PRIVATE SCHOOL VOUCHERS AND STUDENT ACHIEVEMENT: A FIXED EFFECTS QUANTILE REGRESSION EVALUATION OF THE MILWAUKEE PARENTAL CHOICE PROGRAM*

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Abstract. Empirical studies of the Milwaukee Parental Choice program's effect on student achievement have delivered mixed empirical evidence, partially due to a lack of a valid control group. To get around this problem, Rouse (1998) uses a sample of students in the Milwaukee public schools as a comparison group, and individual fixed effects to control for latent characteristics that may differ between treatment and comparison groups. Rouse finds that students selected for the choice program had a positive linear gain in mathematics. Using a newly developed fixed effects form of quantile regression, we find that students' gains are more subtle in nature. While high attainment students had a positive, convexly increasing gain in mathematics, lower attainment students had a nearly linear loss. The evidence also suggests that being selected for the choice program prevented weak students from having an even bigger loss experienced by students in the public schools.

Keywords: School Choice; Vouchers; Milwaukee; Fixed Effects; Quantile Regression.

JEL Codes: I21, J13, I28, C14, C23.

1. Introduction

Fundamental to the recent debate over school choice is the issue of whether voucher programs actually improve students' academic achievement. While Milton Friedman's proposal to use vouchers as a method of improving the quality of education is based on the idea that private schools are more productive than public schools, this is still a highly controversial issue. If private schools are in fact more efficient than public schools, governments can improve the quality of education by offering tuition vouchers to families that want to send their children to private schools. The Milwaukee Parental Choice program, the first program implemented in the US, has been providing vouchers to low-income students to attend private school since 1990.

The simplicity of the program's idea contrasts sharply with the complexities that plague the program's evaluation. The voucher programs' effect, for example from time t to t', is the difference between what would have happened at time t' if the student was selected and remained in a choice school during the time interval, and what would have happened at time t' if the student was not selected, and remained in the Milwaukee public school. This counterfactual exercise is impossible to obtain using observational data (Rubin 1974). It may be possible, however, to construct groups using a randomized experiment (e.g.,

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children randomly assigned to attend choice schools, and to attend public schools). At time t', the difference between students' academic performances could be attributed to the type of school since the initial assignment was random. However, the Milwaukee Parental Choice program was not implemented using random assignment (Witte 2000), and therefore the selection of the control group plays a major role.

Given the lack of a valid control group, it is not surprising that previous empirical studies have delivered mixed findings. Rouse's (1998) seminal study used a sample of students in the Milwaukee public schools as a comparison group and individual fixed effects to control for latent characteristics, such as more motivated parents or student abilities that may differ between treatment and comparison groups[1]. The presented approach builds upon Rouse by employing a newly developed fixed effects form of quantile regression that not only controls for unobserved individual heterogeneity, but also allows an examination of the program effects at different points of the educational attainment distribution.

The empirical literature (e.g., Witte 1997, Green et al. 1997, Rouse 1998) has focused upon estimating how the selection to attend the Milwaukee choice schools affects *mean* test scores[2]. This approach to evaluation may be incomplete for policy analysis of programs serving heterogeneous students. To illustrate, if a stated policy goal is to raise students' achievement to a predetermined minimum standard, it may not be optimal to pursue a program that benefits strong students while causing weaker students to fall further behind. This paper focuses on the estimation of the selection to attend choice schools on the *entire* distribution of test scores, considering patterns of achievement in terms of quantiles[3].

Rouse (1998) finds that (a) being selected to participate in the Milwaukee Parental Choice program increased math achievements of the "average" minority student by 2.3 percentile points per year, (b) the reading scores differences between groups were insignificant, and (c) the selected students had a positive linear gain in mathematics. Our analysis shows that being selected to participate in the program had an heterogeneous effect on educational attainment, which had not been uncovered by the previous work focusing on mean effects. First, we find that the selected students had an increase in math achievements that ranges from 3.1 to 1.2 percentile points per year across quantiles. The program seems to dramatically improve the academic achievements of the weak students, having a relatively modest effect on achievements among strong students. Second, although the mean effect

[1]An additional problem is the endogenous decision to attend choice school that leads to selection bias. Students with mothers with strong preference for private school are more likely to enroll and to have higher scores, thus standard estimation methods (i.e., least squares and quantile regression) tend to overestimate the effect of the voucher program. We use an instrumental variable strategy in quantile regression (Chernozhukov and Hansen 2005) to estimate the causal effect of the program.

[2]Hastings, Kane, and Staiger (2006), and Cullen, Jacob, and Levitt (2005) investigate the effect of school choice on academic performance within the Charlotte-Mecklenburg School district, and the Chicago Public School system, respectively. They analyze how the mean academic performance changes with students characteristics.

[3]The quantile treatment effect, a special case of quantile regression (Koenker and Bassett 1978) when a binary independent variable indicates treatment status, provides information on the impact of the program on the entire distribution of test scores (see, e.g., Chernozhukov and Hansen 2005, Bitler et al. 2006). We consider instead the quantile 'intention-to-treat' effect measuring the vertical distance between test score conditional quantile functions for students selected to attend choice schools, and students in the public schools.

suggests that the program has no effect on reading, we find some evidence suggesting that the program improved and reduced the achievements of the lower and higher attainment students, respectively. Using a new instrumental variable estimator for quantile regression (Chernozhukov and Hansen 2005), we find that the effect of being enrolled in choice schools ranges from 2.3 percentile points per year at the 0.1 quantile of the conditional distribution of reading scores, to -2.4 at the 0.9 quantile. Third, our results reveal that students' gains, measure as the *differences* between test scores conditional on years since application to the program, are subtle in nature. While the "average" student in the program had a linear gain in mathematics, high attainment students had a positive, convexly increasing gain, and low attainment students had a nearly linear loss. However, as we mentioned above, weak students' scores increased dramatically, in *levels*, compared to public school students' scores. Therefore, the evidence suggests that being selected for the choice program prevented weak students from having an even bigger loss experienced by students in the public schools.

The next section briefly introduces a simple behavioral framework, and Section 3 presents models and estimators. Section 4 describes the data, and Section 5 the empirical results. Section 6 offers conclusions.

2. The Behavioral Framework

We develop a simple variation of a model of mothers' decisions to enroll children in preschool (Behrman et al. 2004). In particular, we model the actual attendance to choice schools for eligible families. The approach provides some insight into the selection problem, and a link to Rouse's (1998) structural equation model for a random selection process and the decision to attend choice school. Moreover, the framework models *heterogeneity*, unobserved by the econometrician, that can be recovered using quantile regression techniques (Koenker and Bassett 1978, Koenker 2005).

The mother of student $i \in \mathcal{D} \subset \mathbb{R}^N$ maximizes a time separable utility function $U : \mathbb{R}^2_+ \to \mathbb{R}$ that depends on consumption C and the child's test score T. The utility function is bounded, strictly increasing and strictly concave. There is a technology $T : \mathbb{R}^p \times \{0,1\} \times \mathbb{R} \to R_+$ that produces test scores depending on socioeconomic characteristics $\boldsymbol{x} \in \mathcal{X} \subset \mathbb{R}^p$, attendance to a choice school $P \in \{0,1\}$, and stochastic factors ε_j,

$$T = T(\boldsymbol{x}, P, \varepsilon_j). \tag{2.1}$$

We assume that ε_j is realized after the student attends school. For example, dissatisfaction with teachers, quality of education, school transportation problems associated either with choice school $j = 1$ or public school $j = 0$ attendance. The variable actual attendance to a choice school P is equal to

$$P = aS_{-1}, \tag{2.2}$$

taking value one if the student actually attends a choice school, 0 otherwise. The variable attendance to a choice school $a \in \{0,1\}$ takes the value one if the mother decides that the student should attend a choice school, and the state variable selected to attend choice school in period $t-1$, $S_{-1} \in \{0,1\}$, take the value one if the student was selected. The selection to attend choice schools follows an exogenous two-state Markov process, with transition probabilities equal to the identity matrix. We also assume that each period the mother must spend assets A on consumption and, if she decides to send her child to a choice school, on a fixed cost K,

$$A \geq C + Ka. \tag{2.3}$$

We express the mother's problem as a dynamic programming problem. The choices are $\{a, C\}$, and the states are $\boldsymbol{s} = (A, \boldsymbol{x}, S_{-1})$. The mother of the ith student solves,

$$V(\boldsymbol{s}) = \max_{a,C} U(C, \alpha T) + \delta \mathbb{E}\left\{V(\boldsymbol{s}_{+1}, T)|\mathcal{I}\right\},$$

subject to (2.1)-(2.3). The parameter δ is a discount factor, and α measures mother's weight to her child's academic achievements. The information set at time t, denoted by $\mathcal{I}$, includes all past and current realizations of family, school, and child characteristics. At time t, the mother also knows if her child was selected to attend a choice school. The Bellman equation can be written as

$$\max \left\{ \underbrace{U(A, \alpha T^0) + \delta \mathbb{E}\{V(\boldsymbol{s}_{+1}, T^0)|\mathcal{I}\}}_{v^0}, \underbrace{U(A - K, \alpha T^1) + \delta \mathbb{E}\{V(\boldsymbol{s}_{+1}, T^1)|\mathcal{I}\}}_{v^1} \right\}$$

where $T^z = T(\boldsymbol{x}, zS_{-1}, \varepsilon_z)$, v^1 denotes the value of attending a choice school, and v^0 represents the value of not attending a choice school. If at time t the student was not selected, her mother trivially chooses $a = 0$ because she does not want to give up consumption to pay K. On the other hand, if at time t the student was selected to attend a choice school, the decision is simply,

$$a = 1\{v^1 \geq v^0 | S_{-1} = 1\} \tag{2.4}$$

This decision depends, among other factors, on the cost of attending a choice school, shocks to the quality of the match between selected students and choice schools, and mother's weight to her child educational achievements. These factors may be different among families. As suggested in Witte (2000), the main responses given to the question "What were the reasons your child did not continue in last year's school?", were: distance and transportation problems, lower achievement success, and dissatisfaction with the choice schools. Conditional on being selected, students' actual enrollment are heterogeneous, not possibly characterized by a single, homogeneous response. This is an important difference between our framework and Rouse's structural equation model, as it will be clear below.

The previous behavioral framework impose two restrictions on the evaluation of the voucher program,

$$T_{it} = T(\boldsymbol{x}_{it}, P_{it}, \varepsilon_{it}) = \boldsymbol{x}_{it}'\boldsymbol{\mu} + \beta P_{it} + \varepsilon_{it} \tag{2.5}$$

$$P_{it} = 1\{v_{it}^1 \geq v_{it}^0\} S_{it-1} = \delta + \rho_{it} S_{it-1} \tag{2.6}$$

The endogenous variable P makes it difficult to recover the causal effect of choice schools on academic achievement. Both least squares and quantile regression estimation methods suffer from selection bias since the actual participation is chosen in relation to potential outcomes. However, as long as the selection to attend a choice school S_{-1} and the error term ε are orthogonal, we could generate an unbiased estimator of the effect of being selected to attend choice schools. A key aspect of the program is that students were randomly selected conditional on school and grade to which they applied (Rouse 1998, Witte 2000).

3. Evaluation of the Milwaukee Voucher Program

The assumption of linearity in equations (2.5)-(2.6) gives a direct link to Rouse's (1998) structural equation model. Rouse estimate a reduced form equation assuming that the effect of selection into the voucher program on the probability of attendance is constant among families ($\rho_{it} = \rho$),

$$T_{it} = \pi_0 + \pi_1 S_{it-1} + \boldsymbol{x}'_{it}\boldsymbol{\pi}_2 + v_{it} \tag{3.1}$$

where $\boldsymbol{x}_{it}$ is a vector of independent variables described later on. The parameter "intention-to-treat" effect $\pi_1 = \rho\beta$ merges two effects. On the one hand, the effect of selection on the probability of attendance ρ, and on the other hand, the effect of choice schools over educational attainment β. For instance, if $\rho = 0$, although private schools may be better than the public ones (i.e., $\beta > 0$), there are no gains from the program. The parameter π_1 is interpreted as the potential student's achievement gain from participating in a voucher program.

3.1. The Selection of The Comparison Group.

An enormous difficulty in the evaluation of the Milwaukee Parental Choice program is the lack of a valid control group. *Initial* randomized treatment is needed to obtain an unbiased estimator of π_1 in equation (3.1), but the program's randomization was based on the applicant group. This is the reason why the selection of the comparison group had an important place in previous studies (e.g., Witte 1997, Greene et al. 1997, Rouse 1998). For instance, Greene et al. (1997) used the students not selected to attend choice schools as a comparison group. Although the selected and not selected groups could be identical, Greene's comparison group may lead to selection bias since there are differences over time between groups (Witte 2000). Witte (1997) used a random sample of students from public schools as a comparison group, but as Rouse (1998) pointed out, there are differences between the students that were selected to attend choice schools and the students that remained in the public schools. For instance, consider a family making a decision as to whether or not to apply to the program based on

$$v^j_{i0} = \boldsymbol{x}'_{i0}\boldsymbol{\mu} + \alpha^j_i,$$

where the binary variable j takes the value 1 if the student applies to the program, and the value 0 otherwise. From equation (2.6), the participation in the program may depend entirely on parent's weight to her child educational achievements,

$$P_{i0} = 1\{v^1_{i0} - v^0_{i0} \geq 0\} = 1\{\alpha^1_i - \alpha^0_i \geq 0\}.$$

Only eligible parents who are more interested in their child's achievements apply to the program, which suggests that students who remained in the public system may have parents with a less strong preference for private schools. Also, it is likely that parents who give more weight to their child's academic achievements (e.g., more motivated parents) have children with higher test scores. Consequently, Witte's comparison group may lead to an overestimate of the program's achievements.

3.2. Introducing Individual Fixed Effects.

To get around the problem, Rouse (1998) used individual fixed effects to control for unobservables that are correlated with attending choice schools and explain higher test scores. The conditional mean model estimated using classical fixed effects methods is then,

$$\mathbb{E}(T_{it}|S_{it-1}, \boldsymbol{x}_{it}, \alpha_i) = \pi_0 + \pi_1 S_{it-1} + \boldsymbol{x}_{it}'\boldsymbol{\pi}_2 + \alpha_i \tag{3.2}$$

where α_i is an individual fixed effect (e.g., parents' motivation, 'innate' student ability). In this parametric model, the 'intention-to-treat' effect is simply,

$$\pi_1 \equiv \beta\rho = \mathbb{E}(T_{it}|S_{it-1} = 1, \boldsymbol{x}_{it}, \alpha_i) - \mathbb{E}(T_{it}|S_{it-1} = 0, \boldsymbol{x}_{it}, \alpha_i) \tag{3.3}$$

The empirical literature based their conclusions on the conditional mean approach, but if the students respond differently to being enrolled in private schools as the behavioral framework suggests, the mean may not describe entirely the effect of being selected to attend choice schools on educational attainment.

3.3. **Modeling the Heterogeneous Program's Effect.** Witte (2000) reports that among students who left choice schools, only 15 percent indicated child or family specific reasons. The remaining reasons were related to some aspect of the choice program (e.g., school transportation problems, dissatisfaction with teachers, quality of education, etc.). We simply assume that the effect of selection to attend choice schools on the probability of attendance in equation (2.6) is,

$$\rho_{it} = \rho + \omega_i + \varepsilon_{it}$$

where the variable ω_i represents individual or family reasons to leave the choice schools, and ε_{it} captures choice program or private school factors.

Unobserved factors, on the one hand, may trigger a family's decision to leave the program, but on the other hand, they may affect educational attainment. For instance, the latent quality of education in the choice schools may have an effect not only on the family decision to drop choice schools, but also on test scores levels. Consequently, the fixed effects version of the structural equation model (2.5)-(2.6) may be written as,

$$T_{it} = \pi_0 + \pi_1 S_{it-1} + \boldsymbol{x}_{it}'\boldsymbol{\pi}_2 + \alpha_i + (1 + \beta S_{it-1})\varepsilon_{it} \tag{3.4}$$

where $\pi_1 = \beta\rho$. Equation (3.4) is Rouse's reduced form equation with multiplicative heteroscedasticity, a specification that arises from allowing time-variant heterogeneity in family's decision to enroll her child in a choice school on educational attainment. Although the equation assumes a particular, untestable form of heteroscedasticity, there are gains in terms of interpretation. The iid error model does not impose a pure location shift on the selection to attend choice school,

$$Q_{T_{it}}(\tau_j|S_{it-1}, \boldsymbol{x}_{it}, \alpha_i) = \pi_0(\tau_j) + \pi_1(\tau_j)S_{it-1} + \boldsymbol{x}_{it}'\boldsymbol{\pi}_2 + \alpha_i \tag{3.5}$$

where $Q(\cdot|\cdot)$ is the τ_j-th conditional quantile function, $\pi_0(\tau_j) = \pi_0 + F_\varepsilon^{-1}(\tau_j)$, and $\pi_1(\tau_j) = \beta(\rho + F_\varepsilon^{-1}(\tau_j))$. The individual specific effects α_i are simply location shifts, and the parameters $\pi_1(\tau_1), ..., \pi_1(\tau_J)$ measures the distance between the 'intention-to-treat' and public schools conditional quantiles of the educational attainment distribution,

$$\pi_1(\tau_j) \equiv \beta(\rho + F_\varepsilon^{-1}(\tau_j)) = Q_{T_{it}}(\tau_j|S_{it-1} = 1, \boldsymbol{x}_{it}, \alpha_i) - Q_{T_{it}}(\tau_j|S_{it-1} = 0, \boldsymbol{x}_{it}, \alpha_i)$$

The model, in its simplest version, assumes that π_1 is a combination of two effects: a location shift effect of the private schools on students' performance β and a location-scale shift of the selection to attend choice schools on the probability of attendance $\rho(\tau_j)$[4].

3.4. **Fixed Effects Quantile Regression.** We will estimate the 'intention-to-treat' effect $\pi_1(\tau_j)$ in equation (3.5) using a quantile regression version of the classical fixed effects estimator introduced by Koenker (2004),

$$\{\{\hat{\boldsymbol{\pi}}(\tau_j)\}_{j=1}^{J}, \{\hat{\alpha}_i\}_{i=1}^{N}\} \equiv \arg\min_{\pi,\alpha} \sum_{j=1}^{J}\sum_{t=1}^{T}\sum_{i=1}^{N} \omega_j \rho_{\tau_j}(T_{it} - \pi_0(\tau_j) - \pi_1(\tau_j)S_{it-1} - \alpha_i)$$

where $\rho_{\tau_j}(u) = u(\tau_j - I(u \leq 0))$ is the quantile loss function, and ω_j is the weight given to the jth quantile. We will restrict attention to constant weights equal to $1/J$ over the quantiles. For simplicity, the vector of independent variables $\boldsymbol{x}_{it}$, defined below, is omitted. Parents' and students' unobserved characteristics that may differ between students' selected to attend choice schools and students in the public schools are captured by individual fixed effects α_i's, independent of the quantiles.

We will use panel-bootstrap to estimate the precision of the estimates of the parameters of the model $\hat{\boldsymbol{\pi}}(\tau_j)$. The strategy, recommended for classical estimation methods used in short panels (Davison and Hinkley 1997, Cameron and Trivedi 2005), accommodates to forms of heterocedasticity replacing pairs $\{(\boldsymbol{T}_i, \boldsymbol{S}_i) : i = 1, \ldots, N\}$ over cross-sectional units i. For small and fixed number of time series observations, the standard errors are consistent provided that the number of cross sectional units passes to infinity.

We expect unbiased estimates of the 'intention-to-treat' effect because the students were randomly selected when the school was oversubscribed for a particular grade (Witte 2000, p. 55). In contrast, the estimate of the 'treatment effect', the effect of choice schools on student achievements, may be biased. It was recognized by others that students with mothers having a strong preference for private schools are more likely to enroll and to have higher scores, thus standard estimation methods tend to overestimate the effect of a voucher program.

3.5. **Instrumental Variable Quantile Regression.** We will also implement an instrumental variable form of quantile regression to estimate the causal effect. By accommodating the function $T(\cdot)$ and the error term, equations (2.5)-(2.6) are the system of equations considered by Chernozhukov and Hansen (2005, 3.1), who propose an IV method for estimating quantile regression treatment effects. The behavioral conditions can be written as

$$T_{it} = Q(\boldsymbol{x}_{it}, P_{it}, U_{it}) \quad (3.6)$$

$$P_{it} = \delta(S_{it}, V_{it}) \quad (3.7)$$

where $Q(\cdot)$ is the quantile treatment response function, $\boldsymbol{x}_{it}$ is a vector of exogenous independent variables, and the variable U_{it} is distributed as uniform $\mathcal{U}[0,1]$ independent of the

[4]We need four assumptions to identify $\pi_1(\tau)$. First, for our regression setting, the selection to attend choice school need to be exogenous, orthogonal to the error term. Second, the treatment assignments must occur with positive probability, which is satisfied since the number of applications were greater than the number of available seats (Witte 2000, Table 4.1). Lastly, we need the standard quantile regression conditions about uniqueness, and continuity.

variable selected to attend choice school S_{it}. We will estimate the effect of choice schools on test scores considering,

$$Q_{T_{it}}(\tau|P_{it}, \boldsymbol{x}_{it}) = \gamma(\tau) + \beta(\tau)P_{it} + \boldsymbol{x}_{it}'\boldsymbol{\mu}(\tau) \tag{3.8}$$

where $\beta(\tau)$ is the parameter of interest. The vector $\boldsymbol{x}_{it}$ will include "applicant pool" dummy variables, a dummy variable for gender, family income, an indicator if family income is missing, and the grade level of the student when the student took the test. Since the selection to attend choice school is exogenous conditional on the school and grade to which the student applied, we will use S_{it-1} as an instrument for actual enrollment.

4. Data

4.1. **The Program.** The Milwaukee Parental Choice program was targeted and limited, intended to provide better educational opportunities to poor families. The program target was low income families living in the city of Milwaukee whose children were not attending private schools in the last year. The program limit was initially 1 percent of the Milwaukee public school enrollment, approximately 90,000 students in 1990.

4.2. **Data.** We analyze data from the Milwaukee Parental Choice program, public release data files. The data set contains information on approximately 2,400 applicants to the program, and on 5,400 students from Milwaukee public schools. There is data on reading and math test scores, based on the normal curve equivalent measure (NCE) from the Iowa Tests Basic Skills. In addition to the test scores, the data contains information on race, gender, family income, grade level, whether the student applied and was accepted to the program, and school and family characteristics. The empirical analysis is based on a sample of African-American and Hispanic students who applied to the choice program between 1990 and 1993, and a sample of students from the Milwaukee public schools.

Test Scores: The Iowa Test of Basic Skills (ITBS) is a multiple choice achievement test. The Normal Curve Equivalent (NCE) measure is a transformation of the ITBS that produces an integer-level measure. The NCE test score ranges from 1 to 99, has a national mean of 50, and a standard deviation of 21. We rely on math and reading NCE test scores because (a) the results can be compared with previous paper's findings (e.g., Witte 1997, Rouse 1998), and (b) the NCE measure has the advantage that it can be averaged. According to test makers, the NCE test score is the same if all the students make one year of progress after one academic year. (They may have higher raw scores, but the gain from year-to-year is zero). If some students make more progress in one year than the students in the population of interest, the NCE test score will be higher. On the other hand, if some students make progress at a slower rate, the NCE test score will be lower.

Of course, one-point increase at the quantile τ may not be translated to the same amount of knowledge in different grades[5], but addressing this possibility is beyond the scope of this paper. Rather, the present exercise is focused on an investigation of the changes in the educational attainment conditional distribution for the selected students and public school students. We estimate the quantile 'intention-to-treat' effect of the program as the horizontal distance between the distributions, and use this result to obtain the conditional NCE in levels. We have no reason to believe that the differences across the conditional NCE

[5]Note that this same possibility is present when analyzing mean effects.

Variables	Students		
	Selected	Not Selected	MPS
Proportion currently enrolled in a choice school	0.558	0.010	-
	(0.497)	(0.102)	-
Math (NCE) scores	39.236	38.108	40.411
	(18.706)	(18.777)	(18.483)
Reading (NCE) scores	37.647	37.886	38.700
	(16.265)	(17.090)	(16.461)
Proportion female	0.536	0.470	0.523
	(0.499)	(0.499)	(0.500)
Family income (in thousands of 1994 dollars)	12.052	12.510	21.750
	(5.915)	(5.901)	(8.658)
Proportion missing income family	0.412	0.542	0.747
	(0.492)	(0.498)	(0.435)
Proportion African-American	0.795	0.864	0.868
	(0.404)	(0.343)	(0.338)
Proportion Hispanic	0.205	0.136	0.132
	(0.404)	(0.343)	(0.338)
Grade Level Test	3.767	3.857	4.337
	(2.250)	(2.088)	(2.122)
Proportion with imputed math test	0.074	0.194	0.164
(Rouse 1998 methodology)	(0.262)	(0.396)	(0.371)
Proportion applied in 1990	0.272	0.224	0.372
	(0.445)	(0.417)	(0.483)
Proportion applied in 1991	0.245	0.172	0.210
	(0.430)	(0.378)	(0.408)
Proportion applied in 1992	0.153	0.080	0.148
	(0.360)	(0.272)	(0.355)
Proportion applied in 1993	0.059	0.042	0.094
	(0.235)	(0.200)	(0.292)
Proportion with test score in 1990	0.117	0.158	0.175
	(0.322)	(0.365)	(0.380)
Proportion with test score in 1991	0.168	0.206	0.249
	(0.374)	(0.405)	(0.432)
Proportion with test score in 1992	0.237	0.267	0.240
	(0.425)	(0.442)	(0.427)
Proportion with test score in 1993	0.228	0.218	0.184
	(0.420)	(0.413)	(0.388)
Proportion with test score in 1994	0.250	0.151	0.152
	(0.433)	(0.359)	(0.359)
Number of Observations	2462	859	5408

TABLE 4.1. *Sample Mean and Standard Deviations (in parenthesis) in Rouse's panel data set. MPS stands for Milwaukee public schools.*

scores should be interpreted differently across quantiles. Furthermore, we analyze trends over several years to avoid drawing conclusions based on one-year changes that are likely to be noisy measures of performance (Kane and Staiger 2002).

Mean choice students and the students in the Milwaukee public schools are below the national mean in both math and reading. For instance, the math's mean of the students selected to attend choice school is 39.2 with a standard deviation of 18.7, and the math's mean of the students in the Milwaukee public schools is 40.4 with a standard deviation of 18.5. In some cases, there is no data on math's total score, so we use Rouse's imputed math scores. The proportion of students with imputed math test scores ranges from 0.07 to 0.19[6].

[6]We observe that the proportions of students with imputed math scores in our sample are different than the proportions of students in Rouse (1998, Appendix 1). However, the reproducibility of Rouse's main results (e.g., estimates in Table VI and VII, and Figures I and II) is not compromised because we use the

Race, Gender, and Family Income: The proportion of African-American students is considerably larger than the proportion of Hispanic students. For instance, among the students selected to attend choice school, there are four African-American students for every Hispanic student. The proportion of African-American students increases up to 87 percent in the sample of students of the Milwaukee public schools. On the other hand, the proportion of female students is approximately the same ranging from 0.47 to 0.54.

Rouse constructed family income from survey data, which contains two annual observations for fall and spring. She averaged the reported income, and converted to 1994 dollars. The mean family income for the sample of students in the public schools is \$21,750, considerably higher than the mean family income for the students selected to attend choice school, \$12,052.

Year since application: This variable is defined as the first year in which a student applied if he either was selected the first time he applied or he was never selected to attend choice school. In case a student applied two or more times, the first year she was accepted is considered the year of application. In the case of the students in the Milwaukee public schools, the year of application was imputed considering year t the "year of application" for students who have a valid year $t+1$ test score (Rouse 1998). For example, Rouse considers 1990 the year of application for students who have a valid score in 1991. In case that 1991 test score is missing, Rouse considers the year of application to be 1991 if they have a valid test score in 1992.

Grade at application: The grade at application is the grade level of the test, determined using ITBS, of the spring following the year of application. If a student missed the test the first spring after the year of application, the grade of application is considered to be the first non-missing grade minus the corresponding number of years. For instance, if the student applied in 1990, missed a 1991 test score, and took a 1992 test, the grade of application is 1992 grade minus one. In case the grade levels are missing, Rouse imputed it using administrative data, and grade levels of other years.

Application lotteries: The probability of being selected to attend choice school is random conditional on the school and grade to which the student applied, because the students were randomly selected when the school was oversubscribed for a particular grade. Consequently, we need to control in model (3.8) for the school and grade to which the student applied. The data, however, does not contain information on the choice schools. Previous studies (e.g., Greene et al. 1996, Rouse 1998) infer the lottery from the student's race, grade, and year of application. Rouse (1998) explains that it is possible to do so because "over 80 percent of the choice students were enrolled in one of three schools. Almost all students who applied to one of these schools were Hispanic, and almost all students who applied to the two others were African-American". The application lotteries are time-invariant dummy variables, therefore they will not be included in model (3.5) because the variables are subsumed in the individual effects.

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following samples considered in her paper: the full sample of students, 1991-1993 cohorts only, and a sample that excludes 1994 test scores for the 1990 cohort.

5. Results

We shall present the empirical results, which may be considered as complementary estimates to those found in Rouse's (1998) paper. Instead of the focus on the *mean* achievement, we will report the effect of being selected to attend choice schools on the *entire* distribution of educational attainment.

5.1. **The Heterogeneous Impact.** We will estimate a somewhat more complicated model than (3.5), which contains a treatment (the successful applicants) and two comparison groups (the unsuccessful applicants, and a random sample of students in the public schools). We introduce indicators for the number of years pre- or post application to the program, and interactions between the indicator for whether or not the student was selected to attend a choice school and the years since application because previous researchers (e.g., Greene et al. 1996, Rouse 1998) have argued that child's educational achievement may not improve immediately. We consider first the simplest version, assuming that gains are equal from year-to-year,

$$T_{it} = \pi_0 + \pi_1(d_{it} \times S_{it}) + \pi_2(d_{it} \times N_{it}) + \sum_{k=-3}^{4} \pi_{3k} d_{it-k} + \pi_4 S_{it} + \pi_5 N_{it} + \alpha_i + \varepsilon_{it} \tag{5.1}$$

where d_{it-k} indicates the number of years pre- or post application to the program, $(d_{it} \times S_{it})$ is an interaction between the number of years since application and whether the student was selected to attend choice schools, N_{it} is a dummy variable indicating whether the student applied to the program and was not accepted, and the α_i's are individual fixed effects.

5.1.1. *Fixed Effects Estimates.* Tables 5.1-5.3 present the reduced form results from both the linear conditional mean model and the linear conditional quantile model. The first columns show the results for five equally weighted quantiles $\{0.1, 0.25, 0.5, 0.75, 0.9\}$, and the last column reproduces Rouse's mean estimates. The tables present four different estimation strategies, separated in two groups. The upper blocks present ordinary least squares and quantile regression estimates, and the lower blocks report fixed effects and fixed effects quantile regression estimates.

We report estimates for the full sample in Table 5.1. The OLS result suggests that the student selected to attend choice schools scored 1.3 additional percentile points per year relative to the students in the public schools. The estimated effect is insignificant for reading test scores. Estimates from pooled methods, however, may be subject to selection bias since they do not control for unobserved heterogeneity. On the other hand, the fixed effects estimator may be unbiased because it introduces individual effects to capture differences between treatment and comparison groups (e.g., more motivated parents).

The least squares fixed effect estimates suggests that the student selected for a choice school earn 2.3 additional percentile points per year in math relative to the student in the public schools. If instead of focusing on the mean effect, we consider various quantiles of the math score distribution, we see that the gains have some tendency to decrease as we go across the quantiles. For instance, the estimate changes from 3.1 additional percentile points per year at the 0.25 quantile to 1.2 additional percentile points per year at the 0.9 quantile.

	Quantiles					
	0.1	0.25	0.5	0.75	0.9	Mean
Pooled Methods	Dependent Variable = math (NCE) test score					
Selected to attend choice	-3.170	0.000	-4.000	-4.000	-3.333	-1.760
school (selected)	(2.037)	(1.603)	(1.296)	(1.910)	(2.334)	(1.158)
Not Selected to attend	-4.644	-3.000	-2.321	-2.396	-6.333	-2.091
choice school	(4.717)	(2.293)	(2.781)	(3.273)	(4.458)	(2.069)
Selected × number	1.169	0.000	2.000	1.500	1.333	1.295
of years	(0.828)	(0.732)	(0.649)	(0.841)	(0.896)	(0.491)
Not Selected × number	0.643	0.000	-0.679	-1.104	1.333	0.097
of years	(2.102)	(1.149)	(1.036)	(1.854)	(1.431)	(0.902)
Pooled Methods	Dependent Variable = reading (NCE) test score					
Selected to attend choice	0.000	0.000	-3.000	-0.500	-2.000	0.395
school (selected)	(1.770)	(1.474)	(1.622)	(1.350)	(2.041)	(1.018)
Not Selected to attend	-2.000	-1.000	0.500	0.500	-2.000	1.317
choice school	(3.034)	(2.006)	(2.478)	(2.563)	(3.123)	(1.838)
Selected × number	0.000	0.000	1.000	-0.500	0.000	-0.184
of years	(0.951)	(0.700)	(0.726)	(0.590)	(0.865)	(0.430)
Not Selected × number	0.000	-1.000	-1.500	-0.500	0.500	-0.879
of years	(1.977)	(0.802)	(1.006)	(1.400)	(1.078)	(0.855)
Fixed Effects Methods	Dependent Variable = math (NCE) test score					
Selected to attend choice	-3.649	-4.270	-3.321	-2.288	-1.173	-3.391
school (selected)	(1.866)	(1.429)	(1.167)	(1.192)	(1.633)	(1.114)
Not Selected to attend	-2.758	-5.026	-3.621	-2.769	-1.326	-3.052
choice school	(3.192)	(2.109)	(2.170)	(2.150)	(2.707)	(1.741)
Selected × number	2.323	3.143	2.321	1.685	1.178	2.294
of years	(0.794)	(0.608)	(0.454)	(0.477)	(0.669)	(0.399)
Not Selected × number	0.919	1.681	1.526	0.844	-0.675	0.672
of years	(1.643)	(1.122)	(1.138)	(0.960)	(1.026)	(0.783)
Fixed Effects Methods	Dependent Variable = reading (NCE) test score					
Selected to attend choice	-0.320	-1.390	0.180	1.400	2.780	0.750
school (selected)	(1.625)	(1.372)	(1.254)	(1.169)	(1.412)	(1.027)
Not Selected to attend	-2.140	-3.200	-0.555	1.350	2.605	-0.644
choice school	(3.479)	(2.070)	(2.161)	(2.008)	(2.410)	(1.584)
Selected × number	0.320	0.690	-0.120	-0.700	-1.160	-0.249
of years	(0.687)	(0.630)	(0.541)	(0.472)	(0.635)	(0.368)
Not Selected × number	0.440	1.500	0.555	-0.350	-0.985)	0.247
of years	(1.555)	(1.069)	(0.898)	(0.813)	(1.015)	(0.706)

TABLE 5.1. *Estimates of the selection to participate in the choice program on Math and Reading scores estimates for the full sample. Math regressions include a dummy variable for whether the test score was imputed. The total number of observations are 8729 (Math) and 8751 (Reading). The standard errors (in parenthesis) are obtained after 1000 panel-bootstrap replications.*

Looking at the estimates of the gain in reading, the mean regression suggests that the students selected to attend choice schools did not improve relative to the students in the public schools. We get a bit more detail about the impact of the program by taking a look at various quantiles. Again, we see that there is a tendency to decrease as long as the quantile increases; from 0.7 additional percentile points per year at 0.25 quantile to -1.2 additional percentile points per year at the 0.9 quantile. The program has a modest effect

	Quantiles					
	0.1	0.25	0.5	0.75	0.9	Mean
Pooled Methods	Dependent Variable = math (NCE) test score					
Selected to attend choice	-3.302	0.000	-5.000	-5.000	-4.000	-1.900
school (selected)	(3.943)	(2.435)	(1.858)	(2.627)	(2.112)	(1.501)
Not Selected to attend	-10.369	-4.467	-7.995	-7.514	-6.000	-5.834
choice school	(7.307)	(4.988)	(3.833)	(4.548)	(6.775)	(2.951)
Selected × number	1.302	0.000	3.000	2.000	2.000	1.695
of years	(1.758)	(1.413)	(0.991)	(1.367)	(1.076)	(0.751)
Not Selected × number	3.369	1.467	3.000	2.550	1.000	2.937
of years	(5.777)	(2.839)	(1.972)	(2.165)	(3.657)	(1.774)
Pooled Methods	Dependent Variable = reading (NCE) test score					
Selected to attend choice	0.000	0.000	-6.000	-6.000	-4.000	-2.038
school (selected)	(4.014)	(2.021)	(2.367)	(1.341)	(3.284)	(1.323)
Not Selected to attend	-2.000	-3.000	-3.000	-2.000	-1.000	0.114
choice school	(4.148)	(4.055)	(4.137)	(2.955)	(5.304)	(2.633)
Selected × number	0.000	0.000	2.000	2.000	1.000	0.776
of years	(1.890)	(1.204)	(1.121)	(0.657)	(1.541)	(0.641)
Not Selected × number	0.000	1.000	1.000	1.000	0.000	0.332
of years	(3.140)	(2.940)	(1.662)	(1.624)	(2.920)	(1.534)
Fixed Effects Methods	Dependent Variable = math (NCE) test score					
Selected to attend choice	-5.239	-4.260	-3.763	-3.021	-2.269	-4.201
school (selected)	(2.979)	(1.757)	(1.388)	(1.570)	(2.528)	(1.417)
Not Selected to attend	-9.775	-5.481	-6.408	-4.505	-0.144	-4.387
choice school	(4.887)	(3.327)	(2.692)	(2.822)	(4.545)	(2.511)
Selected × number	3.883	3.984	2.763	1.798	1.677	2.940
of years	(1.488)	(0.955)	(0.638)	(0.828)	(1.398)	(0.638)
Not Selected × number	5.032	2.238	2.768	2.107	-1.087	1.820
of years	(2.755)	(2.241)	(1.771)	(1.662)	(2.345)	(1.493)
Fixed Effects Methods	Dependent Variable = reading (NCE) test score					
Selected to attend choice	-0.500	-2.667	-1.000	-1.333	-2.667	-1.555
school (selected)	(2.157)	(2.008)	(1.662)	(1.586)	(2.050)	(1.319)
Not Selected to attend	-8.312	-5.625	2.083	5.750	6.333	0.414
choice school	(4.267)	(2.989)	(3.005)	(3.209)	(3.383)	(2.247)
Selected × number	0.500	1.667	1.000	0.667	1.667	1.073
of years	(1.154)	(0.977)	(0.791)	(0.679)	(1.064)	(0.598)
Not Selected × number	3.811	2.875	-1.083	-2.750	-3.333	-0.078
of years	(2.201)	(1.638)	(1.683)	(1.468)	(1.762)	(1.327)

TABLE 5.2. *Estimates of the selection to participate in the choice program on Math and Reading scores estimates for the 1991-1993 Cohorts. Math regressions include a dummy variable for whether the test score was imputed. The total number of observations are 7570 (Math) and 7592 (Reading). The standard errors (in parenthesis) are obtained after 1000 panel-bootstrap replications.*

on the lower attainment students, and a negative effect on the higher attainment students, though the effects are insignificant at standard levels.

We also evaluate the sensitivity of the quantile regression estimates to the inclusion of the fourth year test scores of the 1990 cohort. While Table 5.2 presents estimates for the 1991-1993 cohorts, Table 5.3 displays results from a sample that excludes 1994 test scores for the 1990 cohort. Fixed effects quantile regression estimates suggest that the students

	Quantiles					
	0.1	0.25	0.5	0.75	0.9	Mean
Pooled Methods	Dependent Variable = math (NCE) test score					
Selected to attend choice	-2.029	0.000	-4.000	-5.000	-3.500	-1.507
school (selected)	(2.614)	(1.727)	(1.459)	(2.141)	(2.497)	(1.252)
Not Selected to attend	-7.598	-6.909	-5.000	-6.386	-8.500	-4.392
choice school	(3.755)	(3.470)	(3.371)	(2.966)	(12.798)	(2.280)
Selected × number	0.029	0.000	2.000	2.000	1.500	1.123
of years	(1.295)	(0.825)	(0.798)	(0.998)	(1.115)	(0.579)
Not Selected × number	2.814	2.282	1.000	1.462	2.500	1.641
of years	(1.970)	(1.563)	(1.429)	(1.424)	(8.341)	(1.114)
Pooled Methods	Dependent Variable = reading (NCE) test score					
Selected to attend choice	3.000	0.000	-3.000	-1.000	-0.500	0.509
school (selected)	(1.945)	(1.970)	(1.774)	(1.547)	(2.686)	(1.115)
Not Selected to attend	-2.000	-1.000	0.000	-2.000	-1.500	0.599
choice school	(3.272)	(2.440)	(2.537)	(2.786)	(3.665)	(2.054)
Selected × number	-1.000	0.000	1.000	0.000	-0.500	-0.268
of years	(1.133)	(0.999)	(0.839)	(0.743)	(1.187)	(0.517)
Not Selected × number	0.000	-1.000	-1.000	1.000	0.500	-0.401
of years	(2.250)	(1.189)	(1.251)	(1.601)	(1.498)	(1.046)
Fixed Effects Methods	Dependent Variable = math (NCE) test score					
Selected to attend choice	-4.292	-4.364	-3.000	-2.862	-1.233	-3.256
school (selected)	(2.130)	(1.487)	(1.257)	(1.350)	(2.040)	(1.202)
Not Selected to attend	-4.673	-5.740	-5.303	-3.246	-2.352	-4.665
choice school	(3.766)	(2.426)	(2.274)	(2.275)	(2.825)	(1.959)
Selected × number	2.431	3.364	2.000	1.862	0.961	2.163
of years	(1.025)	(0.729)	(0.569)	(0.652)	(0.978)	(0.508)
Not Selected × number	2.348	2.376	2.337	1.246	0.000	1.905
of years	(1.881)	(1.523)	(1.230)	(1.149)	(1.636)	(1.020)
Fixed Effects Methods	Dependent Variable = reading (NCE) test score					
Selected to attend choice	-1.250	-1.250	0.250	1.000	1.000	0.520
school (selected)	(1.906)	(1.612)	(1.382)	(1.447)	(1.735)	(1.115)
Not Selected to attend	-2.125	-4.250	0.500	4.000	3.000	0.165
choice school	(3.621)	(2.516)	(2.236)	(2.473)	(3.124)	(1.781)
Selected × number	0.500	0.750	-0.001	-0.750	-0.250	-0.113
of years	(0.911)	(0.745)	(0.643)	(0.657)	(0.927)	(0.472)
Not Selected × number	0.375	2.250	-0.500	-2.000	-1.500	-0.236
of years	(1.717)	(1.373)	(1.135)	(1.153)	(1.690)	(0.915)

Table 5.3. *Estimates of the selection to participate in the choice program on Math and Reading scores estimates for a sample that excludes 1994 test scores for the 1990 Cohort. Math regressions include a dummy variable for whether the test score was imputed. The total number of observations are 8548 (Math) and 8569 (Reading). The standard errors (in parenthesis) are obtained after 1000 panel-bootstrap replications.*

selected to attend choice school earn one-four additional percentile points per year in math relative to the students in the public schools. We see that the gain again has some tendency to decrease as we go across the quantiles; from 4.0 percentile points at the 0.25 quantile to 1.7 percentile points at the 0.9 quantile in Table 5.2, and from 3.4 percentile points at the 0.25 quantile to 1.0 percentile points at the 0.9 quantile in Table 5.3. The differences in

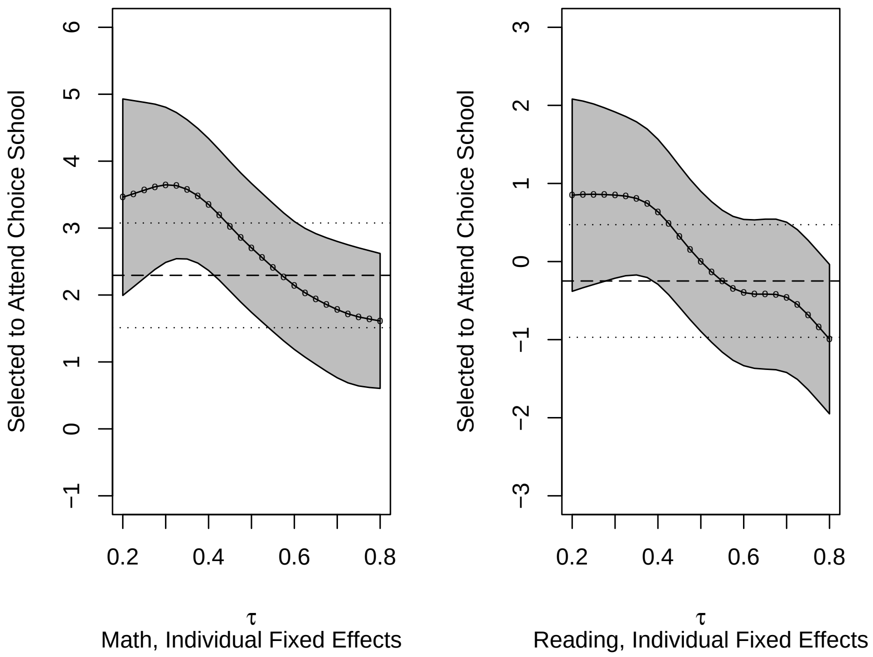

FIGURE 5.1. *Estimated effects of being selected for the choice program times years since application on educational attainment. The panels present the estimated effects (solid line with dots) as a function of the quantiles of the conditional distribution of math and reading scores, estimated using fixed effects. The figure also shows the conditional mean effect (dashed line), and .95 percent (pointwise) confidence interval for the point estimates.*

gain between groups are positive and statistically significant. (The sole exception is higher attainment students $\tau = 0.9$).

In Figure 5.1, we present the effect of the selection to attend choice schools times years since application as a function of the quantiles of the conditional distribution of test scores. We observe that while the conditional mean effect seems to provide an incomplete summary of the effect of being selected to attend choice school on educational attainment, the quantile intention-to-treat effect provides a more detailed assessment of the gains among students. The left panel suggests that being selected to attend choice school has a positive effect on the lower tail of the math score distribution, therefore the program seems to improve the academic achievements of the lower attainment students. For example, the students who did worse than the 0.3 quantile and were selected to attend choice school scored approximately 3.75 additional percentile points per year compared with the students who remained in the public school system. But, there is a modest effect on math and an adverse effect on reading in the right tail, not changing and reducing the achievements of the higher attainment students. For instance, the students selected to the choice program earn approximately -1

	Quantiles					
	0.1	0.25	0.5	0.75	0.9	Mean
Fixed Effects Methods	Dependent Variable = math (NCE) test score					
Enrolled in choice school	-4.337	-4.868	-4.866	-3.866	-2.660	-3.764
	(2.473)	(1.652)	(1.357)	(1.336)	(1.836)	(1.191)
Selected, not currently enrolled in choice school	-3.650	-3.272	-0.316	0.746	1.100	-1.432
	(3.125)	(3.142)	(2.172)	(3.259)	(3.261)	(2.155)
Not Selected for choice school	-2.781	-4.967	-3.464	-2.745	-1.085	-2.858
	(3.448)	(2.165)	(2.058)	(2.107)	(2.735)	(1.749)
Enrolled in choice school × years since application	2.164	3.188	2.866	2.186	1.660	2.379
	(1.195)	(0.774)	(0.550)	(0.560)	(0.784)	(0.481)
Selected, not currently enrolled × years since application	2.706	2.864	1.316	0.614	0.849	1.772
	(1.239)	(1.113)	(0.728)	(1.153)	(1.386)	(0.756)
Not Selected for choice school × years since application	0.779	1.484	1.464	0.745	-0.915	0.437
	(1.717)	(1.106)	(1.093)	(0.931)	(0.983)	(0.786)
Fixed Effects Methods	Dependent Variable = reading (NCE) test score					
Enrolled in choice school	-0.690	-1.293	0.250	0.914	1.767	0.315
	(1.685)	(1.559)	(1.396)	(1.381)	(1.514)	(1.098)
Selected, not currently enrolled in choice school	3.379	0.147	2.586	4.233	5.200	2.783
	(3.307)	(2.731)	(1.983)	(2.126)	(3.398)	(1.987)
Not Selected for choice school	-1.891	-2.897	-0.925	1.422	2.578	-0.660
	(3.513)	(2.135)	(2.159)	(2.044)	(2.540)	(1.591)
Enrolled in choice school × years since application	0.147	0.500	-0.250	-0.603	-0.853	-0.291
	(0.756)	(0.758)	(0.673)	(0.575)	(0.696)	(0.438)
Selected, not currently enrolled × years since application	-0.612	0.621	-0.509	-1.233	-1.623	-0.616
	(1.382)	(1.055)	(0.787)	(0.807)	(1.330)	(0.694)
Not Selected for choice school × years since application	0.365	1.302	0.468	-0.474	-1.026	0.101
	(1.577)	(1.110)	(0.900)	(0.841)	(1.059)	(0.709)

TABLE 5.4. *Individual fixed effects estimates of the effect of choice schools on test scores. The table shows both the gains of the student enrolled in the choice school (treatment effect) and the gains of the students selected, but not actually enrolled (partial treatment effect). The total number of observations are 8729 (Math) and 8751 (Reading). The standard errors (in parenthesis) are obtained after 1000 panel-bootstrap replications.*

percentile points per year relative to the students in the public schools at the 0.8 quantile of the reading score distribution.

We now introduce a small change in equation (5.1) to estimate the achievement gains among the students selected to attend choice school. We divide this group of students in two groups: those who are actually enrolled, and those who are not (Table 5.4). The comparison group is, once again, the students in the public schools.

The enrollment in choice schools seems to have a positive impact on mathematics. We find that students enrolled in choice schools earn 2.4 additional percentile points per year relative to the students enrolled in the Milwaukee public schools. On the other hand, the students who were selected but not enrolled in the choice schools earn 1.7 additional percentile points. Considering the effect of being enrolled at various quantiles of the math score distribution, we also find that the estimated effects are positive, ranging from 3.2 percentile points per year at the 0.25 quantile to 1.7 percentile points per year at the 0.9 quantile. The effect of being selected but not enrolled is positive and statistically significant in the lower tail, but insignificant in the upper tail. For instance, the estimate is equal to 0.614 percentile points with a standard error of 1.153 at the 0.75 quantile.

	Quantiles					
	0.1	0.25	0.5	0.75	0.9	Mean
Pooled Methods	Dependent Variable = math (NCE) test score					
Currently Enrolled in Choice School	1.644 (1.346)	2.559 (1.061)	1.516 (0.873)	-1.286 (0.934)	-1.412 (1.398)	0.555 (0.714)
Pooled Methods	Dependent Variable = reading (NCE) test score					
Currently Enrolled in Choice School	1.137 (1.046)	0.823 (0.830)	0.203 (0.730)	-2.258 (0.804)	-1.994 (0.968)	-0.462 (0.604)
IV Methods	Dependent Variable = math (NCE) test score					
Currently Enrolled in Choice School	2.331 (1.701)	3.688 (1.399)	2.766 (1.090)	0.182 (1.206)	0.605 (1.901)	1.701 (0.926)
IV Methods	Dependent Variable = reading (NCE) test score					
Currently Enrolled in Choice School	2.308 (1.378)	2.293 (1.080)	0.556 (0.971)	-1.738 (1.126)	-2.417 (1.288)	-0.103 (0.810)

TABLE 5.5. *Instrumental variables estimates of the causal effect of choice schools on math and reading test scores. The regressions include a constant, "applicant pool" dummy variables, gender dummy variable, family income, indicator for missing income, and test grade level. Math regressions include a dummy variable for whether the test score was imputed. The total number of observations are 3177 (Math) and 3163 (Reading). The IV variable is whether the child was randomly selected to attend choice schools.*

Considering both math and reading test scores, we observe that the students who were selected to attend choice and remained in the program earn more percentile points than the students who were selected but dropped the program. For example, at the median of the math score distribution, the students who are enrolled in choice schools earn an increment of 2.9 percentile points per year, but the students who dropped choice schools earn just 1.3 percentile points. The exceptions are the 0.1 quantile of the math score distribution, and the 0.25 quantile of the reading score distribution.

5.1.2. *IV Estimates.* A crucial (explicitly neglected) aspect of Table 5.4 is the difficulty of interpreting the results as estimates of the causal effect of choice school on academic achievements, because students were not randomly assigned into enrollment status. We now estimate equation (3.8), and we present the estimates in Table 5.5. We follow Rouse (1998) using whether or not the child was randomly selected to attend choice schools as an instrument for enrollment in choice schools.

The least squares IV estimates suggest that the students enrolled in choice schools earn 1.7 additional percentile points per year in mathematics relative to the students enrolled in the public schools. Looking at the various quantiles of the math score distribution, we observe that the estimated effects are positive, and different across quantiles. The estimated

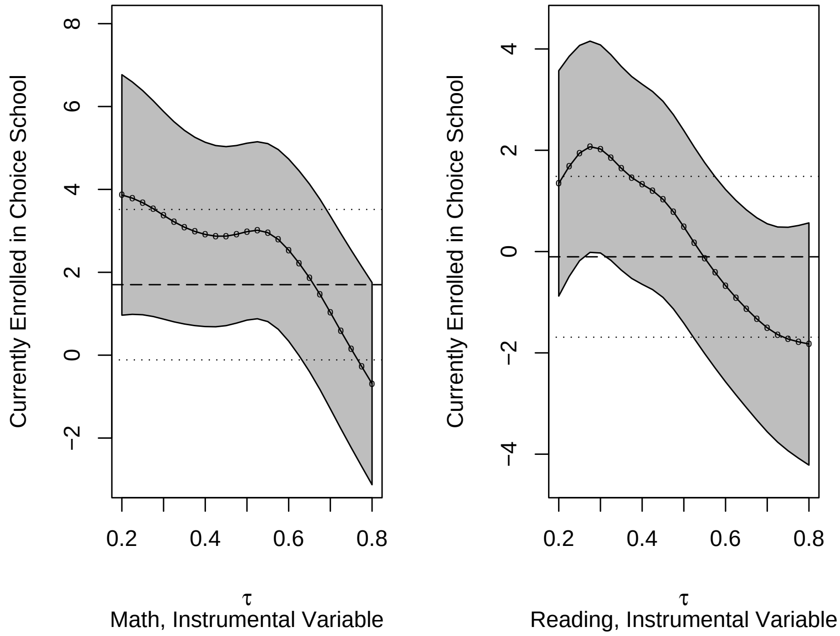

FIGURE 5.2. *Estimates of the treatment effect using a form of instrumental variable for quantile regression (Chernozhukov and Hansen 2005). The panels present the estimated effects (solid line with dots) as a function of the quantiles of the conditional distribution of math and reading scores. The figure also shows the conditional mean effect (dashed line), and .95 percent (pointwise) confidence interval for the point estimates.*

causal effect on math scores is positive and large for low attainment students, but small and statistically indistinguishable from zero for high attainment students. For example, the gain is 3.7 additional percentage points per year with a standard error of 1.4 at the 0.25 quantile, but 0.2 additional percentage points per year with a standard error of 1.2 at the 0.75 quantile. The mean effect also suggests that the program has a negative, insignificant effect on reading. But this is an incomplete, possibly wrong, conclusion because there is a tendency to decrease as we go across the quantiles. The gain ranges from 2.3 additional percentile points per year at the 0.1 quantile to -2.4 additional percentile points per year at the 0.9 quantile. The mean effect misses a lot.

Looking at the estimated effect presented in Figure 5.2, we observe an heterogeneous impact that decreases as the quantile increases. The panels suggest that the Milwaukee Parental Choice program has a positive effect on the lower tail of math and reading conditional distributions, but no effect on math, and an adverse effect on reading in the right tail. The right panel suggests that the program improved and reduced reading achievements of the lower and higher attainment students, respectively. While students who did worse than

	Quantiles					
Years since Application to the Program	0.1	0.25	0.5	0.75	0.9	Mean
Selected to Attend Choice Schools	Dependent Variable = math (NCE) test score					
One year	29.23	35.91	39.00	42.12	48.12	39.65
	(1.25)	(0.96)	(0.76)	(0.79)	(1.03)	(0.73)
Two years	29.12	35.12	39.00	43.91	48.25	39.84
	(1.39)	(1.04)	(0.88)	(1.02)	(1.08)	(0.78)
Three years	28.12	35.12	40.12	45.12	49.23	40.62
	(1.71)	(1.08)	(0.98)	(1.22)	(1.59)	(0.90)
Four years	28.00	36.01	42.00	47.12	51.91	41.73
	(2.88)	(2.06)	(1.46)	(1.34)	(1.98)	(1.28)
Not Selected to Attend Choice Schools	Dependent Variable = math (NCE) test score					
One year	27.00	33.20	37.74	40.99	45.91	37.66
	(1.97)	(1.34)	(1.49)	(1.47)	(1.86)	(1.25)
Two years	29.03	31.99	37.45	42.20	48.17	38.35
	(1.85)	(1.70)	(1.72)	(2.14)	(2.84)	(1.46)
Three years	28.00	28.99	37.20	43.17	43.99	36.97
	(2.98)	(2.49)	(2.47)	(2.50)	(2.25)	(2.04)
Four years	16.51	25.62	36.67	41.53	41.53	33.08
	(4.66)	(5.55)	(4.17)	(2.64)	(2.33)	(2.64)
Milwaukee Public School Sample	Dependent Variable = math (NCE) test score					
One year	31.91	37.00	40.00	42.73	47.91	40.39
	(0.70)	(0.61)	(0.52)	(0.58)	(0.78)	(0.37)
Two years	28.00	33.49	39.00	44.91	50.52	39.54
	(1.06)	(0.68)	(0.62)	(0.73)	(1.12)	(0.45)
Three years	25.00	30.00	36.04	42.00	46.49	36.76
	(1.09)	(0.73)	(0.71)	(0.83)	(1.10)	(0.56)
Four years	22.51	27.05	35.00	42.91	46.70	35.53
	(1.21)	(0.93)	(1.07)	(0.94)	(1.30)	(0.72)
Selected to Attend Choice Schools	Dependent Variable = reading (NCE) test score					
One year	29.00	35.00	39.00	43.00	48.00	39.04
	(1.12)	(1.01)	(0.93)	(0.97)	(1.02)	(0.67)
Two years	28.00	33.00	38.00	42.00	47.00	37.63
	(1.25)	(0.99)	(0.90)	(0.85)	(1.11)	(0.72)
Three years	27.00	32.00	37.00	43.00	48.00	37.38
	(1.67)	(1.13)	(1.06)	(1.18)	(1.68)	(0.83)
Four years	22.00	29.00	36.00	41.00	43.00	35.06
	(2.03)	(1.92)	(1.67)	(1.24)	(1.47)	(1.17)
Not Selected to Attend Choice Schools	Dependent Variable = reading (NCE) test score					
One year	26.00	34.00	38.00	44.00	48.00	38.13
	(2.43)	(1.46)	(1.67)	(1.61)	(2.01)	(1.14)
Two years	26.00	33.00	39.00	43.00	48.00	37.59
	(2.94)	(1.66)	(1.86)	(1.59)	(1.76)	(1.32)
Three years	25.00	32.00	35.00	40.00	42.00	35.69
	(3.73)	(2.55)	(2.25)	(1.94)	(2.94)	(1.82)
Four years	23.00	31.00	38.00	45.00	47.00	37.52
	(4.89)	(4.12)	(3.13)	(3.10)	(2.83)	(2.39)
Milwaukee Public School Sample	Dependent Variable = reading (NCE) test score					
One year	29.00	35.00	39.00	42.00	46.00	38.39
	(0.83)	(0.67)	(0.62)	(0.65)	(0.75)	(0.34)
Two years	27.00	32.00	38.00	43.00	47.00	37.85
	(1.00)	(0.76)	(0.69)	(0.72)	(0.80)	(0.40)
Three years	26.00	32.00	37.00	42.00	46.00	36.88
	(0.96)	(0.84)	(0.75)	(0.81)	(0.78)	(0.47)
Four years	23.00	29.00	36.00	42.00	46.00	35.62
	(0.97)	(0.93)	(0.95)	(0.85)	(1.07)	(0.57)

TABLE 5.6. *Adjusted Math and Reading (NCE) Test Scores by year after application to the choice program. The last column shows Rouse's (1998) mean results. The standard errors (in parenthesis) are obtained after 1000 panel-bootstrap replications.*

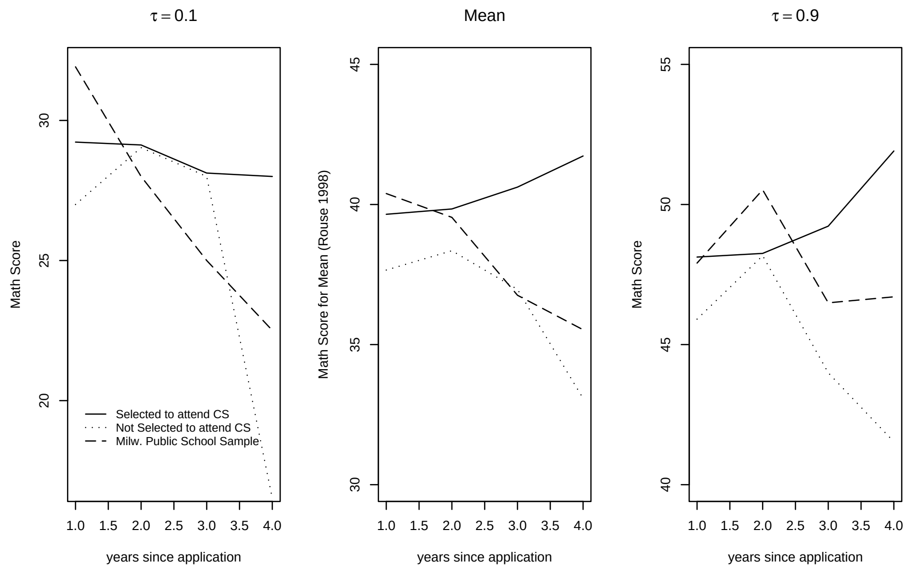

Figure 5.3. *Adjusted Math Test Scores by Years since Application to the Choice Program. While the mean effect implies a linear gain in mathematics for the students selected to attend the choice school (CS), lower attainment students have a negative linear gain, and higher attainment students have a positive, convexly increasing gain.*

the 0.3 quantile earned approximately 2 additional percentile points per year compared with the students in the public school system, the students who did better than the 0.7 quantile scored approximately -2 percentile points per year relative to the students in the Milwaukee public schools.

5.2. **Educational Achievements Beyond the Average Student.** We consider equation (7) in Rouse (1998) with individual fixed-effects,

$$T_{it} = \pi_0 + \sum_{k=1}^{4} \pi_{1k}(d_{it-k} \times S_{it-k}) + \sum_{k=1}^{4} \pi_{2k}(d_{it-k} \times N_{it-k}) + \sum_{k=-3}^{4} \pi_{3k} d_{it-k} + \alpha_i + \varepsilon_{it} \tag{5.2}$$

where, as before, d_{it-k} is a dummy variable indicating the number of years pre- or postapplication to the program, S_{it-k} indicates whether the student was selected to attend a choice school, and N_{it-k} indicates whether the student was not selected. The comparison group is a random sample of Milwaukee public schools students. We employ the fixed effects method to estimate the panel data-quantile regression model,

$$Q_{T_{it}}(\tau_j | d_{it-k}, S_{it-k}, N_{it-k}, \alpha_i),$$

evaluated by years since application to the program. Table 5.6 shows coefficient estimates from the τ_j-th conditional quantile function $\hat{Q}_{T_{it}}(\tau_j|\cdot)$, and the conditional mean function $\hat{\mathbb{E}}(T_{it}|\cdot)$[7]. The underlying estimates $\hat{\pi}$'s are presented in Tables B.1 and B.2 (Appendix B).

The students selected to attend choice schools had a roughly linear gain in mathematics, scoring approximately 2 additional points after four years (from 39.6 to 41.7 (NCE) points). Part of the increase is explained by the performance of the students in the public schools, who had a negative 4.9 point gain, going from 40.4 to 35.5 points. We also see that lower attainment students in the public schools have a significant loss, while higher attainment students have a negligible loss after four years. For example, we observe that the estimate drops 9.4 points (from 31.9 to 22.5 points) at the 0.1 quantile, but decreases 1.2 points (from 47.9 to 46.7 points) at the 0.9 quantile. The relatively large and positive effect in the lower tail observed in Figure 5.1 is therefore partially explained by the poor performance of the weakest students in the Milwaukee public schools.

At first glance, one may find the estimates in Table 5.6 contradicting those presented in Table 5.1. For instance, we see now that weak students selected to attend choice schools had roughly a point loss in math, but we concluded that these students were benefited by the program. This paradox is easily explained by the fact that we are now relaxing the assumption of equal gains over the years, considering differences in conditional test score levels instead of levels. We offer a simple exercise to see the point. The average difference between the continuous line and the dashed line in the panels of Figure 5.3 should be positive, and decreasing beyond the 0.25 quantile (Figure 5.1). We find differences equal to $\{1.76, 3.66, 2.52, 1.43, 1.47\}$ points at the $\{0.1, 0.25, 0.5, 0.75, 0.9\}$ quantiles.

Considering math scores for the students selected to attend choice schools, we find that the gains also vary across the quantiles. For example, the test score does not increase from one year to four years since application at the 0.25 quantile, but increases by 5.0 points at the 0.75 quantile. Moreover, the test score decreases 1.2 points at the 0.1 quantile, and increases 3.8 points at the 0.9 quantile.

Figure 5.3 provides an efficient way to summarize the effect of being selected to attend choice school on achievement gains. Rouse (1998) found that there is a linear gain in mathematics for students selected to attend choice schools (middle panel). We get more detail about the effect of being selected to attend choice schools over time by focusing on the math scores for the weakest and strongest students. While higher attainment students have a positive, convexly increasing gain, lower attainment students have a nearly linear loss. The declining test score may suggest that the weakest students scored below where they were relative to the national sample, but the program helped them because their scores, relative to the students in the public schools, increased dramatically in four years. Providing vouchers for private schooling seems to prevent the weakest students from having an even bigger loss experienced by the students in the public schools. Figure 5.4 summarizes the

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[7]Rouse (1998) graphs estimates of the coefficients (adjusted test scores) to summarize test score gains. For instance, the reading score estimate for the students selected to attend choice schools one year since application in model (5.2) is $\hat{\pi}_0 + \hat{\pi}_{11} + \hat{\pi}_{31} + \hat{\alpha}_i$. The introduction of individual effects raises questions about the choice of $\hat{\alpha}_i$. The mean appears as a natural candidate giving an estimate that is equal to zero, which is expected because the model includes an overall intercept. Thus, the sum of the estimates could be interpreted as the predicted reading scores of the students selected to the choice program one year since application, which is equal to 39.04.

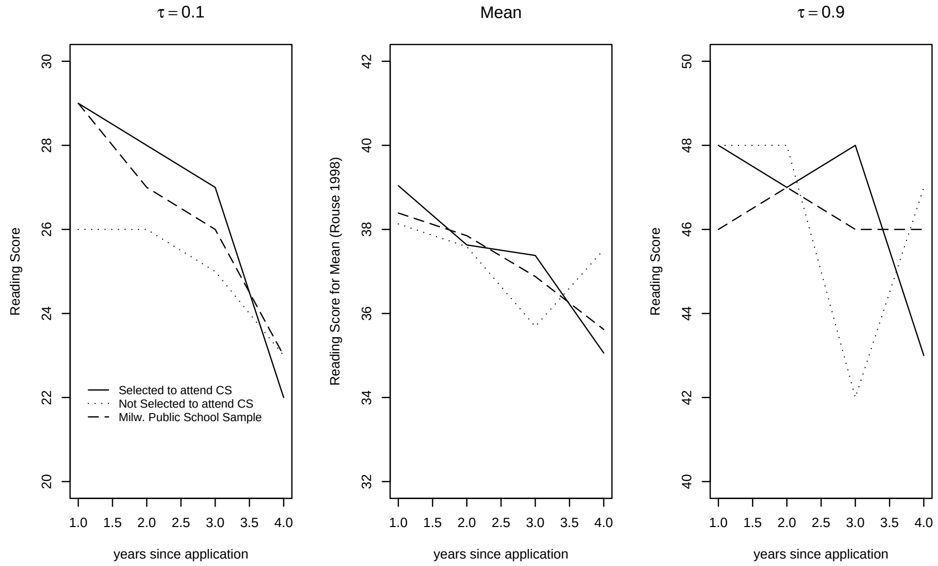

FIGURE 5.4. *Adjusted Reading Test Scores by Years since Application to the Choice Schools (CS).*

result for reading scores. The evidence suggests that there are no differences among the groups of students in the lower and upper tails of the score distribution.

We now test if the gains are significantly different considering Koenker and Bassett (1982) framework for hypothesis testing, described in detail in Appendix A. Note that the estimates in Table 5.6 are test scores resulting from a model evaluated at several years since application to the program (from one to four years), quantiles (from 0.1 to 0.9 quantiles), and groups (students selected to attend choice schools, students not selected to attend choice schools, and students in the Milwaukee public schools). We test two hypotheses. First, we check whether the adjusted test scores are significantly different across several quantiles. We found that these differences were statistically significant across the quantiles of the math and reading score distributions (p-values were 0.000). Second, we test the equality of test scores across several years since application to the program. In Table 5.7, the first entry tests the differences among the scores of the selected students at the 0.1 quantile of the math distribution across years since application to the program.

We see that the adjusted test scores are in general statistically different across years since application to the program among students who were selected to attend choice schools and students who remained in the public schools. In mathematics, for instance, there is evidence that the test scores of students selected to attend choice schools vary significantly across years since application at the 0.75 quantile. We observe a high p-value at the 0.9 quantile, which is expected given the small difference between the adjusted scores in the first and second year since application to the program. In contrast, the difference between the scores in the first and fourth year of application is significant at the standard 5 percent level (p-value equal to 0.046). There is also evidence that math scores are statistically different

Years after application		Quantiles				
		0.1	0.25	0.5	0.75	0.9
Group of Students	H_0	Math (NCE) test score				
Selected to Attend Choice Schools	I	0.937	0.873	0.181	0.001	0.233
	II	0.681	0.963	0.039	0.000	0.046
Not Selected to Attend Choice Schools	I	0.028	0.352	0.994	0.843	0.188
	II	0.025	0.179	0.800	0.836	0.102
Milwaukee Public School Sample	I	0.000	0.000	0.000	0.000	0.019
	II	0.000	0.000	0.000	0.845	0.384
Selected and Milwaukee Public School Sample	I	0.000	0.000	0.000	0.000	0.032
	II	0.000	0.000	0.000	0.002	0.113
All Groups	I	0.000	0.000	0.000	0.000	0.013
	II	0.000	0.000	0.000	0.005	0.024
Group of Students	H_0	Reading (NCE) test score				
Selected to Attend Choice Schools	I	0.017	0.014	0.234	0.289	0.013
	II	0.002	0.003	0.078	0.132	0.003
Not Selected to Attend Choice Schools	I	0.939	0.831	0.354	0.108	0.255
	II	0.576	0.472	1.000	0.729	0.752
Milwaukee Public School Sample	I	0.000	0.000	0.001	0.396	0.591
	II	0.000	0.000	0.000	1.000	1.000
Selected and Milwaukee Public School Sample	I	0.000	0.000	0.004	0.453	0.060
	II	0.000	0.000	0.001	0.502	0.029
All Groups	I	0.000	0.000	0.014	0.282	0.098
	II	0.000	0.000	0.005	0.540	0.087

TABLE 5.7. *Tests for the equality of the adjusted test scores across years since application to the program. The null hypothesis I considers the equality of coefficients from the conditional quantile model across years since application to the choice program. The null hypothesis II considers the equality of coefficients from the conditional quantile model between the first and fourth year since application to the program. The table reports p-values.*

among the three groups of students. For instance, the p-value is 0.000 at the 0.1 quantile, and 0.013 at the 0.9 quantile. Not surprisingly, there is weaker evidence that predicted reading scores are different across the years since application to the program.

6. Conclusions

Empirical studies of the Milwaukee Parental Choice program have delivered mixed empirical evidence on educational achievement, partially due to a lack of a valid control group. To get around the problem, Rouse's (1998) novel empirical approach uses a sample of students in the Milwaukee public schools as a comparison group, and individual fixed effects to control for latent characteristics that may differ between treatment and comparison groups. Her results suggest that being selected to participate in the choice program increased math achievements of the "average" minority student by 2.3 percentile points per year. Our results suggest an increase in math achievements that ranges from 1.2 to 3.1 percentile points per year across quantiles. The findings also present some support for a positive effect in the lower tail of the reading conditional distribution, and a negative effect in the upper tail.

Our analysis also suggests that students selected for the program make progress at different rates relative to the students in the public schools. While the mean effect suggests a linear gain in mathematics for students selected to attend choice schools, higher attainment students have a positive, convexly increasing gain, and lower attainment students have a nearly linear loss. However, weak students' scores increased dramatically compared to public school students' scores. Providing vouchers for private schooling seems to prevent the weakest students from having an even bigger loss experienced by the students in the public schools.

Finally, although the conditional mean approach is simple and useful, the analysis reveals that quantile regression methods provide an informative, complementary approach. The estimation of patterns of achievement in terms of quantiles may lead to a richer debate on school choice, a debate beyond the educational attainment of the "average" low-income student.

Appendix A. General Linear Hypothesis

We use Koenker and Bassett (1982) framework for hypothesis testing considering general linear hypothesis on the vector $\boldsymbol{\xi}$ of the form $\mathrm{H}_0 : \boldsymbol{R}\boldsymbol{\xi} = \boldsymbol{r}$, where $\boldsymbol{R}$ is a matrix that depends on the type of restrictions imposed. We evaluate the significance of differences across coefficient estimates from model (5.2) at different quantiles, and the significance of differences across coefficient estimates at different years since application on a vector with typical element,

$$\xi_j^k = Q_T^k(\tau_j),$$

where $Q_T^k(\tau_j)$ denotes the coefficients from the τ_j-th conditional quantile function k years after application to the choice program. For example, when we test whether the adjusted test score is significantly different across several quantiles one year after application, the vector is $\boldsymbol{\xi}_j^1 = (Q_T^1(0.1), ..., Q_T^1(0.9))'$, and when we test the equality of the adjusted test scores at the 0.1 quantile across several years since application, $\boldsymbol{\xi}_1^k = (Q_T^1(0.1), ..., Q_T^4(0.1))'$. The test statistics,

$$\mathcal{T}_{NT} = NT(\boldsymbol{R}\hat{\boldsymbol{\xi}} - \boldsymbol{r})' \left[\boldsymbol{R}\hat{\boldsymbol{V}}^{-1}\boldsymbol{R}'\right]^{-1} (\boldsymbol{R}\hat{\boldsymbol{\xi}} - \boldsymbol{r})$$

is asymptotically distributed as χ_q^2 under H_0, where q is the rank of the matrix $\boldsymbol{R}$ and $\hat{\boldsymbol{V}}$ is the estimated covariance matrix. The implementation of the test is based on the function `anova.rq` in Koenker (2006).

References

Behrman, J., Y. Cheng, and P. Todd (2004): "Evaluating Preschool Programs when Length of Exposure to the Program Varies: A Nonparametric Approach," *Review of Economics and Statistics*, 86(1), 108–132.

Bitler, M., J. Gelbach, and H. Hoynes (2006): "What Means Impact Miss: Distributional Effects of Welfare Reform Experiments," *forthcoming American Economic Review.*

Cameron, A. C., and P. K. Trivedi (2005): *Microeconometrics: Methods and Applications.* Cambridge University Press.

Chernozhukov, V., and C. Hansen (2005): "An IV Model of Quantile Treatment Effects," *Econometrica*, 73(1), 245–262.

Cullen, J., B. Jacob, and S. D. Levitt (2005): "The Impact of School Choice on Student Outcomes: An Analysis of the Chicago Public Schools," *Journal of Public Economics*, 89(5-6), 729–760.

Davison, A. C., and D. V. Hinkley (1997): *Bootstrap Methods and Their Applications.* Cambridge University Press.

Green, J. P., P. Peterson, and J. Du (1997): "The Effectiveness of School Choice: The Milwaukee Experiment," Harvard University Education Policy and Governance Occasional Paper 97-1.

Green, J. P., P. Peterson, J. Du, L. Boeger, and C. Frazier (1996): "The Effectiveness of School Choice: A Secondary Analysis of Data from the Program's Evaluation," University of Houston mimeo.

Hastings, J., T. Kane, and D. Staiger (2006): "Preferences and Heterogeneous Treatment Effects in a Public School Choice Lottery," NBER Working Paper, W12145.

Kaine, T., and D. Staiger (2002): "The Promise and Pitfalls of Using Imprecise School Accountability Measures," *Journal of Economic Perspectives*, 16(4), 91–114.

Koenker, R. (2004): "Quantile Regression for Longitudinal Data," *Journal of Multivariate Analysis*, 91, 74–89.

——— (2006): "quantreg: Quantile Regression," R package version 3.90, `http://www.r-project.org`.

Koenker, R., and G. Bassett (1978): "Regression Quantiles," *Econometrica*, 46, 33–50.

——— (1982): "Tests of Linear Hypothesis and ℓ_1 Estimation," *Econometrica*, 50, 1577–1584.

Rouse, C. (1998): "Private School Vouchers and Student Achievement: An Evaluation of the Milwaukee Parental Choice Program," *Quarterly Journal of Economics*, pp. 553–602.

Rubin, D. (1974): "Estimating Causal Effects of Treatments in Randomized and Non-randomized Studies," *Journal of Educational Psychology*, 66, 668–702.

Witte, J. (1997): "Achievements Effects of the Milwaukee Voucher Program," mimeo, University of Wisconsin.

——— (2000): *The Market Approach to Education: An Analysis of America's First Voucher Program.* Princeton University Press.

Appendix B. Point Estimates of Model 5.2

	Quantiles					
	0.1	0.25	0.5	0.75	0.9	Mean
	Dependent Variable = math (NCE) test score					
Three years before application	2.977	4.654	3.908	1.908	1.908	2.332
	(3.434)	(2.616)	(2.111)	(2.387)	(3.192)	(1.754)
Two years before application	3.215	3.654	4.908	4.908	3.908	3.557
	(2.087)	(1.813)	(1.511)	(1.500)	(1.668)	(1.057)
One year before application	5.020	4.654	3.908	3.908	3.123	3.615
	(1.733)	(1.090)	(0.983)	(1.464)	(1.372)	(0.809)
One year after application	5.004	3.746	1.000	-2.267	-3.092	0.766
	(1.034)	(0.737)	(0.598)	(0.806)	(0.943)	(0.519)
Two years after application	1.092	0.237	0.000	0.000	-0.477	-0.083
	(1.270)	(0.749)	(0.643)	(0.887)	(1.236)	(0.575)
Three years after application	-1.908	-3.254	-2.959	-3.000	-4.509	-2.863
	(1.298)	(0.816)	(0.775)	(0.976)	(1.203)	(0.660)
Four years after application	-4.401	-6.203	-4.000	-2.093	-4.295	-4.090
	(1.426)	(1.037)	(1.112)	(1.099)	(1.383)	(0.787)
Selected to attend choice schools	-2.686	-1.092	-1.000	-0.609	0.215	-0.740
× one year after application	(1.428)	(1.142)	(0.912)	(0.941)	(1.260)	(0.941)
Selected to attend choice schools	1.123	1.633	0.000	-1.004	-2.269	0.301
× two years after application	(1.728)	(1.218)	(1.083)	(1.295)	(1.582)	(1.027)
Selected to attend choice schools	3.122	5.123	4.083	3.123	2.736	3.863
× three years after application	(1.908)	(1.273)	(1.204)	(1.450)	(1.869)	(1.154)
Selected to attend choice schools	5.493	8.952	7.000	4.216	5.204	6.191
× four years after application	(3.104)	(2.235)	(1.716)	(1.587)	(2.310)	(1.503)
Not selected to attend choice schools	-4.913	-3.803	-2.262	-1.740	-2.000	-2.733
× one year after application	(2.017)	(1.387)	(1.502)	(1.522)	(1.993)	(1.357)
Not selected to attend choice schools	1.028	-1.500	-1.552	-2.716	-2.350	-1.191
× two years after application	(2.064)	(1.799)	(1.786)	(2.237)	(2.980)	(1.573)
Not selected to attend choice schools	3.000	-1.007	1.156	1.172	-2.498	0.214
× three years after application	(3.095)	(2.564)	(2.581)	(2.586)	(2.429)	(2.123)
Not selected to attend choice schools	-5.995	-1.431	1.672	-1.376	-5.173	-2.457
× four years after application	(4.708)	(5.600)	(4.235)	(2.669)	(2.443)	(2.710)
Constant	26.908	33.254	39.000	45.000	51.000	39.624
	(0.914)	(0.661)	(0.588)	(0.761)	(0.742)	(0.361)

Table B.1. *Individual fixed effects estimates of the effect of selection to attend choice school on Math scores. The models also include a dummy variable for whether the test score was imputed. The comparison group is Rouse's (1998) sample of Milwaukee Public School students. The number of observations is 8729. The standard errors (in parenthesis) are obtained after 1000 panel-bootstrap replications.*

	Quantiles					
	0.1	0.25	0.5	0.75	0.9	Mean
	Dependent Variable = Reading (NCE) test score					
Three years before application	4.000	4.000	3.000	3.000	2.000	2.803
	(2.372)	(2.558)	(1.567)	(2.624)	(1.805)	(1.603)
Two years before application	4.000	2.000	4.000	2.000	1.000	2.512
	(1.806)	(1.343)	(1.183)	(1.117)	(1.777)	(0.956)
One year before application	3.000	3.000	3.000	1.000	1.000	2.312
	(1.578)	(1.051)	(0.846)	(1.038)	(1.335)	(0.731)
One year after application	2.000	2.000	1.000	-2.000	-3.000	0.031
	(1.014)	(0.691)	(0.652)	(0.731)	(0.868)	(0.477)
Two years after application	0.000	-1.000	0.000	-1.000	-2.000	-0.504
	(1.171)	(0.724)	(0.646)	(0.771)	(0.889)	(0.525)
Three years after application	-1.000	-1.000	-1.000	-2.000	-3.000	-1.476
	(1.108)	(0.814)	(0.760)	(0.851)	(0.883)	(0.576)
Four years after application	-4.000	-4.000	-2.000	-2.000	-3.000	-2.738
	(1.151)	(0.910)	(0.949)	(0.869)	(1.155)	(0.656)
Selected to attend choice schools	0.000	0.000	0.000	1.000	2.000	0.649
× one year after application	(1.299)	(1.112)	(1.061)	(1.060)	(1.152)	(0.868)
Selected to attend choice schools	1.000	1.000	0.000	-1.000	0.000	-0.222
× two years after application	(1.519)	(1.198)	(1.074)	(1.049)	(1.330)	(0.945)
Selected to attend choice schools	1.000	0.000	0.000	1.000	2.000	0.498
× three years after application	(1.838)	(1.330)	(1.224)	(1.403)	(1.851)	(1.057)
Selected to attend choice schools	-1.000	0.000	0.000	-1.000	-3.000	-0.559
× four years after application	(2.177)	(2.104)	(1.847)	(1.475)	(1.810)	(1.379)
Not Selected to attend choice schools	-3.000	-1.000	-1.000	2.000	2.000	-0.255
× one year after application	(2.515)	(1.469)	(1.710)	(1.662)	(2.081)	(1.240)
Not Selected to attend choice schools	-1.000	1.000	1.000	0.000	1.000	-0.268
× two years after application	(3.009)	(1.733)	(1.934)	(1.661)	(1.873)	(1.436)
Not Selected to attend choice schools	-1.000	0.000	-2.000	-2.000	-4.000	-1.194
× three years after application	(3.834)	(2.663)	(2.314)	(2.018)	(2.982)	(1.924)
Not Selected to attend choice schools	0.000	2.000	2.000	3.000	1.000	1.902
× four years after application	(4.921)	(4.207)	(3.246)	(3.196)	(2.983)	(2.487)
Constant	27.000	33.000	38.000	44.000	49.000	38.357
	(0.897)	(0.702)	(0.650)	(0.702)	(0.743)	(0.327)

TABLE B.2. *Individual fixed effects estimates of the effect of selection to attend choice school on Reading scores. The comparison group is Rouse's (1998) sample of Milwaukee Public School students. The number of observations is 8751. The standard errors (in parenthesis) are obtained after 1000 panel-bootstrap replications.*