behavior of the regression's dependent variable, quantile regression models allow for a full characterization of the conditional distribution of that, in other words, it can reveal the asymmetric behavior. Based on such an advantage, quantile regression has been widely used in labor and education economics to study determinants of wages, discrimination effect and trends in income inequality（Koenker and Hallock, 2001；Yu, Lu, and Stander, 2003）. For instance, Chamberlain（1994）points out that those with lower wage have more wage compensation than those with higher wage. In ecology, theory often suggests how observable covariates affect limiting sustainable population size, and quantile regression has been used to directly estimate models for upper quantiles of the conditional distribution rather than the models based on conditional central tendency. For example, it is used to estimate changes in Lahontan cutthroat trout density as a function of the ratio of stream width to depth for 7 years and 13 streams in the eastern Lahontan basin of the western US（Cade and Noon, 2003）. Koenker and Hallock（2001）analyze the impact of various demographic characteristics and maternal behavior on the birthweight of infant. They indicate that most of the analysis of birthweight has employed conventional least squares regression method, but the resulting estimates of various effects of the

[2] As $\hat{\beta}(\theta)$ does not have a closed form, it must be computed by linear programming. See Koenker and Bassett（1978）for detail.

conditional mean of birthweight were not necessarily indicative of the size and nature of these effects on the lower tail of the birthweight distribution.

While quantile regression offers a natural complement to OLS and is both theoretically important and empirically useful, so far this method has not yet been introduced into the real estate literature, to the best of our knowledge. In this paper we are primarily interested in understanding whether the pricing structure of sellers and brokers are heterogeneous across different quantiles of conditional house price distribution.

3 Data and Econometric Model

This study uses data from a survey of homebuyers conducted by the Taiwan Real Estate Information Center in 2004. This survey was collected from the mortgage borrowers at banks. After eliminating incomplete or faculty questionnaires, the database totaled 2,819 observations. The variables used in the study are defined in Table 1.

【Table 1 about here】

Table 2 displays summary statistics from the survey sample, categorized by whether the transaction was broker-assisted （N1=1,445, 51.26%）or non-broker-assisted（N2=1,374, 48.74%）. The average selling price is $526 NTD for full sample, $537 NTD for non-broker-assisted and $515 NTD for broker-assisted. Table 3 describes the value of main quantile, skewness and kurtosis.

【Tables 2 and 3 about here】

A home seller or buyer can either attempt to search for the counterpart on his own efforts or utilize brokerage service. While the selling price of each property in the sample can be observed, what cannot be observed is what the property would have been had it sold using the alternative search method. Including a dummy variable for broker-assisted purchase assumes that the brokerage service is exogenous. However, if the choice is endogenous, specifically if the choice is associated with a price affecting variables that has been omitted from the hedonic model, the price effect properly attributed to the omitted variable may be attributed to the broker. Following Buchinsky（2001）, to control this possible sample selection bias caused by those who use an agent are predisposed to pay a higher or lower price, the Heckman 2-step correction procedure will be used. Instead of running OLS, quantile regression is used in the second step of the procedure.

$$BROKER = f(INC2 - INC6, NOEXP, DIS, AGE, YEARS). \qquad (5)$$

where BROKER is a dummy variable that takes on the value of 1 if the buyer employs a broker, and a value of 0 if the buyer on his own effort. The decision to use a broker is modeled as a function of five types of variables. Buyer income monthly（INC2-INC6）is employed as a measure of the opportunity cost of search. If higher income buyers have higher opportunity costs, we would expect that they would choose to buy through a real estate broker（Zumpano, Elder, and Baryla, 1996）. First-time homebuyer without prior experience（NOEXP）and buyers relocating from a distance（DIS） may seek out the services of a broker to improve their market access and acquire more information about the market. The age of the buyer（AGE）is a characteristic to affect the decision to use a broker. According to Chang’s survey（1989）,young buyers prefer to use a broker compared to elders. The last variable, YEARS, indicates whether the sale transaction is a new or old property, and was included to control for the fact that most new houses are marketed by builders.

The parameter value of a selectivity variable for the density (φ) and cumulative density (Φ) distributions in the Mills ratios are obtained from equation (5)：

$$\lambda_i = \frac{\phi(Z_i)}{1-\Phi(Z_i)} = \frac{\phi(Z_i)}{\Phi(-Z_i)}$$

In the second stage, selling price is modeled as a Rosen(1974) hedonic price function of the buyer characteristics, the physical characteristics of the house, the presence or absence of broker assistance, and, from the first stage, λ. The inclusion of this last variable allows us to test for self-selection bias. By following this approach, consistent estimates can be obtained using OLS and quantile regression procedures.

$$\begin{aligned} LnP = g(&LOAC1-5, PING, TOP, GROUND, GARAGE, YEARS, \\ &, INC2-INC6, AGE, NOEXP, DIS, BROKER, \lambda) \end{aligned} \tag{6}$$

where *LnP* is the log of selling price. LOCA1-LOCA5 are the variables representing the location of the house. GROUND and TOP are the variables representing the floor of the house in a building. PING is the size unit of the house in Taiwan. GARAGE is an indicator variable that takes the value of 1 if a house with a garage, and 0 otherwise.

4 Empirical Results

4.1 The broker-choice equations

The probit estimates of the broker-choice decision are found in Table 4. In general, the results correspond to the anticipated findings. As expected buyer income and the use of a real estate broker are positively related. As the degree of income increase, the probability of using a broker increases. The inexperienced and less informed buyer, NOEXP[3] and DIS, are more likely to use a real estate broker than experienced and local buyers. The age of buyers, as measured by AGE, does

[3] The variable, NOEXP, is not significant in Zumpano, Elder, and Baryla（1996）. The authors explain that the first-time homebuyers, possibly unaware if true search costs, may be seeking out bargain prices by avoiding broker-listed houses.

not appear significant difference. The last variable, YEARS, included to control for the fact that most existing homes are sold through real estate brokers, is positive and highly significant.

【Table 4 about here】

4.2 Price effect estimates of broker

Table 5 portrays the ordinary least squares（OLS）estimates of the selling price equation without and with selection correction, λ. The primary variables of interest are BROKER and λ from the probit model. The correction term, λ, is positive and significant. BROKER is negative but low correlated with selling price for both results, without or with λ. As expected, buyer income is positive and highly significant. All the physical characteristics and size variables are correctly signed, as expected. Interestingly, DIS and NOEXP are not significant without selection correction but highly significant with selection correction, indicating that less informed buyers pay more for their homes. This result is the same as the Turnbull and Sirmans（1993）but is very different from the Zumpano, Elder, and Baryla（1996）.

【Table 5 about here】

We now turn to quantile estimation results for the price-equation with price effect of broker across different points of the house price distribution, conditional on the linear function of the explanatory variables specified. Table 6A and 6B report the coefficients estimated at the .10, .25, .50, .75, and .90 quantiles, while *p*-values obtained from significance tests of inter-quantile differentials（Gould, 1997） are shown in Table 7. Figure 1 depicted in more details the estimated coefficients at 19 points of the conditional price distribution in increments of 0.05 for each variable included in the model, along with the associated 95% confidence intervals (in shadow).

The OLS estimates are also plotted in the figure; see the three horizontal dash-lines, with the middle one indicating the magnitude of the OLS coefficient and the other two banding its 95% confidence intervals.

【Tables 6A, 6B, 7 and Figure 1 about here】

Notice first that the coefficients of BROKER, the primary variable of interest, are from positive to negative and almost highly significant. As we can see in Table 6A, 6B, and Figure 1, significant price differential to broker choice are higher in the magnitude for lower-priced houses, with a coefficient of 4.3% at the .10 quantile and drop in the magnitude for higher-priced houses, with coefficient of -5.7% at the .75 quantile. However, there is no serious self-selection bias problem while considering selection correction, λ（ see Table 6B ）. In addition, the inter-quantile differences in broker-assisted price effect are very statistically significant between the two tails（ see *p*-values reported in Table 7 ）. In sum, we find that broker-assisted price effect is statistically significant and different across the conditional house price distribution. This result presents an asymmetric price effect and is obviously different from the estimates of OLS. This finding is consistent with Yavas and Colwell（ 1995 ）model implying that broker-assisted purchase play a decisive role in the process of price stratification.

Next, we brief the structural effects on selling price of the other key explanatory variables included in the model. First of all, NOEXP and DIS present price premium at low quantile and price discount at high quantile, but the price differential is not significant. The positive effect of size（ PING ）decrease monotonically from the .10 quantile to the .90 quantile. It may indicate that quality but not quantity is the key to add value for higher-price houses. As expected, buyer income is positive and highly significant. The effects for each income dummy variable

（INC2-INC6）, however, decrease monotonically from the .10 quantile to the .90 quantile.

5 Conclusion

A number of past and recent studies provided conflicting empirical answers to the effect of real estate brokerage service on housing price. Yavas and Colwell's search model indicates that there are two opposing impacts of pricing on the broker's search effort level: one is that a higher price means a higher commission fee in the event of a sale. Also, buyers overpay for the house to trade off their search costs. The other effect is that a higher price means a smaller probability that a buyer will purchase the house. Their model provides that there are asymmetric effects of brokerage service for higher-priced and lower-priced houses. Therefore, we employ quantile regression to capture the behavior at each quantile of conditional house price distribution and to test the asymmetric effects of brokerage service.

An important findings of this paper is that whether selection bias is controlled or not, the price effects of real estate brokerage service are significant heterogeneous across the conditional price distribution. The significant price differential to broker choice are higher in the magnitude for lower-priced houses, with a coefficient of 4.3% at the .10 quantile and drop in the magnitude for higher-priced houses, with coefficient of -5.7% at the .75 quantile.

The contribution of this paper to the prior literature is to provide empirical evidence by showing that broker might have a positive, negative, or zero impact on the housing prices based on Yavas and Colwell's theoretical model and numerical examples.

References

Chang, Chin-Oh（1989）*A Study of Real Estate Transaction System: Brokerage Service*, the Ministry of the Interior, Taiwan. (in Chinese)

Buchinsky, M.(2001), "Quantile Regression with Sample Selection: Estimating Women's Return to Education in the U.S.," *Empirical Economics*, 26, 87-113.

Cade, Brian S. and Barry R Noon （2003）, "A Gentle Introduction to Quantile Regression for Ecologists," *Frontier Ecological Environment*, 1(8): 412-420.

Chamberlain, G（1994）, "Quantile Regression, Censoring and the Structure of Wages," in *Advance in Econometrics*. Christopher Sims, ed. New York: Elsevier: 171-209.

Doiron, J.C., J.D. Shilling and C.F. Sirmans （1985）, "Owner versus Broker Sales: Evidence on the Amount of the Brokerage Commission Capitalized," *Real Estate Appraisal and Analyst*: 44-48.

Elder, H.A., L.V. Zumpano, and E.A. Baryla (2000), "Buyer Brokers: Do They Make a Difference? Their Influence on Selling Price and Search Duration," *Real Estate Economics,* 28,2: 337-362.

Frew, J. and G. D. Jud(1987), "Who Pays the Real Estate Broker's Commission?," *Research in Law and Economics*, 10: 177-187.

Gould, W. W. (1992), sg11.1: Quantile regression with bootsrapped standard errors. *Stata Technical Bulletin* 9: 19-21. Reprinted in Stata Technical Bulletin Reprints. 2: 137-139.

Gould, W. W. (1997), sg70: Interquantile and simultaneous-quantile regression. *Stata Technical Bulletin* 38: 14-22. Reprinted in Stata Technical Bulletin Reprints. 7:167-176.

Green, William H. (1993), *Econometric Analysis*. New York: Macmillan.

Hartog, J., Pedro T. Pereira and Jose Vieira（2001）, "Changing Returns to Education in Portugal during the 1980s and Early 1990s: OLS and Quantile Regession Estimators," *Applied Economics*, 33: 1021-1037.

Heckman, James J. (1979), "Sample Selection Bias as a Specification Error," *Econometrica*, 47: 153-161.

Janssen, C.T.L. and J. D. Jobson (1980), "Applications and Implementation on the Choice of

Realtor," *Decision Sciences*, 11: 299-311.

Jud, G..D. (1983), "Real Estate Brokers and the Market for Residential Housing," *American Real Estate and Urban Economics Association Journal*, 11: 69-82.

Jud, G. D. and James Frew (1986) , "Real Estate Brokers, Housing Prices, and the Demand for Housing," *Urban Studies*, 23: 21-31.

Kamath, R. and K. Yantek (1982) , "The Influence of Brokerage Commissions on Prices of Single-family Homes," *Appraisal Journal*: 63-70.

Koenker, R. and G. Bassett, Jr. (1978), "Regression Quantiles," *Econometrica*, 46: 211-244.

Koenker, R. and K. F. Hallock, (2001), "Quantile Regression," *Journal of Economic Perspectives*, 15, Num 4: 143-156.

Mortensen, D.T.,(1982), The Matching Process as a Noncooperative Bargaining Game. J.J. McCall, editor, *Economics of Information and Uncertainty*. University of Chicago Press.

Lee, L.,(1978), Unionism and Wage Rates: A Simultaneous Equations Models with Qualitative and Limited Dependent Variables, *International Economic Review*, 19: 415-33.

Reck, Clayton, (2003), Heterogeneity and Black-White Labor Market Differences: Quantile Regression with Censored Data 1979-2001, working paper, Dept of Economics, UIUC.

Roger, W. H. (1992), sg11: "Quantile regression standard errors". *Stata Technical Bulletin* 9: 16-19. Reprinted in Stata Technical Bulletin Reprints, 2: 133-137.

Rosen, S. (1974), "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition", *Journal of Political Economy*, 82: 34-55.

Salant, S. W. (1991) , "For Sale by Owner: When to Use a Broker and How to Price the House," *Journal of Real Estate Finance and Economics*, 4: 157-173.

Turnbull, G.K. and C.F. Sirmans(1993), "Information, Search, and House Prices," Regional Science and Urban Economics 23: 545-557.

Wu C. and P. F. Colwell(1986), “Equilibrium of Housing and Real Estate Brokerafe Markets Under Uncertainty, *American Real Estate and Urban Economics Association Journal*, 14,1: 1-23.

Yavas, A. (1992), “A Simple Search and Bargaining Model of Real Estate Markets,” *American Real Estate and Urban Economics Association Journal*, 20, 4: 533-548.

Yavas, Abdullah and Peter F. Colwell (1995) , “A Comparison of Real Estate Marketing System: Theory and Evidence,” *The Journal of Real Estate Research*, 10, No. 5: 583-599.

Yinger, J. (1981), “A Search Model of Real Estate Broker Behavior,” *American Economic Review*, 71: 591-605.

Yu, Keming, Zudi Lu, and Julian Stander (2003) , “ Quantile Regression: Applications and Current Research Areas,” *The Statistician*, 52,3: 331-350.

Zumpano, L.V., H. Elder, and E.A. Baryla (1996), “Buying a House and the Decision to Use a Real Estate Broker,” *Journal of Real Estate Finance and Economics*, 13: 169-181.

Table 1. Variable descriptions.

Variable	Description
P	House selling price
NOEXP	1 if the buyer is the first time homebuyer；0 otherwise.
DIS	1 if the buyer is out-of-town homebuyer；0 otherwise.
PING	The size of the house in Chinese area unit； 1 Ping is about 3.3057 m^2
PING2	The quadratic term of the size
AGE	The age of homebuyer
INC1 INC2 INC3 INC4 INC5 INC6	A vector of categorical monthly income variables, equaling 1 if the buyer's income falls into that category, 0 otherwise. The categories are: \$0-\$30,000；\$30-\$60,000；\$60-\$90,000；\$90-\$120,000；\$120-\$150,000；\$150,000 and up. （in New Taiwan Dollars, NTD/USD is about 33/1）
GARAGE	1 if the house sale with a garage；0 otherwise.
TOP	1 if the house is at the top floor；0 otherwise.
GROUND	1 if the house is at the ground floor；0 otherwise.
YEARS	The age of the house
YEARS2	The quadratic term of the years
LOCA1 LOCA2 LOCA3 LOCA4 LOCA5 LOCA6	1 if the house is located in Taipei city；0 otherwise. 1 if the house is located in Taipei county；0 otherwise. 1 if the house is located in Taichung city；0 otherwise. 1 if the house is located in Taichung county；0 otherwise. 1 if the house is located in Koushung city；0 otherwise. 1 if the house is located in Koushung county；0 otherwise.
BROKER	1 if the buyer purchase the house with broker assistance；0 otherwise.

Table 2. Descriptive Statistics of Variables

	Full Sample		Non-Broker-Assisted Purchase		Broker-Assisted Purchase	
Variables	Mean	S.D.	Mean	S.D.	Mean	S.D.
P	526.958	310.383	537.826	315.614	515.529	304.482
NOEXP	0.559	0.497	0.535	0.499	0.585	0.493
DIS	0.463	0.499	0.453	0.498	0.474	0.499
PING	40.084	18.852	42.235	20.117	37.821	17.141
AGE	37.320	7.565	37.367	7.785	37.271	7.329
INC2	0.374	0.484	0.383	0.486	0.364	0.481
INC3	0.347	0.476	0.346	0.476	0.347	0.476
INC4	0.149	0.356	0.150	0.357	0.147	0.354
INC5	0.048	0.214	0.042	0.201	0.054	0.226
INC6	0.042	0.199	0.035	0.185	0.048	0.214
GARAGE	0.393	0.488	0.424	0.494	0.360	0.480
TOP	0.154	0.361	0.151	0.358	0.156	0.363
GROUND	0.054	0.227	0.064	0.245	0.044	0.204
YEARS	9.217	8.485	7.515	8.437	11.008	8.164
LOCA1	0.159	0.366	0.131	0.337	0.189	0.392
LOCA2	0.390	0.488	0.331	0.471	0.452	0.498
LOCA3	0.093	0.291	0.087	0.282	0.100	0.300
LOCA4	0.097	0.296	0.122	0.328	0.070	0.255
LOCA5	0.172	0.378	0.208	0.406	0.135	0.341
LOCA6	0.088	0.284	0.120	0.326	0.055	0.227
No. of Observation	2,819		1,445		1,374	

Table 3. Price distribution, Skewness, and Kurtosis

Main quantile	House price
0.01	130
0.05	210
0.10	250
0.25	330
0.50	465
0.75	625
0.90	850
0.95	1050
0.99	1700
Skewness	3.27
Kurtosis	23.73

Table 4. Probit estimates of choice of broker

Variable	Coefficient	t-Ratio
CON	-0.404	-2.30
NOEXP	0.166	3.29
DIS	0.088	1.82
YEARS	0.032	11.13
AGE	-0.003	-0.90
INC2	-0.001	-0.01
INC 3	0.060	0.48
INC 4	0.063	0.47
INC 5	0.257	1.58
INC 6	0.282	1.67

Log likelihood= -1881.4088
LR chi2(9)= 143.36
Significance level= 0.0000

Table 5. House price estimates: Ordinary least squares (dependent variable is log(sale price)).

Variable	A Without selection correction		B With selection correction	
	Coefficient	t-Ratio	Coefficient	t-Ratio
CON	4.881	91.45	2.807	3.02
NOEXP	5×10^{-4}	0.00	0.208	2.21
DIS	0.001	0.11	0.111	2.19
LOCA1	0.775	32.60	0.776	32.64
LOCA2	0.368	18.84	0.369	18.92
LOCA3	-0.041	-1.40	-0.040	-1.36
LOCA4	-0.037	-1.30	-0.037	-1.29
LOCA5	0.021	1.00	0.022	1.03
PING	0.022	30.33	0.022	30.39
PING2	6×10^{-5}	-19.43	6×10^{-5}	-19.46
TOP	0.012	0.69	0.012	0.68
GROUND	0.131	4.73	0.131	4.73
AGE	0.004	4.52	2×10^{-4}	0.12
INC2	0.103	3.21	0.104	3.23
INC 3	0.181	5.58	0.258	5.45
INC 4	0.243	6.92	0.324	6.43
INC 5	0.314	7.39	0.629	4.28
INC 6	0.451	10.10	0.796	4.95
GARAGE	0.128	8.87	0.128	8.89
BROKER	-0.015	-1.13	-0.016	-1.24
YEARS	-0.024	-11.01	0.020	0.99
YEARS2	0.001	8.68	8×10^{-4}	3.02
λ *	--	--	1.938	2.24
Adjusted R-squared	0.5679		0.5686	

* λ is Inverse Mills ratio.

Table 6A. House price estimates: Quantile Regression without selection correction **
(dependent variable is log(sale price)).

Variable	Quantile at 0.10 Coef	0.10 t-Ratio	0.25 Coef	0.25 t-Ratio	0.50 Coef	0.50 t-Ratio	0.75 Coef	0.75 t-Ratio	0.90 Coef	0.90 t-Ratio
CON	4.095	28.16	4.443	39.24	4.734	52.48	5.227	54.75	5.480	50.32
NOEXP	0.015	0.79	0.010	0.61	0.011	0.75	0.010	0.60	-0.022	-0.96
DIS	0.014	0.90	0.017	1.25	0.004	0.42	-0.005	-0.55	0.004	0.18
LOCA1	0.769	10.94	0.857	19.55	0.858	40.89	0.740	16.55	0.708	15.89
LOCA2	0.400	7.07	0.439	15.57	0.441	18.87	0.316	10.12	0.270	7.46
LOCA3	-0.066	-0.97	-0.007	-0.22	0.024	0.84	-0.053	-1.28	-0.029	-0.68
LOCA4	-0.081	-1.40	-0.081	-1.95	-0.032	-1.04	-0.050	-1.37	-0.003	-0.06
LOCA5	0.002	0.03	0.041	1.10	0.011	0.35	-0.060	-1.85	0.030	0.58
PING	0.032	8.76	0.029	9.79	0.026	10.30	0.021	10.52	0.018	14.21
PING2	1×10^{-4}	-3.99	1×10^{-4}	-4.00	8×10^{-5}	-3.62	5×10^{-5}	-4.17	4×10^{-5}	-6.01
TOP	-0.014	-0.52	0.027	1.38	0.010	0.50	0.028	1.63	0.043	1.26
GROUND	0.083	1.82	0.064	1.28	0.139	4.33	0.182	5.01	0.183	3.37
AGE	0.004	2.00	0.004	3.05	0.005	7.06	0.004	5.99	0.005	4.27
INC2	0.271	4.28	0.106	1.62	0.047	1.33	-0.019	-0.45	-0.030	-0.54
INC3	0.362	6.06	0.184	2.87	0.117	4.09	0.063	1.57	0.024	0.43
INC4	0.381	5.16	0.228	3.31	0.173	5.43	0.105	2.05	0.126	1.79
INC5	0.440	6.50	0.280	3.87	0.217	6.56	0.206	4.09	0.243	3.66
INC6	0.455	4.01	0.341	4.40	0.289	6.51	0.377	5.33	0.530	3.97
GARAGE	0.080	2.61	0.112	6.55	0.091	5.21	0.128	5.87	0.142	5.09
BROKER	0.043	1.96	-0.011	-0.69	-0.027	-1.77	-0.057	-2.92	-0.058	-3.83
YEARS	-0.029	-9.69	-0.024	-14.19	-0.023	-12.85	-0.019	-5.84	-0.016	-4.00
YEARS2	0.001	8.44	0.001	11.52	0.001	7.94	0.001	5.02	5×10^{-4}	3.64
Pseudo R2	0.346		0.363		0.382		0.379		0.388	

** In our empirical analysis, we employ the statistics software STATA that can compute bootstrapped standard errors for quantile regression estimators（Gould, 1992；Roger, 1992）.

Table 6B. House price estimates: Quantile Regression with selection correction **
(dependent variable is log(sale price)).

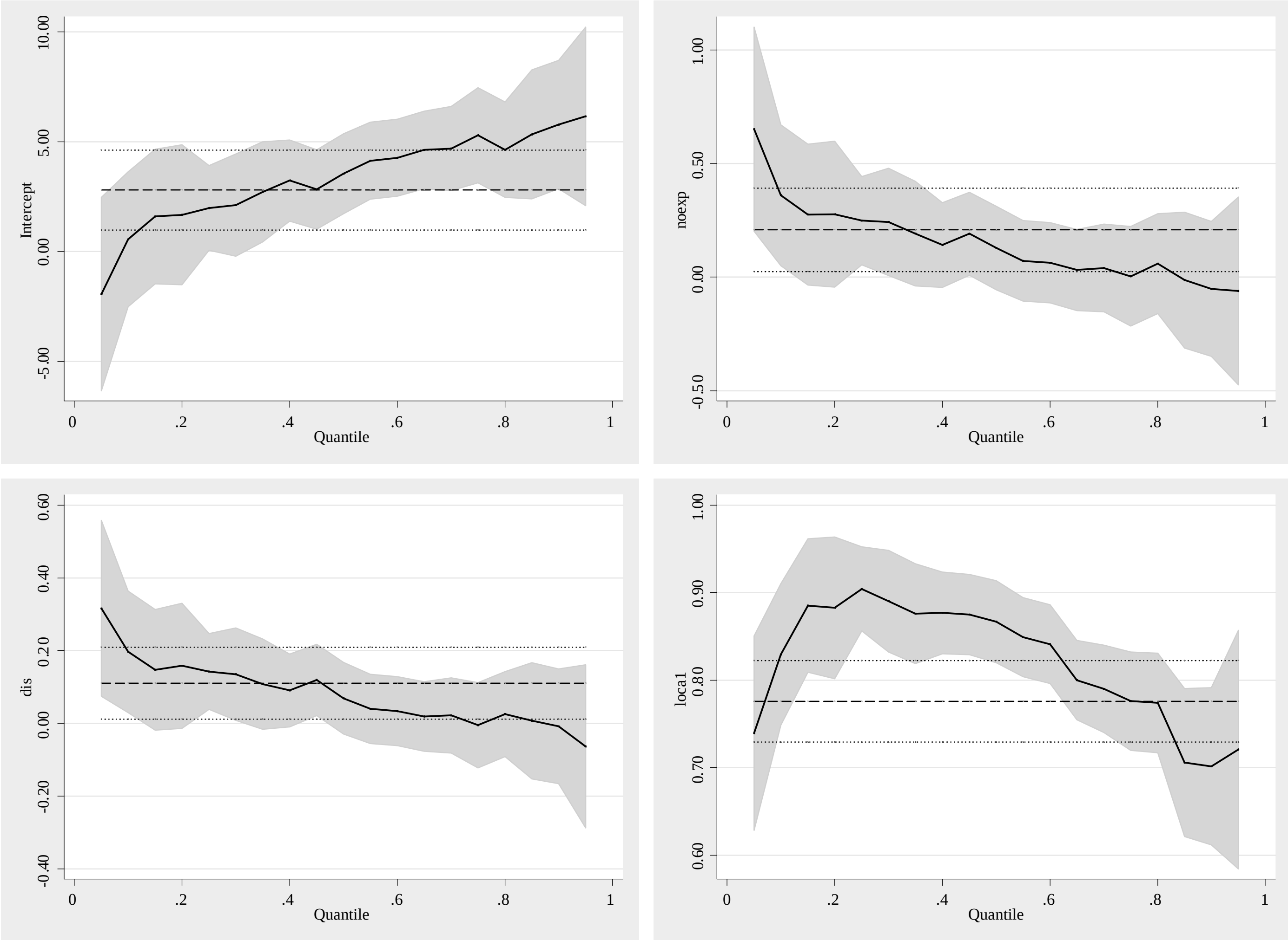
Variable	Quantile at									
	0.10		0.25		0.50		0.75		0.90	
	Coef	t-Ratio	Coef	t-Ratio	Coef	t-Ratio	Coef	t-Ratio	Coef	t-Ratio
CON	0.561	0.40	1.970	2.62	3.544	4.41	5.293	4.76	5.777	3.74
NOEXP	0.360	2.40	0.249	3.14	0.128	1.54	0.004	0.03	-0.052	-0.33
DIS	0.197	2.51	0.143	3.55	0.069	1.53	-0.005	-0.09	-0.008	-0.09
LOCA1	0.829	21.56	0.904	26.72	0.867	34.94	0.776	29.56	0.702	18.59
LOCA2	0.451	13.40	0.486	14.41	0.451	25.64	0.349	14.92	0.266	9.02
LOCA3	-0.053	-1.11	-0.006	-0.18	0.015	0.54	-0.052	-1.44	-0.036	-1.10
LOCA4	-0.077	-1.74	-0.083	-2.40	-0.032	-1.16	-0.049	-1.26	-0.003	-0.09
LOCA5	0.055	2.45	0.084	3.46	0.020	1.16	-0.035	-1.80	0.021	0.41
PING	0.033	8.49	0.030	7.78	0.026	10.25	0.021	8.61	0.018	8.58
PING 2	-1×10^{-4}	-4.37	-1×10^{-4}	-3.59	-8×10^{-5}	-3.78	-5×10^{-5}	-2.72	-5×10^{-5}	-3.30
TOP	-0.014	-0.35	0.021	0.82	0.009	0.34	0.028	1.11	0.041	1.08
GROUND	0.087	1.84	0.075	1.22	0.140	3.92	0.178	6.11	0.182	4.01
AGE	-0.002	-0.74	-3×10^{-4}	-0.25	0.003	1.69	0.004	1.81	0.006	1.77
INC2	0.276	2.43	0.113	1.53	0.048	1.30	-0.026	-0.53	-0.030	-0.48
INC3	0.506	4.66	0.276	3.41	0.160	3.63	0.049	0.75	0.015	0.17
INC4	0.545	4.81	0.329	4.20	0.222	5.00	0.089	1.59	0.118	1.33
INC5	0.974	4.82	0.607	4.62	0.397	3.13	0.182	0.89	0.193	0.73
INC6	1.016	4.40	0.744	4.90	0.483	3.11	0.339	1.62	0.483	1.72
GARAGE	0.073	3.29	0.112	6.66	0.092	5.65	0.127	8.46	0.144	5.54
BROKER	0.042	2.58	-0.009	-0.77	-0.029	-2.43	-0.058	-4.15	-0.055	-2.28
YEARS	0.045	1.46	0.025	1.72	0.002	0.12	-0.021	-0.90	-0.022	-0.68
YEARS2	3×10^{-4}	1.69	4×10^{-4}	5.17	0.001	5.60	0.001	4.34	0.001	2.66
λ	3.202	2.40	2.267	3.17	1.117	1.45	-0.087	-0.08	-0.267	-0.18
Pseudo R2	0.348		0.364		0.383		0.379		0.388	

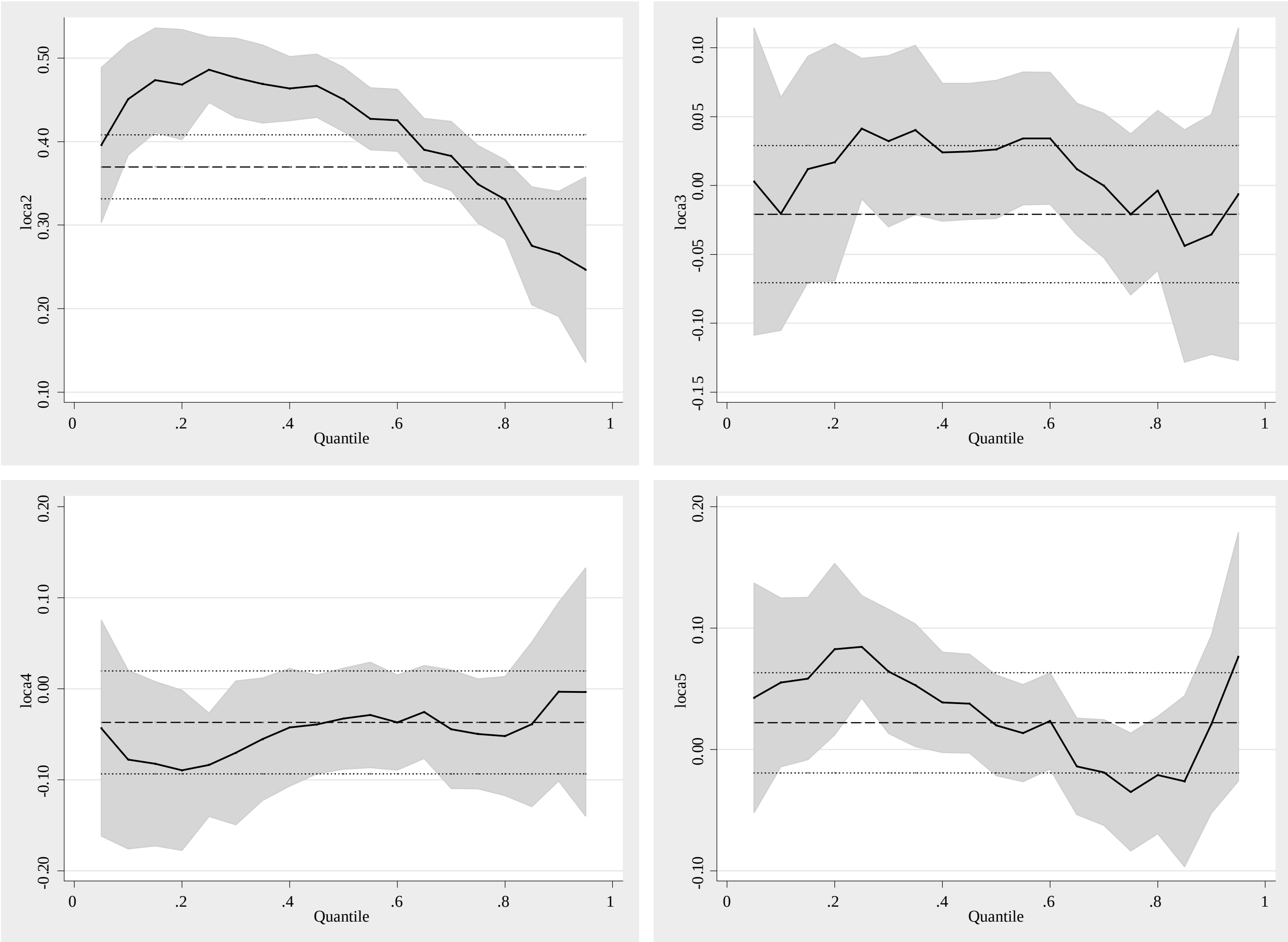
** In our empirical analysis, we employ the statistics software STATA that can compute bootstrapped standard errors for quantile regression estimators (Gould, 1992 ; Roger, 1992) .

Table 7. *p* value test of inter-quantile differentials for BROKER

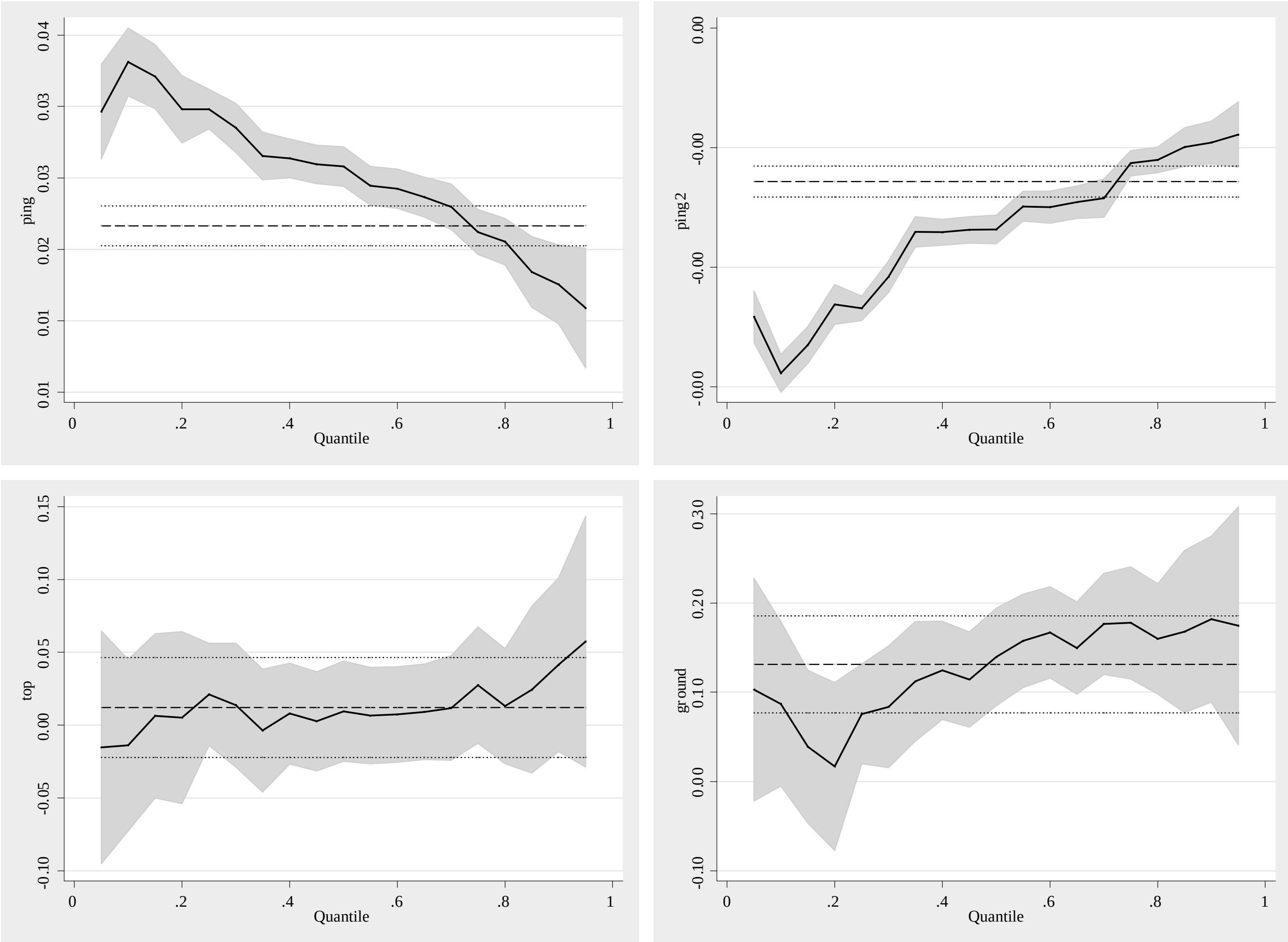
Q	0.05	0.15	0.25	0.35	0.45	0.50	0.55	0.65	0.75	0.85	0.95
0.05		※	⊚	⊚	⊙	⊙	⊙	⊙	⊙	⊚	⊙
0.15			⊚	⊚	⊙	⊙	⊙	⊙	⊙	⊙	⊙
0.25				※	⊚	※	※	○	⊚	※	※
0.35					※	※	※	※	○	※	※
0.45						※	※	※	※	※	※
0.50							※	※	※	※	※
0.55								※	※	※	※
0.65									※	※	※
0.75										※	※
0.85											※
0.95											

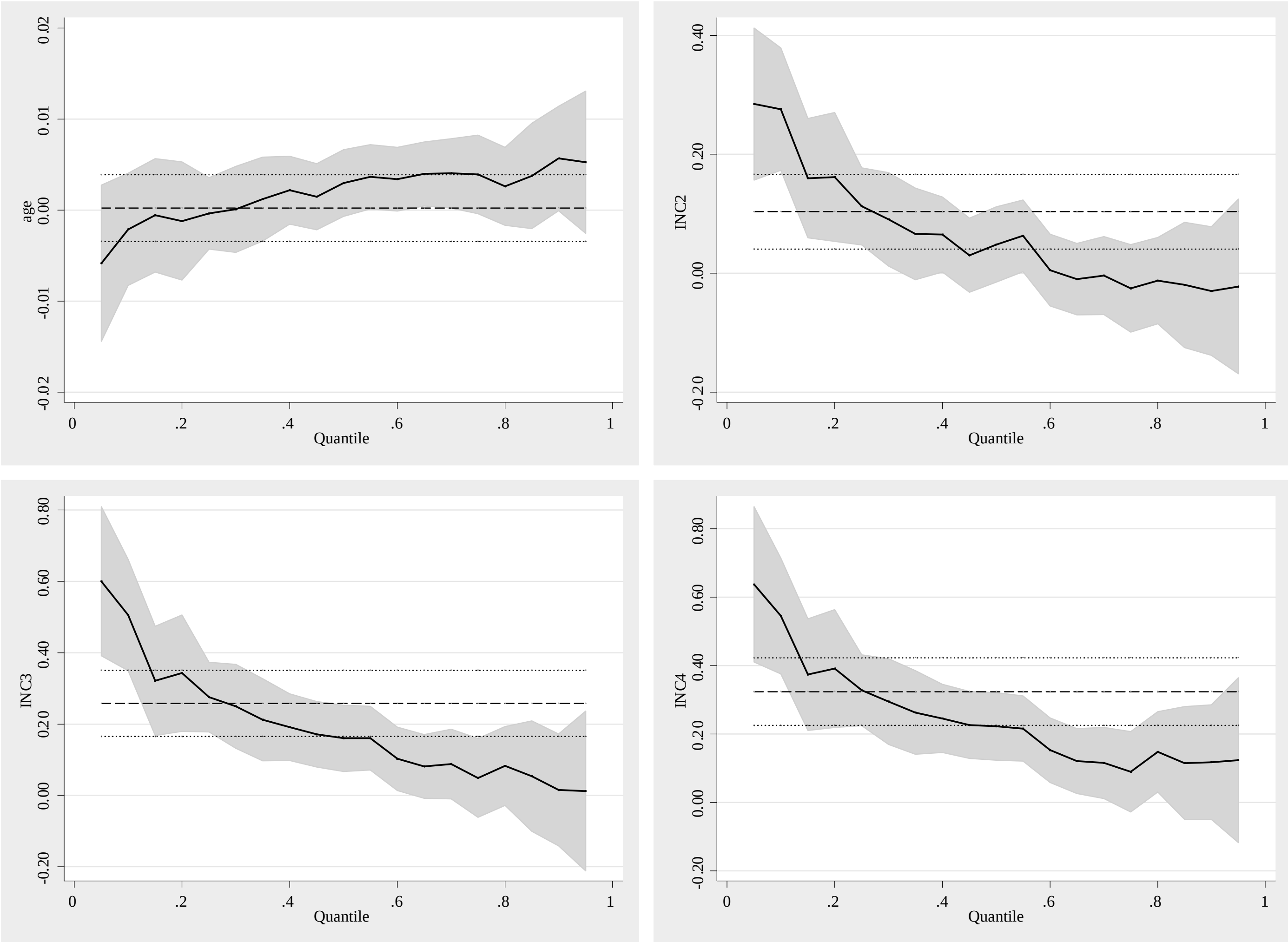
⊙ *p*-value at the level of 1%；⊚ *p*-value at the level of 5%；○ *p*-value at the level of 10%；□ not significant

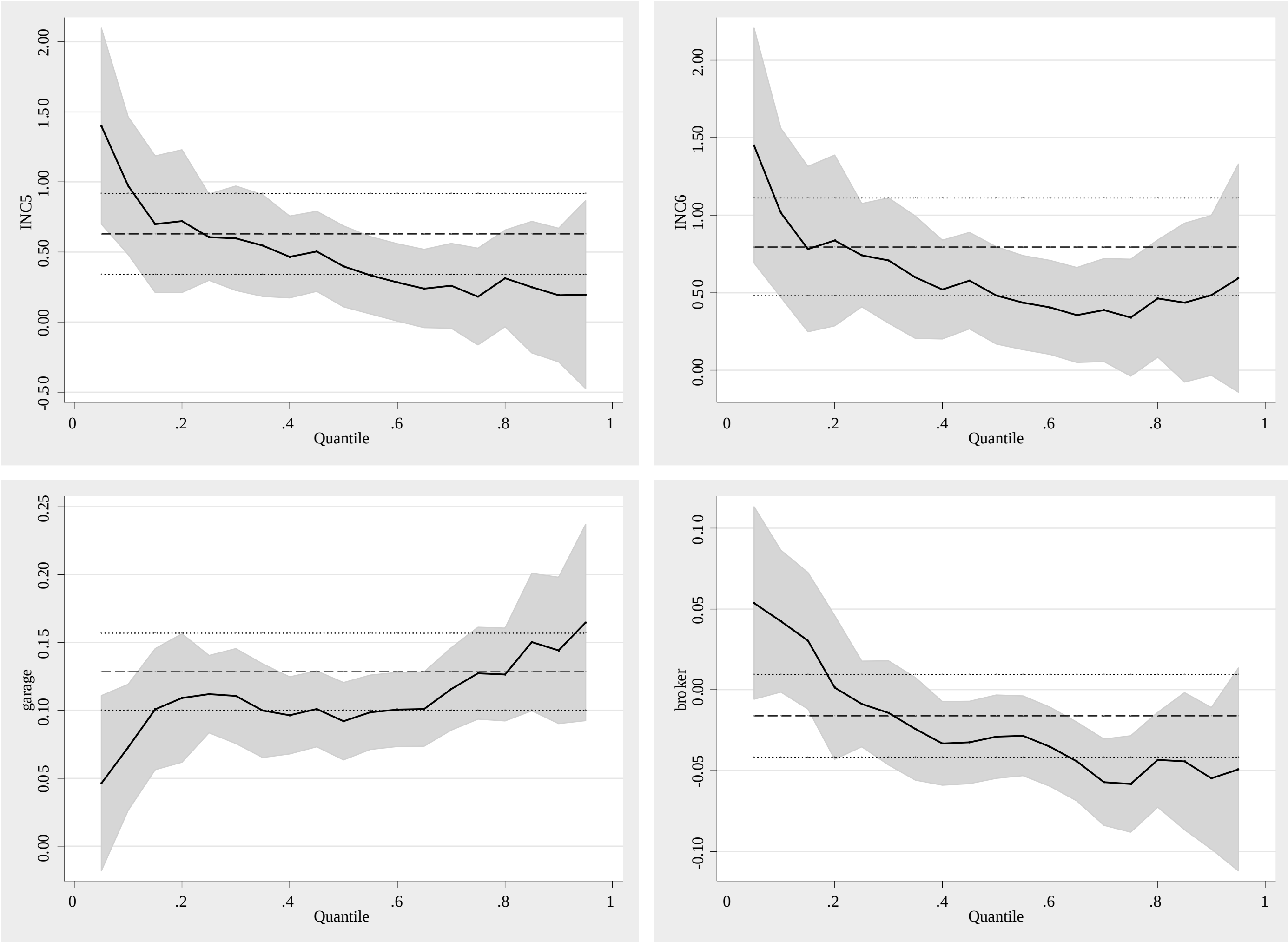

Intercept
10.00
5.00
0.00
-5.00
0
.2
.4
.6
.8
1
Quantile
noexp
1.00
0.50
0.00
-0.50
0
.2
.4
.6
.8
1
Quantile
dis
0.60
0.40
0.20
0.00
-0.20
-0.40
0
.2
.4
.6
.8
1
Quantile
loca1
1.00
0.90
0.80
0.70
0.60
0
.2
.4
.6
.8
1
Quantile



loca2
0.10
0.20
0.30
0.40
0.50
0
.2
.4
.6
.8
1
Quantile
loca3
-0.15
-0.10
-0.05
0.00
0.05
0.10
Quantile
loca4
-0.20
-0.10
0.00
0.10
0.20
Quantile
loca5
-0.10
0.00
0.10
0.20
Quantile


ping
0.04
0.03
0.03
0.02
0.01
0.01
0
.2
.4
.6
.8
1
Quantile
ping2
0.00
-0.00
-0.00
-0.00
Quantile
top
0.15
0.10
0.05
0.00
-0.05
-0.10
Quantile
ground
0.30
0.20
0.10
0.00
-0.10
Quantile


age
0.02
0.01
0.00
-0.01
-0.02
Quantile
INC2
0.40
0.20
0.00
-0.20
Quantile
INC3
0.80
0.60
0.40
0.20
0.00
-0.20
Quantile
INC4
0.80
0.60
0.40
0.20
0.00
-0.20
Quantile
0
.2
.4
.6
.8
1


INC5
INC6
garage
broker
Quantile

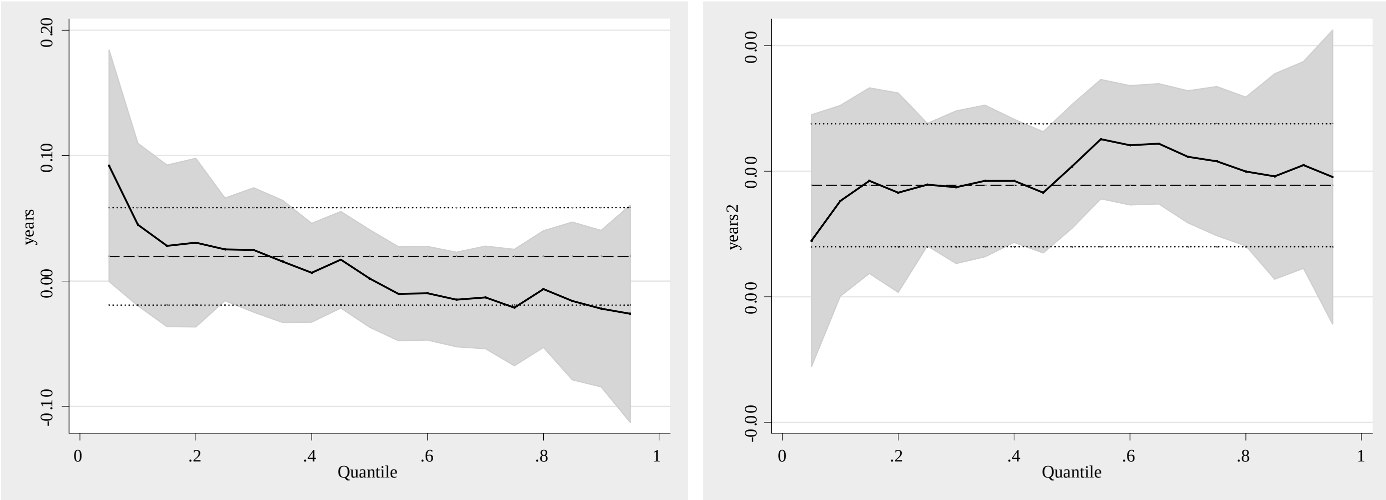


Figure 1. Quantile Estimates for the House Price Model