Distribution of Demand for School Quality: Evidence from Quantile Regression

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ABSTRACT

Our results show that high-income families place significantly higher value on academic achievement than low-income families. High-income families are also more likely to penalize house price for non-desirable non-academic school quality. This paper uses quantile regression to examine the distribution of demand for school quality. For academic achievement, the average effects as estimated by OLS are biased toward zero due to "aggregation" of families' willingness to pay. We take advantage of a court-ordered redistricting as a quasi-random assignment of school quality. Subdivision and school fixed-effects are used to control for unobserved characteristics.

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I. INTRODUCTION

School choice programs are expected to improve access to academically superior schools and reduce educational inequality. An important underlying assumption is that parents choose schools based on academic achievement. Critics of school choice programs, however, argue that low-income families are more likely to make their decisions based on non-academic criteria.[1] If low-income families have significantly less demand for academic achievement, then school choice programs may not be as effective in improving school quality or education equity.

This paper uses quantile regression to examine the distribution of parents' demand for school quality with respect to family income. The existing economic literature is mixed on parents' reactions to qualitative rankings of school performance.[2] According to Schneider and Buckley (2002), survey-based studies indicate the demand for academic achievement is stronger among low-income families, but these studies have been criticized for not being based on actual behavior. A recent study using parental ranking of teachers by Jacob and Lefgren (2007) found that low-income families rank academic achievement higher than student satisfaction, while the reverse is true for high-income families. This finding is in contract from another recent study based on a school choice experiment by Hastings, Kane, and Staiger (2005), who found the demand for academic achievement increases with family income.

Economists have traditionally used housing market data to examine the demand for school quality. In a pioneering study, Black (1999) showed that one standard deviation rise in test scores is worth about a 2 percent increase in house price. Haurin and Brasington (1996) find positive relationships between standardized test scores and house prices. These studies have generally found that parents are willing to pay more for superior academic achievement (e.g. Haurin and Brasington, 1996; Black, 1999; Figlio and Lucas, 2004). The distribution of willingness to pay, however, has not been closely examined.

An effective method for examining the distribution of demand is quantile regression. Quantile regression allows the estimated coefficients to vary along the conditional distribution of the dependent variable. Hence, it can be used to investigate distributional or equity aspects of outcomes. It is used in this paper to examine the distribution of demand for school quality. According to findings by Jacob and Lefgren (2007), examining across the distribution is important because the average effects can hide significant heterogeneity in parents' demand for school quality. This study also takes advantage of a court-ordered school redistricting in Louisiana as a random assignment of school quality that can address the usual problems associated with potential endogeneity of school quality. Following Figlio (2004), school and subdivision fixed-effects are used to control for unobserved time-invariant characteristics, including those normally considered as a part of spatial correlations.

After controlling for relevant characteristics, we find that the estimated willingness to pay is remarkably sensitive to the distribution of house price. High-income families place significantly higher value on academic achievement than low-income families. The average effect as estimated by OLS significantly understates the demand for school quality due to "aggregation" of families' willingness to pay. High-income families are more likely to penalize house price for non-desirable non-academic school qualities. These results are similar to the conclusion drawn by Hastings, Kane, and

Staiger (2005) who found the demand for academic achievement to be increasing with family income. Because parent demand for school achievement appears to be strongly affected by the availability of household resources, merely improving access to schools may not be as effective in delivering quality education to children of all backgrounds.

II. Model and Estimation Strategy

This study uses purchase history for single-unit houses in the East Baton Rouge Parish, Louisiana that spans a four-year period from 1999 to 2002. This area is served by the East Baton Rouge Parish School System, which consists of 90 schools with approximately 46,200 students. It is the largest school district in the state. By using the data from a single school system with a single city-county government structure, unobserved differences in property tax rates or public services can be minimized. This study is limited to elementary schools due to data availability.

Hedonic model of house price with quantile regression

The outcomes of interest are the purchase price of single-unit dwellings in the area. The marginal willingness to pay for local school quality is likely to differ across the range of house prices. Recent research shows that purchasers of higher-end houses value house characteristics, such as square footage or the number of bathrooms, differently from buyers of lower-end houses (Sirmans et. al., 2005).[3] To investigate differences in willingness to pay for school quality, we examine the willingness to pay along the distribution of house prices at various quantiles or percentiles. To this end, quantile regression estimates a series of linear hedonic price equations that might look like this:

$$\ln(\text{price}_\tau) = c_\tau + \alpha_\tau \mathbf{H} + \beta_\tau \mathbf{N} + \delta_\tau \mathbf{M} + \gamma_\tau \mathbf{S} + \varphi_\tau \mathbf{F} + \varepsilon \qquad (1)$$

in which the natural log of house price, $\ln(\text{price}_\tau)$, is a function of the vectors of house characteristics **H**, neighborhood characteristics **N**, house market conditions **M**, school characteristics **S**, and the fixed effects **F** for geographic locations, neighborhood schools, and year and season of sale. Locations fixed-effects control for time-invariant unobserved characteristics. The estimated coefficients depend on the quantile or percentile, τ, of the distribution of the natural log of house price.[4]

For hedonic price equations, quantile regression allows researchers to examine the marginal effects at the either ends the dependent variable without having to impose strict parametric assumptions associated with segmenting or partitioning data (Buchinsky, 1994; Mata and Machado, 1996; and Koenker and Hallock, 2001).[5] Unlike OLS, quantile regression can be employed to explain the determinants of the dependent variable at any point of the distribution of the dependent variable. Symmetric weights are used for the median (quantile = 0.5) while asymmetric weights are used for all other quantiles. We also use bootstrapped standard errors, which are significantly less sensitive to heteroskedasticity than analytic standard errors (Gould, 1992, 1997).

Quasi-random experiment in school redistricting

Our dataset is built around a quasi-random experiment in which a series of court-orders redistricted the Baton Rouge school system. This redistricting resulted in random changes in school quality for some houses due to reassignment. The federal court initially ordered redistricting in 1981 for the purpose of desegregating schools in response to a lawsuit, *Davis et al. v. East Baton Rouge Parish School Board*. It closed several schools and randomly assigned students to schools with a different racial majority. This resulted in widespread busing of students, which proved highly unpopular and disruptive.[6] In 1996 the federal court reversed itself and ordered the reestablishment of local school attendance zones with less busing. This, however, led to serious overcrowding. The final round of redistricting was ordered in 2001 to alleviate the crisis. The last redistricting created a lot of uncertainty with highly divergent plans being considered until the last minute.[7] Students from 11 schools were finally reassigned to 16 other schools in a rushed manner in September of the same year.

These circumstances point to the random or unexpected nature of the redistricting along the dimensions of interest. We argue that the final redistricting in response to overcrowding can be used to reveal the relationship between house price and school quality because it was externally imposed by the federal court and not based on geographic or neighborhood proximity. This represents a quasi-random assignment of school quality in which some houses were unpredictably reassigned to a higher quality school and others to a lower quality school. Such reassignments can be used to solve the typical identification problems associated with regression analyses.

III. Data

Our sample consists of 7,502 house sales that occurred in the East Baton Rouge Parish School System between 1999 and 2002. Table 1 gives the summary statistics of the variables of interest. The dependent variable, house price, has a mean of just under $129,000 in 1999 dollars. House prices were deflated using the region-specific Consumer Price Index from the U.S. Bureau of Labor Statistics. There are 343 subdivisions and 43 elementary schools in this area. An average home in our sample has 3.25 bedrooms and 2 bathrooms. The subdivisions in this area were established anywhere from very recently to 60 years ago, with 25 percent of houses built 20-30 years ago. Approximately 5.6 percent of houses were reassigned to different schools at the end of summer in 2001. To control for the effect of reassignment, our specification includes the interaction between the indicator for reassignment and various measures of school characteristics. This will account for the instances in which improved school quality arises from reassignment.

School Attributes and School Performance

The vectors of school characteristics **S** we use to measure academic quality in this paper include the Iowa Tests of Basic Skills given to third graders (mean of 50 and standard deviation of just over 12). We use percentile ranking relative to the national norms, which is the standard. An Iowa score of 78, for example, would mean the average score at the school is higher than 78 percent of students in the U.S. In addition to being readily available to parents, the percentile Iowa scores avoid the problem of subjectivity associated with qualitative rankings of school performance.

Two other school attributes normally associated with academic school quality include the proportion of teachers with a master's degree (43.3 percent) and the average class size (16.75 students per class). The proportion of faculty with advanced degrees is a part of district-determined school inputs into the education production function.[8] The average class size is another.[9] A lower student to teacher ratio may be instrumental in promoting student learning, especially in lower elementary grades. A comprehensive review by Hanushek (1986) indicates that the effect of class size reduction on achievement is at best ambiguous, with various studies showing both positive and negative results.

Non-academic school attributes of interest include the proportion of black students (62.6 percent), total number of students, the proportion of students with subsidized lunch (64.2 percent), and the straight-line distance from house to school (1.59 miles).[10] Regression studies have generally shown that student racial compositions and physical proximities to school are also important characteristics of the school environment (Weiher and Tedin, 2002; and Schneider and Buckley, 2002). Some research indicates that proximity to a school is actually a nuisance (Emerson, 1972), while other research indicates that proximity to a school has an impact equivalent to that of an increase in school test scores (Kane, et al. 2003). The distance between a residence and its assigned school should have important impacts on the premium homebuyers pay for residences that are close to good schools.[11]

House Price and Market Conditions

Each house is geocoded to a specific elementary school and subdivision. The vector of house characteristics **H** includes the usual variables such as number of bedrooms, number of bathrooms, age, living area, and net area. Living area and net area are the total area under the roof measured in thousands of square feet. To control for the potential effects of spatial correlation, we follow Figlio (2004) by including subdivision fixed-effects. These fixed-effects also control for unobserved time-invariant location amenities. The physical integrity of each subdivision was verified by mapping them onto a twodimensional surface. Two-way fixed-effects for four seasons and four years are also included to control for seasonality in house price.

Our neighborhood housing market conditions, **M**, are measured in part by the number of competing houses that are for sale at the same time a house is on the market. The number of houses for sale in an area around a house can have localized effects on the distribution of prospective buyers and sellers. We can consider this as a part of time-variant spatial interdependencies. A greater supply of houses for sale increases the competition among sellers for buyers considering houses in the neighborhood — the localized competition effect. Similarly, a greater number of houses for sale may draw more prospective buyers to the neighborhood, potentially increasing the chance of matching a particular house with a buyer — the shopping externality effect.

Following Turnbull and Dombrow (2006), neighborhood market conditions are measured by the average number of competing listings in the neighborhood each day the house is on the market – listing density. This measure for each house *i* is calculated as follows:

$$\text{Listing Density} = \sum \frac{\left(1 - D(i,j)\right)^2 O(i,j)}{s(i) - l(i) + 1} \tag{5}$$

where the summation is taken over all houses within 20 percent larger or smaller (in terms of living area) that are within one mile of house *i*. Here, $l(i)$ and $s(i)$ are the listing date and sales date for house *i*, respectively, so that time-on-market is $s(i)-l(i)+1$. $O(i,j)$ represents the overlapping marketing duration for contemporaneously listed houses *i* and *j,* and is defined as $O(i,j) = \min[s(i), s(j)] - \max[l(i), l(j)] + 1$. $D(i,j)$ is the distance in miles between houses *i* and *j*. The calculation of this variable for each house in the data set includes all applicable competing house sales, including houses in areas geographically neighboring our sample as well as any house listed before our sample period with time-on-market that overlaps with our sample period.

IV. Results

Table 2 reports estimates of the relationship between school quality measures and house price. All of the models include subdivision dummies and school dummies as neighborhood controls. Column (1) represents the baseline results using OLS. The OLS results for school attributes are mixed and often not significant. The various measures of academic school quality (the average Iowa test score, the proportion of teachers with a master's degree, and the average class size) have non-significant statistical significance. Non-academic school qualities, on the other hand, are more likely to be statistically significant. House price is slightly penalized when there is an increasing percentage of black students and total number of students. An increase in students with subsidized lunch by 1 percent is expected to increase house price by 0.2 percent. The marginal effect of being reassignment under the court-ordered redistricting translates into a price penalty of about 0.5 percent and is not significant.[12]

Columns (2)-(6) contain the results from quantile regression at various quantile or percentiles across the conditional distribution of house price.[13] The results from the quantile regression are noticeably different and make more sense than the OLS result. With the exception of the class size, we see a clear trend in which the effect of academic school quality rises with the house price. The effects of academic school qualities also become significant but only at the higher end of the house market. The marginal effect of the Iowa test score rising from -0.02 percent at the 10th percentiles to 0.07 percent at the

90th percentiles. The effect of Iowa test also changes from negative and not significant to positive and highly significant. The effect of proportion of teachers with a master's degree similarly rises across the distribution of house price and become statistically significant.

At the 90th percentile, one standard-deviation rise in the Iowa score (about 24 percentage points) is worth about 0.9 percent of the house price. This is about $1100 at the average house price of $129,000, or about $1800 at the 90th percentile of the house price. The one standard-deviation effect of master's degree is worth about 0.7 percent of the house price. These results are about the half of the effect estimated by Black (1999) for one standard deviation improvement in school quality.

For the effect of the average Iowa test score, it is notable that the OLS coefficient takes a value (5.07e-05) that is located in the middle of the range of values taken by the quantile regression coefficients (-0.000215 to 0.000745). This suggests that the estimated coefficient for OLS is potentially biased downward due to the aggregation of the negative and positive effects at either end of the distribution. Because OLS is a conditional means estimator, it does not account for possibly opposing effects at either end of the house price distribution.

The changes in the estimated coefficients across the percentiles or the distribution of house price are visibly illustrated in the collection of graphs in the Figure 1. We see that the estimated willingness to pay for the Iowa test score or the proportion of teachers with master's degree rises across the distribution of house price. The increasing valuations attached to academic quality as a function of house price indicate that the households with higher family incomes have a significantly stronger demand for academic achievement than lower-income families. In contrast, the demand for academic achievement at the lower end of the distribution is not significantly different from zero and, in fact, has a negative sign for the average Iowa test score.

The sign for the estimated effect of the average class size is positive and increasing with house price. Because we already control for academic achievement through the inclusion of Iowa test score, and class size is an input rather than an output of educational process, we do not view this as evidence that academic quality lowers house price. As noted earlier, the effect of class size on academic achievement is a subject of much controversy. The positive association found in our study may be due to the fact that schools in the older neighborhoods with lower house prices are more likely to have smaller classrooms. Special education classes also tend to have a small class sizes and associated with significantly lower academic performance. We do not address these possibilities due to the lack of data.

The results for the non-academic school qualities indicate that high-income families are also more likely to penalize house price for the presence of non-desirable non-academic qualities. The marginal effect of distance to school and the school size as measured by the student population is negative. The effect is significantly larger at the upper end of the distribution. The presence of black students and the students receiving subsidized lunch may or may not be negative in these neighborhoods considering that the average proportion of black students is 62 percent and the students receiving subsidized lunch is 64 percent. The estimated effect of proportion of black students is negative but they tend to move around without a clear trend across the distribution of house price, which suggests the housing market directly discounts schools based on race but not necessarily associated due to income differences. The coefficient on proportion of students with subsidized lunch, however, is positive and significant in both OLS and quantile estimations. This further suggests that house price is not systematically influenced by socioeconomic integration. We also draw attention to the fact that the state of Louisiana focuses a large share of financial rewards on schools that meet or exceed achievement growth targets, including students who are placed on school lunch subsidies. After controlling for school fixed effects, we cannot ascertain whether the housing market shares state policymakers' enthusiasm for these measures or that the housing market values the incremental state resources for schools with improved performance.

Note that the coefficient estimates on physical house characteristics are all reasonable and very robust across the specifications. This finding is supportive of the idea that omitted housing attributes do not vary systematically across neighborhoods. If omitted attributes varied systematically across subdivisions, the attributes would likely be correlated with observed variables, like square footage and number of bedrooms, and therefore cause bias in the cross-sectional estimated coefficients for those variables. We do not discuss coefficients on physical house characteristics as they are not the focus of our study.

Robustness Check

One way to control for omitted variables is to use a repeat sales model that differences out constant factors. There are 274 repeat sales in our sample where a house was sold before and after the court-assigned redistricting.[14] This represents a unique sample in which the reassigned school represents a quasi-random change in school characteristics for the same set of houses. Although the sample size is not large enough to run a full specification, it can be used to validate our earlier findings. The results of the long-differenced model with a limited specification using the 274 repeat sales are presented in Table 3. None of the estimated coefficients are statistically significant, but we are able to observe a similar trend across OLS and various percentiles of quantile regression. The OLS specification in Column 1 takes a value that is between the estimated coefficients for the 25th and 50th percentiles for quantile regressions. This result reinforces our earlier finding from the full specification in which the estimated effect of Iowa test score is apparently cancelled out due to the “aggregation” of the estimated coefficients.

Although it is not estimated with sufficient precision, the estimated effect of Iowa test score at the 90th percentile is about three times larger than the non-differenced results from Table 2. The rest of school characteristics in Table 3 generally have the same signs but do not appear to trend towards being smaller or larger in magnitude than the non-differenced estimations in Table 2.

V. Conclusion

A majority of empirical studies on the parent demand for school quality have examined the average behavior. In this paper we use quantile regression to estimate the marginal effect of a school with superior academic achievement at different points in the distribution of house price. The uniqueness of the Baton Rouge experience enables us to deal effectively with a number of issues of concern in the housing literature. First, we found a trend in which the demand for quality school increases significantly with family resources. This is not unexpected given the fact that quality is generally considered to be a normal good. Although not statistically significant, the negative effect of the Iowa test score towards the lower end of the housing market suggests reduced demand for education quality. Combined with a general downward trend towards the lower end, it indicates significantly reduced willingness to pay for academic school quality by families with limited resources.

Second, we found that for the Iowa test score and the proportion of teachers with a master's degree, the result for OLS takes roughly the middle value between the extreme ends of distribution from the quantile regression. This suggests that OLS results are biased towards zero due to "aggregation" of the estimated demand from either end of the house price distribution. Because OLS is a conditional means estimator, it is unable to account for changes in the willingness to pay across the distribution of house price. The "aggregation" bias is therefore a potential factor in mixed results previously reported by other empirical studies.

Third, the estimated demands for school quality are not especially large even among the relatively well-off families. One standard deviation rise in the average Iowa test score is worth about 0.9 percent of the house price. Considering that the willingness to pay becomes negligible towards the middle of the distribution and negative thereafter, the estimated willingness to pay appears to be small.

Fourth, high-income families are more likely to penalize house price for having non-desirable non-academic school qualities such as increased distance to school or larger school size. The presence of subsidized school lunch appears to be valued more by the lower-income families, perhaps indicating a more supportive atmosphere for the families of limited means.

These results generally paint a picture in which only high-income families have a strong demand for school quality. Low-income families with limited resources appear to be significantly less willing to pay for academic achievement. Our findings provide evidence in support of the argument that school choice programs may not deliver significantly improved education quality and equity. The expanded educational choice may in fact lead to a situation where parents will use the improved access to education to self-segregate into groups.

REFERENCES

Annual Financial and Statistical Report. Baton Rouge: Louisiana Department of Education, 1982-2004.

Bayer P., F. Ferreira and R. McMillan (2005) "Tiebout Sorting, Social Multipliers and the Demand for School Quality," NBER Working Paper 11087.

Black, S. (1999)."Do better schools matter? Parental valuation of elementary education." *Quarterly Journal of Economics* 114(2), 579-599.

Brasington, D. M., and D. R. Haurin. 2006. "Educational outcomes and house values: A test of the value added approach." *Journal of Regional Science* 46 (2), 245–268.

Buchinsky, M. (1994) "Changes in the U.S.Wage Structure 1963-1987: Application of Quantile Regression" *Econometrica* 62, 405-458.

Carnegie Foundation. (1992). School choice. Menlo Park, CA: Carnegie Foundation for the Advancement of Teaching.

Davis, Jr., et al. v. E. Baton Rouge Parish School Bd., et al. (D La., Baton Rouge Div., Civ. #1662.) 1956.

Davis, Jr., et al. v. East Baton Rouge Parish School Bd., 514 F. Supp. 869 (1981), p. 877.

Downes, T. A., and J. E. Zabel. 2002. "The impact of school characteristics on housing price: Chicago 1987-1991." *Journal of Urban Economics,* 52, 1-25.

Emerson, F.C. (1972). "Valuation of residential amenities: an econometric approach." *The Appraisal Journal* 40(2), 268–78.

Figlio, D.N. (1999). "Functional form and the estimated effects of school resources."

Economics of Education Review, 18(2), 241-252.

Figlio D. N., and M. E. Lucas. (2004). “What's in a grade? School report cards and housing price.” *American Economic Review*, 94(3), 591-604.

Gould, W.W. (1992). “Quantile Regression with Bootstrapped Standard Errors.” *Stata Technical Bulletin*, 9, 19-21.

Gould, W.W. (1997). “Interquantile and Simultaneous-Quantile Regression.” *Stata Technical Bulletin*, 38, 14-22.

Hastings, J. S., T. J. Kane, and D. O. Staiger, (2005). “Parental Preferences and School Competition: Evidence from a Public School Choice Program.” National Bureau of Economic Research Working Paper No. 11805.

Haurin, D. R. and D. Brasington. 1996. “School quality and real housing price: inter- and intrametropolitan effects.” *Journal of Housing Economics,* 5(4): 351-68.

Hayes, K. J. and L. L. Taylor. 1996. “Neighborhood school characteristics: What signals quality to homebuyers?” *Economic Review – Federal Reserve Bank of Dallas* 4th Quarter: 2-9.

Jacob, B. A. and L. Lefgren (2007). “What Do Parents Value in Education? An Empirical Investigation of Parents' Revealed Preferences for Teachers.” *Quarterly Journal of Economics* 122(4): 1603-1637.

Kane, T., D. O. Staiger and G. Samms. 2003. “School Accountability Ratings and Housing Values.” *Brookings-Wharton Papers on Urban Affairs*, Brookings Institution Press, Washington DC.

Koenker, R. and Bassett, G. (1978). “Regression Quantiles.” *Econometrica*, 46, 33-50.

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

Mata, J., and J.A.F. Machado. 1996. “Firm Start-up Size: A Conditional Quantile Approach.” *European Economic Review* 40, 1305-1323.

Lacombe, D. 2004. “Does econometric methodology matter? An Analysis of public policy using spatial econometric techniques,” *Geographical Analysis,* 36, 105-118.

Ries, J. and T. Somerville. 2004. “School Quality and Residential Property Values: Evidence from Vancouver Rezoning,” Working Paper, Department of Economics, University of British Columbia.

Rossell, C. 2000. “Report on Proposed Modifications to the Consent Decree,” a report to the Court in the case of Davis et al., v. East Baton Rouge Parish School Board.

Schneider, M. and J. Buckley. (2002) “What Do Parents Want from Schools? Evidence from the Internet.” *Educational Evaluation and Policy Analysis*, 24:2, 133–144.

Sirmans, G. S., Macpherson, D. A. and Zietz, E. N. (2005). “The Composition of Hedonic Pricing Models.” *Journal of Real Estate Literature*, 13:1, 3-46.

Turnbull, G.K. and J. Dombrow. 2006. “Spatial competition and shopping externalities: Evidence from the housing market.” *Journal of Real Estate Finance and Economics,* 32(4):391-408.

Weiher, Gregory R., and Kent L. Tedin. (2002). “Does Choice Lead to Racially Distinctive Schools? Charter Schools and Household Preferences.” *Journal of Policy Analysis and Management*, 21(3) 79–92.

Table 1
Summary Statistics

Variables	Mean	Std. Dev
Academic school quality:		
Average Iowa Test Percentile	50.31	12.38
Proportion of teachers with master's degree	43.33	8.502
Average class size	16.75	4.802
Non-academic school quality:		
Total number of students	466.5	118
Distance to school (miles)	1.590	1.616
Proportion of black students	0.622	0.199
Proportion of students with subsidized lunch	0.642	0.173
Reassigned	0.057	0.231
House attributes:		
House price sold (1999 dollars)	129,000	53,858
Log of house price sold (1999 dollars)	11.69	0.395
Number of days on the market	68.50	44.48
Number of fire place	0.716	0.507
Number of bedrooms	3.250	0.619
Number of bathrooms	2.036	0.478
Living area (thousands of sq. feet)	1.879	0.541
Non-living area (thousands of sq. feet)	0.677	0.278
1-3 years old	0.0561	0.23
4-5 years old	0.0479	0.213
6-10 years old	0.0882	0.284
11-15 years old	0.0833	0.276
16-20 years old	0.136	0.343
20-30 years old	0.257	0.437
31-40 years old	0.154	0.361
41-50 years old	0.0805	0.272
Local market conditions:		
Listing Density	3.810	2.385
Vacant	124.2	73.54
Indicator for year 2000	0.192	0.394
Indicator for year 2001	0.229	0.42
Indicator for year 2002	0.201	0.401
Spring	0.287	0.452
Summer	0.270	0.444
Fall	0.219	0.413
Number of schools	43	
Number of subdivisions	433	
Number of observations	7502	

Table 2
OLS and Quantile Estimation of House Price

Natural Log of House Price (1999 dollar)	(1) OLS	(2) Quantile 0.10	(3) Quantile 0.25	(4) Quantile 0.50	(5) Quantile 0.75	(6) Quantile 0.90
Academic school quality:						
Average Iowa Test Percentile	5.07e-05	-0.000215	9.12e-05	6.80e-05	0.000357	0.000745**
	(0.000282)	(0.000423)	(0.0368)	(0.000298)	(0.000267)	(0.000376)
Proportion of teachers with master's degree	0.000242	0.000166	0.000144	0.000203	0.000511	0.000822*
	(0.000303)	(0.000437)	(0.0347)	(0.000329)	(0.000311)	(0.000434)
Average class size	0.000589	7.09e-05	-0.000743	0.000386	0.00126**	0.000984
	(0.000555)	(0.000845)	(0.0147)	(0.000489)	(0.000527)	(0.000683)
Non-academic school quality:						
Total number of students	-8.21e-05*	1.51e-05	-1.50e-06	-3.74e-05	-5.46e-05	-6.47e-05
	(4.53e-05)	(8.13e-05)	(0.0171)	(4.31e-05)	(4.29e-05)	(5.54e-05)
Distance to school (miles)	-0.0106	-0.00426	-0.000907	-0.00292	-0.00692	-0.00781
	(0.00706)	(0.0143)	(1.370)	(0.00733)	(0.00798)	(0.0127)
Proportion of black students	-0.0798*	-0.0782	-0.122	-0.0942**	-0.0340	-0.00574
	(0.0480)	(0.0806)	(16.02)	(0.0429)	(0.0487)	(0.0605)
Proportion of students with subsidized lunch	0.226***	0.225***	0.299	0.240***	0.179***	0.179***
	(0.0535)	(0.0861)	(17.84)	(0.0470)	(0.0536)	(0.0670)
Marginal effect of school reassignment+	-0.00495	-0.0262	-0.0203	-0.0044	-0.0077	0.0217
	(0.0215)	(0.0458)	(6.497)	(0.0266)	(0.0292)	(0.0412)
House attributes:						
Number of days on the market	-0.000186***	-0.000161***	-0.000185	-0.000155***	-0.00017***	-0.000158***
	(3.00e-05)	(5.25e-05)	(0.00114)	(3.26e-05)	(2.98e-05)	(4.33e-05)
Number of fire place	0.0202***	0.0135**	0.0140	0.0156***	0.0129***	0.0145***
	(0.00329)	(0.00533)	(0.267)	(0.00332)	(0.00371)	(0.00456)

Number of bedrooms	0.0142***	0.0329***	0.0195	0.0112**	0.00301	-0.00503
	(0.00329)	(0.00529)	(0.718)	(0.00442)	(0.00455)	(0.00520)
Number of bathrooms	0.0211***	0.0261***	0.0209	0.0220***	0.0194***	0.0133**
	(0.00392)	(0.00667)	(0.934)	(0.00394)	(0.00471)	(0.00524)
Living area (thousands of sq. feet)	0.318***	0.267***	0.299	0.320***	0.351***	0.392***
	(0.00499)	(0.0115)	(0.581)	(0.00779)	(0.00760)	(0.0111)
Non-living area (thousands of sq. feet)	0.0998***	0.104***	0.0876	0.0740***	0.0671***	0.0705***
	(0.00580)	(0.0113)	(0.609)	(0.00632)	(0.00653)	(0.00920)
Local market conditions:						
Listing Density	0.000324	0.00183*	0.000528	-3.80e-05	-0.000979	-0.00216***
	(0.000834)	(0.00104)	(0.139)	(0.000764)	(0.000713)	(0.000825)
Vacant	0.000179*	0.000420	-0.000132	-5.00e-06	7.38e-05	0.000115
	(0.000103)	(0.000332)	(0.0172)	(0.000253)	(0.000269)	(0.000262)
Constant	10.26***	9.849***	10.09	10.31***	10.14***	10.88***
	(0.231)	(0.456)	(586.9)	(0.353)	(0.386)	(0.437)
Number of observations	7502	7502	7502	7502	7502	7502
R-square or Pseudo R-square	0.928					

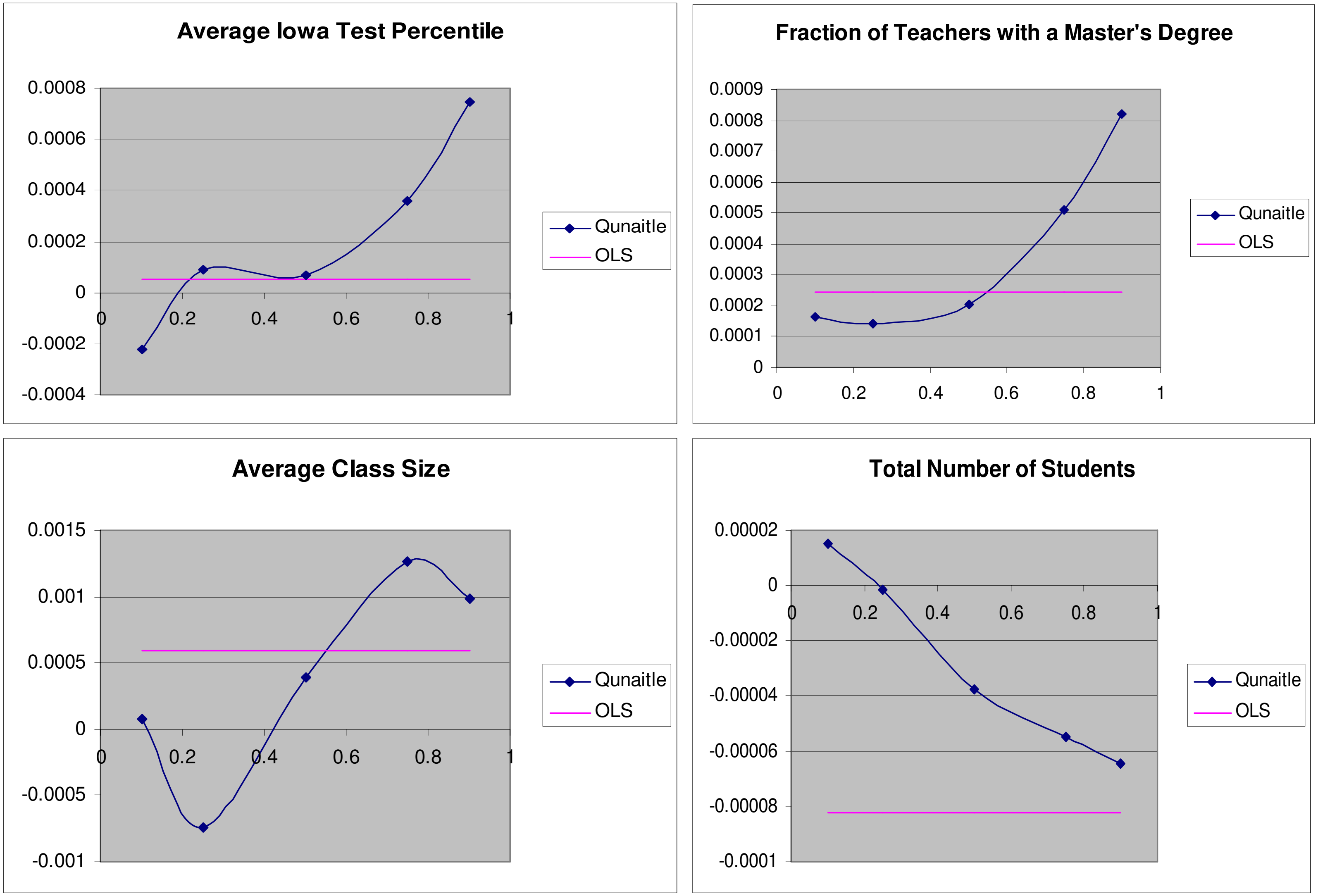
*** p<0.01, ** p<0.05, * p<0.1. Robust standard errors in parentheses for OLS. Bootstrapped standard errors with 99 replications for quantile regressions. Also controlled for 7 indicators for age of the house, 3 indicators for year, 3 indicators for seasons of sale, 42 indicators for schools, and 432 indicators for subdivisions, and interactions terms between reassignment and various measures of school quality (average Iowa Test Percentile, Proportion of black students, total number of students, proportion of students with subsidized lunch, average class size, proportion of teachers with a master's degree, and miles to school). + The marginal effects of being assigned were computed as the linear combination of the coefficients and the mean for the reassignment and the interactions between reassignment and various measures of school quality.

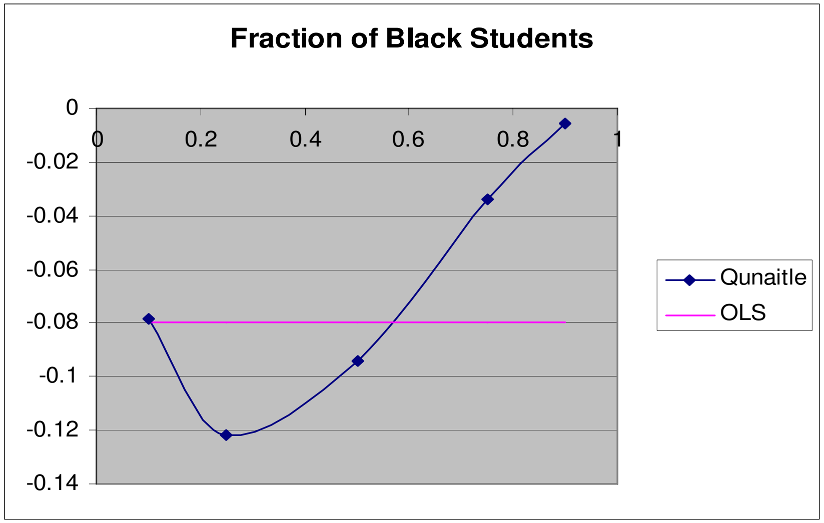
Table 3
Differenced OLS and Quantile Estimation of House Price using Repeat Sales

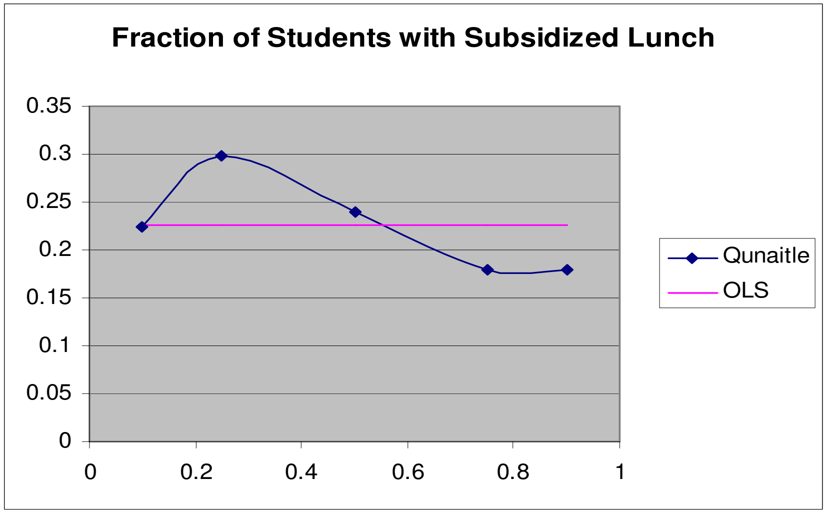
Natural Log of House Price (1999 dollar)	(1) OLS	(2) Quantile 0.10	(3) Quantile 0.25	(4) Quantile 0.50	(5) Quantile 0.75	(6) Quantile 0.90
School Attributes:						
Average Iowa Test Percentile	-0.000222	-0.000868	-0.000514	-0.000400	0.00121	0.00210
	(0.000771)	(0.00140)	(0.000710)	(0.000808)	(0.00122)	(0.00179)
Proportion of teachers with master's degree	8.77e-05	-0.000518	3.21e-05	-0.000161	0.000399	0.00219
	(0.000741)	(0.00147)	(0.000718)	(0.000761)	(0.000893)	(0.00143)
Average class size	0.000183	0.000738	-0.000306	-0.000312	9.27e-05	0.00192
	(0.00139)	(0.00265)	(0.00142)	(0.00149)	(0.00168)	(0.00292)
Total number of students	-3.86e-05	-0.000120	-5.43e-05	0.000151	-0.000156	-0.000263
	(9.58e-05)	(0.000187)	(8.55e-05)	(9.30e-05)	(0.000160)	(0.000242)
Proportion of black students	-0.120	-0.0841	-0.0840	0.0349	-0.0786	-0.0132
	(0.111)	(0.209)	(0.108)	(0.113)	(0.164)	(0.258)
Proportion of students with subsidized lunch	-0.0921	-0.0241	-0.0152	-0.0580	0.0805	-0.450
	(0.149)	(0.271)	(0.135)	(0.129)	(0.213)	(0.417)
Miles to school	0.0245**	0.0194	0.0121	0.00684	0.0120	0.0691*
	(0.0122)	(0.0162)	(0.00825)	(0.0110)	(0.0215)	(0.0361)
Observations	274	274	274	274	274	274

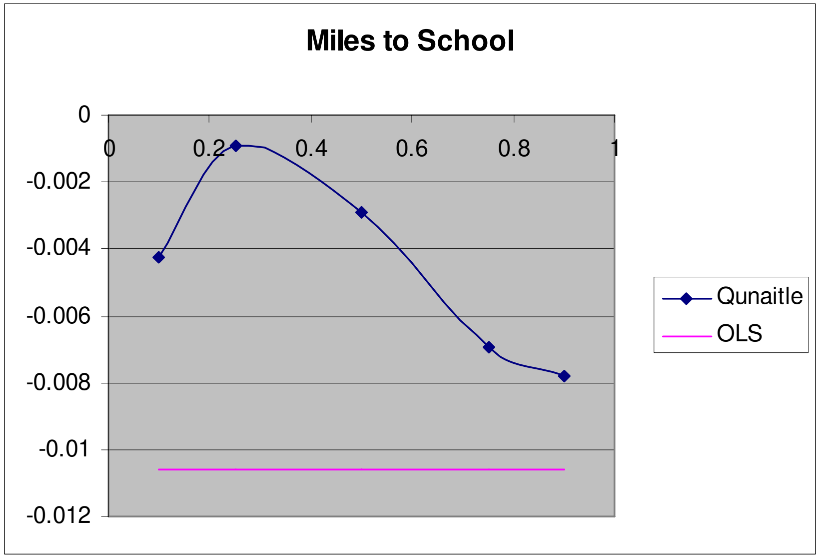
*** p<0.01, ** p<0.05, * p<0.1. Standard errors in parentheses. Quantile regression standard errors were bootstrapped 99 times. Al so controlled for days on the market, year dummies, season dummies, and listing density.

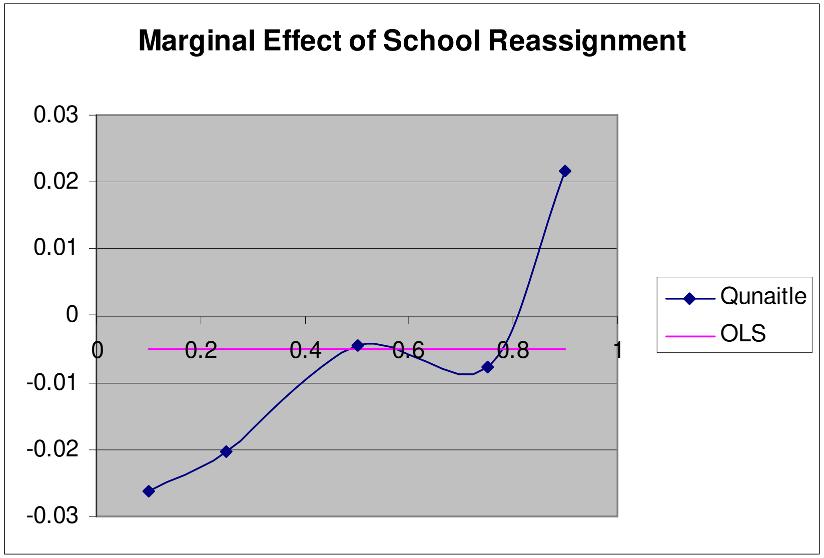
Figure 1
Graphical Illustrations of Marginal Effects as Estimated by OLS and Quantile Regressions from Table 2




Fraction of Black Students
0
-0.02
-0.04
-0.06
-0.08
-0.1
-0.12
-0.14
0
0.2
0.4
0.6
0.8
1
Qunaitle
OLS


Fraction of Students with Subsidized Lunch
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
0
0.2
0.4
0.6
0.8
1
Qunaitle
OLS


Miles to School
0
-0.002
-0.004
-0.006
-0.008
-0.01
-0.012
0
0.2
0.4
0.6
0.8
1
Qunaitle
OLS


Marginal Effect of School Reassignment
0.03
0.02
0.01
0
-0.01
-0.02
-0.03
0
0.2
0.4
0.6
0.8
1
Qunaitle
OLS

Footnotes:

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[1] See Moe (1995) and Schneider and Buckley (2002) for discussions regarding the criticisms of school choice. See the Carnegie Foundation (1992) and Schneider et al. (2000) for evidence regarding the effect of non-academic factors on parent's choice of schools.

[2] See Fischel (2001), Ross and Yinger (1999), and Kane, et al. (2003) for overviews of the empirical public service quality and property tax capitalization literatures. Some education and labor economists suggest that school achievement might not be the proper measure of school quality. Instead, they suggest focusing on the growth in achievement scores over time as a measure of schools' marginal contribution to educational outcome (Hanushek and Taylor, 1990; Hayes and Taylor, 1996; Figlio, 1999; Downes and Zabel, 2002; and Brasington and Haurin, 2006).

[3] OLS regression has typically been used in housing research to determine the relationship of a particular housing characteristic with selling price. Results differ across studies, not only in terms of size of OLS coefficients and statistical significance, but sometimes in the direction of effects.

[4] Quantile regression minimizes a weighted sum of the absolute deviations,

$$\min_{b(j)} \sum_i \left| y(i) - \sum_{j=0}^{k} b(j)x(i,j) \right| h(i)$$

, where q is the quantile or percentile between 0 and 1, $h(i) = 2q$ if the residual is positive and $h(i) = 2 - 2q$ if non-positive (Koenker and Bassett, 1978; Koenker and Hallock, 2001). In contrast, OLS minimizes the sum of the squared residuals in the following form,

$$\min_{b(j)} \sum_i \left(y(i) - \sum_{j=0}^{k} b(j)x(i,j) \right)^2$$

. Hence a classical OLS regression can said to estimate conditional mean functions.

[5] An alternative to using quantile regression is to stratify dependent variables into subsets according to its unconditional distribution and then applying OLS on the subsets. Ries and Somerville (2004) show that after segmenting a sample into quantiles based on the price-per-square foot of housing, measures of school quality only affect high-end houses most likely purchased by high-income buyers. Our technique of estimating a conditional quantile function avoids such truncation on the dependent variable. As argued by Heckman (1979), truncation of the dependent variable may create biased parameter estimates. Segmenting the data and estimating each section of the unconditional distribution yields incorrect results (Koenker and Bassett, 1978).

[6] An immediate withdrawal of 8,000 white students from the public school system resulted in the percentage of black students in the system rising from 41 percent in 1981 to 70 percent in 2000. Enrollment data are from Louisiana Department of Education, Annual Financial Report, various years.

[7] For example, School Superintendent Gary Mathews and the school board's desegregation expert, David Bartz, proposed a plan that called for 4,800 to 4,900 students to be transferred. The main idea behind Bartz's plan was to provide stability by getting schools far enough below their limits that zones would not have to be changed again immediately. At the same time, the NAACP proposed a plan that would reassign fewer students — about 1,900 — by raising some enrollment caps and opening a new magnet school to try to lure students out of overcrowded schools voluntarily.

[8] Spending differences for other district-determined school inputs are minimal because of court mandated equalized spending. District-reported data are obtained from the Annual School Report (ASR) produced by the Louisiana Department of Education. According to the Louisiana State Board of Elementary and Secondary Education, small classes are designed to allow more time for individual pupil-teacher interactions. Based on this belief, the State Board has set specific limits on the maximum size of classes at various grade levels.

[9] It is calculated as the total number of students divided by the total number of classes for each school and for each school year.

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[10] Following convention, the relevant school measures are lagged one year. This ensures full exposure of the house seller and buyer to the school ranking at the time the property is put on the market.
[11] Another reason we include the distance measure is that the survey of school parents showed that while the majority of parents support the neighborhood schools, between 51 and 58 percent of parents would withdraw their child if reassigned to a school that is further away than a 30-minute bus ride.
[12] The marginal effect was calculated as a linear combination of estimated coefficients and the means for the reassignment and its interactions terms.
[13] The standard errors were bootstrapped 99 times. The results did not noticeably change from the results using 49 replications.
[14] Of the 274 repeat sales, 30 houses were assigned to different school due to the court-ordered redistricting. This is not a large enough sample size to estimate as a separate group.