# VOUCHER PROGRAM INCENTIVES AND SCHOOLING PERFORMANCE IN COLOMBIA: A QUANTILE REGRESSION FOR PANEL DATA APPROACH[*]

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Abstract. Angrist et al. (2002) study is reconsidered using a relatively new quantile regression approach for panel data models. The evidence suggests that the effect of winning a Colombian voucher is largest in the lower tail of the educational attainment distribution, a possibility that was conjectured by the original authors, but could not be confirmed empirically using existing regression methods. This finding supports the hypothesis that lottery winners' incentive to study harder could account for the impact of the vouchers, including lower repetition rate.

**Keywords:** Colombian Vouchers, Incentives, Panel Data, Quantile Regression.

**JEL Codes:** I28, C13.

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## 1. Introduction

Vouchers programs, notably the Colombian voucher program implemented in 1991 that served over 100,000 students, may include policies that could differently affect the performance of weak students. There is consequently a growing empirical interest on the effect of voucher programs on the lower quantiles of the attainment distribution (see, e.g., two recent papers published in this Review: Angrist, Bettinger, Bloom, King, and Kremer 2002; Angrist, Bettinger, and Kremer 2006). The Colombian vouchers were assigned using lotteries, and were renewable as long as the students maintained good academic progress. This second aspect of the program may provide incentives for students to work harder, therefore the Colombian vouchers may be expected to have "effects similar to merit-based college scholarships and test-based achievement awards" (Angrist, Bettinger, and Kremer 2006). Angrist et al. (2002) find lower repetition rates for lottery winners, possibly explained by the

> "... increased effort by voucher recipients in order to avoid failing a grade and losing their vouchers ... This would imply that the primary incentive effect should be on those who are near the margin for passing on to the next grade. However, quantile regression estimates (not reported here) suggest that the increase in test scores is not confined to low quantiles of the score distribution. For reading and writing, there is no strong pattern of differential effects across quantiles, while for math, the effects are, if anything, larger at the top of the distribution"

Angrist et al. (2002) also estimate a classical Gaussian random effects model, but this approach precludes estimating effects other than the mean. To get around the problem, we employ a relatively new quantile regression method for panel data. The results of this Comment suggest that the effect of winning a voucher is largest in the lower tail of the educational attainment distribution as was conjectured by the original authors, although this could not be confirmed empirically using existing regression approaches. The evidence suggests that the impact of the Colombian vouchers could be explained by lottery winners' incentive to devote more effort to school.

## 2. The Conjecture

Let $Y$ denote educational attainment (e.g., test scores), and $D$ voucher status (e.g., $D = 1$ indicates lottery winners and $D = 0$ indicates lottery losers). In what follows, $Q_Y(\tau|\cdot)$ denotes the $\tau$-th conditional quantile function, and $\boldsymbol{z}$ a vector of observable variables.

Angrist et al. (2002) conjectured that students in the margin for passing on to the next grade may have different incentives than non-voucher students because vouchers were renewable only conditional on good academic standing. It is natural then to be interested in the quantile treatment effect (QTE), $Q_Y(\tau|D = 1, \boldsymbol{z}) - Q_Y(\tau|D = 0, \boldsymbol{z})$, for a lower-tail quantile $\tau$ of the educational attainment distribution[1]. We also consider the QTE without observable variables $\boldsymbol{z}$, suggesting an interpretation that fits nicely into the two-sample treatment response model (see, e.g., Lehmann 1974, Doksum 1974, Koenker 2005). In the original Lehmann-Doksum framework, the quantile treatment effect is defined as the horizontal distance $\Delta(x)$ between the distribution function of the treatment responses $G$, and the distribution function of the control responses $F$, $G(x + \Delta(x)) = F(x)$; thus, $\Delta(x) = G(F(x))^{-1} - x$. Considering $\tau = F(x)$, and changing variables, we have $\Delta(F(\tau)^{-1}) = \delta(\tau) = G(\tau)^{-1} - F(\tau)^{-1}$. This quantity may be estimated non parametrically, but quantile regression methods suggest a direct way for estimation of $\delta(\tau)$. The familiar linear conditional

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[1] "The random assignment of vouchers facilitates a natural-experiment research design in which losers provide a comparison group for winners" (Angrist, Bettinger, and Kremer 2006). This parameter of interest, however, is simply introduced to formally discuss the conjecture in the context of the Colombian voucher program.

quantile function,

$$Q_{Y_i}(\tau|D_i) = \beta(\tau) + \delta(\tau)D_i, \tag{1}$$

can be estimated using quantile regression methods yielding $\hat{\beta}(\tau) = \hat{F}(\tau)^{-1}$, and $\hat{\delta}(\tau) = \hat{G}(\tau)^{-1} - \hat{F}(\tau)^{-1}$. It is possible to consider that the distance between the (marginal) distribution functions is a location shift, $\delta(\tau) = \delta$, a scale shift, $\delta(\tau) = \gamma F(\tau)^{-1}$, or a location-scale shift $\delta(\tau) = \delta + \gamma F(\tau)^{-1}$. Although these models capture a variety of distances, they are still restrictive since the treatment appears to be continuous on $\tau$.

Angrist et al. (2002) seem to suggest that the effect of winning Colombian vouchers operates differently over $\tau$ shifting from a location shift to a location-scale shift (and viceversa) as we consider pieces of the marginal distribution functions. We consider instead a shift $\delta(\tau) = \delta + \gamma(\tau)F(\tau)^{-1}$, where $\gamma(\tau) = \gamma$ for $\tau$'s in $\mathcal{T}$, a set that includes quantiles representing the proportion of students at risk of repeating a grade, and $\gamma(\tau) = 0$ elsewhere. The effect of winning a Colombian voucher operates now as a location shift for quantiles outside the set $\mathcal{T}$, and as a location-scale shift in the set $\mathcal{T}$.

The previous cross sectional equation (1), however, may confound students' effort to maintain the voucher status and students' unobserved characteristics (e.g., skills) since both could have a positive impact on test scores. We may be able to identify them assuming that students' unobserved characteristics does not change over subjects and that students' effort does change. We reformulate then the model simply as,

$$Q_{Y_{is}}(\tau|D_i,\alpha_i) = \beta + \delta D_i + \alpha_i + (1+\gamma(\tau)D_i)F_u(\tau)^{-1} \tag{2}$$

where $s$ denotes subjects (i.e., mathematics, reading, writing). The variable $u_{is}$ may represent students' effort in subject $s$ to maintain the voucher status, so it is natural to consider that it is iid taken from a uniform distribution function $\mathcal{U}[0,1]$. Angrist et al. (2002) estimated equation (1), and the classical Gaussian random effects version of model (2). While quantile regression estimates did not provide empirical support for their conjecture, random effects estimates could not be used to evaluate it. The random effects exclusive focus of the program's effect on the conditional mean is a limitation if the interest is on the lower quantiles.

## 3. DATA AND METHOD

We use Angrist et al. (2002) data set, but we consider instead a "feasible" version of the penalized quantile regression estimator,

$$\arg\min_{\boldsymbol{\beta},\boldsymbol{\delta},\boldsymbol{\alpha}} \sum_{j=1}^{J}\sum_{s=1}^{S}\sum_{i=1}^{N} \omega_j \rho_{\tau_j}(y_{is} - \boldsymbol{x}_{is}'\boldsymbol{\theta}(\tau_j) - \alpha_i) + \lambda \sum_{i=1}^{N} |\alpha_i|$$

where $\rho_{\tau_j}(u) = u(\tau_j - I(u \leq 0))$ is the quantile loss function, $\boldsymbol{x}_{is} = [\boldsymbol{z}_{is}, D_i]'$, $\boldsymbol{\theta}(\tau_j) = (\boldsymbol{\beta}(\tau_j), \delta(\tau_j))'$, and $\omega_j$ is the weight given to the $j$th quantile. We will restrict attention to constant weights equal to $1/J$ over the quantiles $\{0.1, 0.25, 0.5, 0.75, 0.9\}$.

The approach proposes to estimate directly a vector of individual effects because the standard least squares transformations to deal with a large number of parameters are not available in quantile regression. The estimation of these parameters increases the variability of the estimates of the effect of winning a voucher lottery, but shrinkage of the individual effects, controlled by $\lambda$, helps to reduce the inflation effect. The estimator may be implemented directly by choosing any $\lambda \in (0, \infty)$, although finding precisely the optimal value remains unclear (see, e.g., Koenker 2004).

Lamarche (2006) investigates this issue showing that the class of estimators for models with exogenous regressors are asymptotically unbiased and Gaussian. The optimal $\lambda$ can thus be selected to minimize estimated asymptotic variance. He considers the following conditions:

**A 1.** The variables $y_{is}$ are independent with conditional (on $\boldsymbol{x}_{is}$, and $\alpha_i$) distribution $F_{is}$, and continuous densities $f_{is}$ uniformly bounded away from 0 and $\infty$ at the points $\xi_{is}(\tau_j)$ for $j = 1, \ldots, J$, $s = 1, \ldots, S$ and $i = 1, \ldots, N$.

**A 2.** The random variables $\alpha_i$, stochastically independent of $\boldsymbol{x}_{is}$, are exchangeable, identically, and independently distributed with unconditional distribution function $G_i$ with median zero, and continuous densities $g_i$ for $i = 1, \ldots, N$.

**A 3.** $\max||\boldsymbol{x}_{is}||/\sqrt{SN} \to 0$.

**A 4.** There exists a constant $c > 0$ such that $N^c/S \to 0$.

**A 5.** The regularization parameter $\lambda_S/\sqrt{S} \to \lambda \geq 0$.

**A 6.** There exist limiting positive definite matrices $\mathbf{\Gamma}_0$ and $\mathbf{\Gamma}_1$ with a typical block composed by,

$$\begin{aligned}\mathbf{\Gamma}_{0kj} &= \lim_{S,N\to\infty}\frac{1}{SN}\left\{\Omega_{kj}\sum_{i=1}^{N}\sum_{s=1}^{S}\ddot{\boldsymbol{x}}_{isk}\ddot{\boldsymbol{x}}_{isj}' + \frac{\lambda^2}{4}\sum_{i=1}^{N}\tilde{\boldsymbol{x}}_{ik}\tilde{\boldsymbol{x}}_{ij}'\right\}\\ \mathbf{\Gamma}_{1jj} &= \lim_{S,N\to\infty}\frac{1}{SN}\left\{\omega_j\sum_{i=1}^{N}\sum_{s=1}^{S}f_{is}(\xi_{is}(\tau_j))\ddot{\boldsymbol{x}}_{isj}\ddot{\boldsymbol{x}}_{isj}' + 2\lambda\sum_{i=1}^{N}g_i(0)\tilde{\boldsymbol{x}}_{ij}\tilde{\boldsymbol{x}}_{ij}'\right\}\end{aligned}$$

where $\Omega_{kj} = \omega_k(\tau_k \wedge \tau_j - \tau_k\tau_j)\omega_j$, $\ddot{\boldsymbol{x}}_{isj} = (\boldsymbol{x}_{is} - \tilde{\boldsymbol{x}}_{ij})$, $\tilde{\boldsymbol{x}}_{ij} = \sum_s w_{isj}\boldsymbol{x}_{is}$, $w_{isj} = \omega_j f_{is}(\tau_j)/(S^{-1}\sum_s \omega_j f_{is}(\tau_j))$, and $\xi_{is}(\tau_j)$ is the conditional quantile function.

**Theorem 1** (The Statistical Implication)**.** *Under regularity conditions A1-A6, the quantile regression estimator* $\hat{\boldsymbol{\theta}}(\boldsymbol{\tau},\lambda)$ *is asymptotically normally distributed with mean* $\boldsymbol{\theta}(\boldsymbol{\tau})$ *and covariance matrix* $\mathbf{\Gamma}_1(\lambda)^{-1}\mathbf{\Gamma}_0(\lambda)\mathbf{\Gamma}_1(\lambda)^{-1}$.

The result, shown in Lamarche (2006) and briefly presented here to not repeat his discussion, provides a step forward in the process of employing the method. The estimator $\hat{\boldsymbol{\theta}}(\boldsymbol{\tau},\lambda)$ is asymptotically unbiased if A1-A6 holds, suggesting that the choice of the parameter $\lambda$ should consider minimizing estimated asymptotic variance. Unfortunately, the implementation of this strategy within the context of the Colombian voucher program considers estimation of the nuisance parameters $f(\xi(\tau))$ and $g(0)$ using a small number of observations on each student (e.g., students' total number of subjects is 3, at most). To avoid estimating the densities, we have decided to use resampling strategies (e.g., panel boostrap) to obtain standard errors.

Given the program's experimental research design that includes using a lottery to select the beneficiaries, we employ the method considering a simple empirically based-variance minimizing strategy because the bias contribution should be small. The estimate $\hat{\lambda}$ minimizes $\hat{g}(\lambda)$, where $g$ is estimated using cubic smoothing splines (see, e.g., Hastie and Tibshirani 1990, Cameron and Trivedi 2005, p. 321) based on

$$\frac{1}{J}\sum_{j=1}^{J}\left(\frac{1}{(B-1)}\sum_{b=1}^{B}\left(\hat{\delta}_b(\tau_j,\lambda)-\bar{\hat{\delta}}_b(\tau_j,\lambda)\right)^2\right)^{1/2},$$

with $\bar{\hat{\delta}}_b(\tau_j,\lambda) = B^{-1}\sum_b \hat{\delta}_b(\tau_j,\lambda)$, the average over $B$ bootstrap estimates of $\delta^2$. Given the random assignment of vouchers, we estimate the precision of the penalized estimator $\hat{\delta}(\boldsymbol{\tau},\lambda)$ sampling pairs $\{(\boldsymbol{y}_i, D_i) : i = 1,...,N\}$ with replacement.

## 4. Results

4.1. **Estimating the optimal $\lambda$.** We now give some insight into the process of selecting $\lambda$ using Figure 1. The panels (a) and (b) show results from model (2) with and without covariates (see, e.g., Angrist et al. 2002, p. 1545). We observe an average

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[2] The estimate of the degree of shrinkage $\hat{\lambda}$ is obtained after a particular resampling method is used to estimate the precision of $\hat{\delta}$. We evaluated resampling strategies considering several Monte Carlo simulations assuming (i) exogenous regressors, and (ii) non-spherical errors. We constructed coverage empirical probabilities based on mainly three bootstrap approaches: residual bootstrap, wild bootstrap, and panel bootstrap (Davison and Hinkley 1997, Cameron and Trivedi 2005). We observed that the panel bootstrap strategy is quite reliable in term of size. The performance of the residual bootstrap was acceptable but less satisfactory, as expected given the moderate degree of heterocedasticity in the simulations. The wild bootstrap tended to overestimate the precision of the penalized estimator. Moreover, the performance of the panel bootstrap method was invariant to the degree of shrinkage $\lambda$. For instance, at the 0.05 nominal size and $\tau = 0.5$, the method gave similar frequencies for different $\lambda$'s ranging from 0.93 to 0.98. The exercise suggests that, in the case of exogenous regressors, the bias of $\hat{\delta}(\tau,\lambda)$ should be small conditional on any positive value of $\lambda$.

variance reduction that ranges from 15 to 20 percent for $\lambda$ approximately equal to 1.5. In panel (b), for instance, we see that the average standard error decreases from 0.128 to 0.117, and then it starts to increase very slowly. This unique global minimum, however, gives the (sometimes) false impression that we could select $\lambda$ automatically. In panel (a), the dotted line represents the average standard error of the estimates $\hat{\delta}$ of the entire vector of treatment effects, suggesting that the bootstrap $\lambda$ selection function might have multiple local minimums, a common problem in other smoothing selection strategies such as generalized cross-validation and cross-validation (Hastie and Tibshirani 1990). We found that the multiple local minimums could be explained by the lack of precision of estimating quantiles in the tails of the conditional educational attainment distribution, so we averaged the standard error of the quantile treatment effects over the quantiles around the median, resulting in the continuous line that can be seen in panel (a). Consequently, we complement the graphical device selecting the value of the shrinkage parameter that produces the minimum estimated value, as reported by the $\lambda$'s equal to 1.34 in panel (a), and 1.50 in panel (b).

4.2. **Panel Data Estimates.** Table's 1 last column reports similar estimates to the ones presented in Angrist et al. (2002). They do not offer quantile regression estimates for the cross-sectional equation, but our evidence supports their conclusion that the main effect of the program is not confined to low quantiles of the score distribution. In light of the conjecture, we would expect to see the largest estimate $\hat{\delta}(\tau)$ around

| | | Quantiles | | | | | |
|---|---|---|---|---|---|---|---|
| Dependent Variable | $\hat{\lambda}$ | 0.1 | 0.25 | 0.5 | 0.75 | 0.9 | Mean |
| Cross-Section Methods | | Model Without Covariates | | | | | |
| Total Points | - | 0.101 | 0.203 | 0.203 | 0.304 | 0.023 | 0.217$^{\ddagger}$ |
| | | (0.206) | (0.152) | (0.162) | (0.205) | (0.157) | (0.121) |
| Mathematics Scores | - | 0.405* | 0.000 | 0.202 | 0.000 | 0.405 | 0.178 |
| | | (0.157) | (0.163) | (0.151) | (0.193) | (0.247) | (0.118) |
| Reading Scores | - | 0.000 | 0.242 | 0.000 | 0.242 | 0.000 | 0.203$^{\ddagger}$ |
| | | (0.271) | (0.206) | (0.174) | (0.188) | (0.153) | (0.123) |
| Writing Scores | - | 0.305 | 0.000 | 0.000 | 0.302 | 0.305$^{\ddagger}$ | 0.126 |
| | | (0.321) | (0.167) | (0.184) | (0.205) | (0.173) | (0.122) |
| Cross-Section Methods | | Model With Covariates | | | | | |
| Total Points | - | 0.348$^{\ddagger}$ | 0.234 | 0.284$^{\ddagger}$ | 0.000 | 0.081 | 0.194$^{\ddagger}$ |
| | | (0.202) | (0.185) | (0.166) | (0.169) | (0.177) | (0.112) |
| Mathematics Scores | - | 0.212 | 0.063 | 0.158 | 0.040 | 0.358 | 0.128 |
| | | (0.212) | (0.167) | (0.146) | (0.175) | (0.239) | (0.114) |
| Reading Scores | - | 0.110 | 0.376$^{\ddagger}$ | 0.190 | 0.068 | 0.040 | 0.212$^{\ddagger}$ |
| | | (0.320) | (0.197) | (0.150) | (0.178) | (0.159) | (0.118) |
| Writing Scores | - | 0.199 | 0.071 | 0.036 | 0.172 | 0.183 | 0.123 |
| | | (0.256) | (0.160) | (0.167) | (0.142) | (0.193) | (0.119) |
| Panel Methods | | Model Without Covariates | | | | | |
| Pooled Test Scores (Math, | 1.340 | 0.305$^{\ddagger}$ | 0.060 | 0.115 | 0.199 | 0.184 | 0.174$^{\ddagger}$ |
| Reading, and Writing) | | (0.161) | (0.130) | (0.125) | (0.122) | (0.132) | (0.095) |
| Math and Reading | 2.060 | 0.330$^{\dagger}$ | 0.202 | 0.243$^{\ddagger}$ | 0.000 | 0.243$^{\ddagger}$ | 0.192$^{\ddagger}$ |
| Test Scores | | (0.138) | (0.145) | (0.133) | (0.143) | (0.142) | (0.101) |
| Math and Writing | 2.030 | 0.405$^{\dagger}$ | 0.000 | 0.153 | 0.036 | 0.305$^{\dagger}$ | 0.159 |
| Test Scores | | (0.166) | (0.117) | (0.131) | (0.145) | (0.141) | (0.098) |
| Reading and Writing | 1.530 | 0.000 | 0.026 | 0.092 | 0.243$^{\ddagger}$ | 0.147 | 0.170 |
| Test Scores | | (0.165) | (0.137) | (0.148) | (0.144) | (0.127) | (0.105) |
| Panel Methods | | Model With Covariates | | | | | |
| Pooled Test Scores (Math, | 1.500 | 0.274$^{\ddagger}$ | 0.157 | 0.114 | 0.077 | 0.158 | 0.158$^{\ddagger}$ |
| Reading, and Writing) | | (0.141) | (0.111) | (0.103) | (0.107) | (0.116) | (0.088) |
| Math and Reading | 2.440 | 0.337$^{\ddagger}$ | 0.245$^{\ddagger}$ | 0.151 | 0.020 | 0.151 | 0.171$^{\ddagger}$ |
| Test Scores | | (0.183) | (0.132) | (0.114) | (0.133) | (0.149) | (0.096) |
| Math and Writing | 2.760 | 0.320$^{\dagger}$ | 0.034 | 0.052 | -0.007 | 0.147 | 0.127 |
| Test Scores | | (0.163) | (0.110) | (0.120) | (0.119) | (0.147) | (0.091) |
| Reading and Writing | 2.650 | 0.273 | 0.229$^{\ddagger}$ | 0.124 | 0.052 | 0.053 | 0.169$^{\ddagger}$ |
| Test Scores | | (0.187) | (0.125) | (0.118) | (0.129) | (0.113) | (0.100) |

TABLE 1. *Estimates of the effect of winning a voucher lottery on test scores. The conditional mean models are estimated by OLS and random effects. All models include site dummies, and the models with covariates include the controls considered in Angrist et al. (2002). The symbols* $\ddagger, \dagger, \ast$ *denote statistically different from zero at the 0.10, 0.05, and 0.01 level of significance. The standard error are obtained after 1000 panel bootstrap repetitions.*

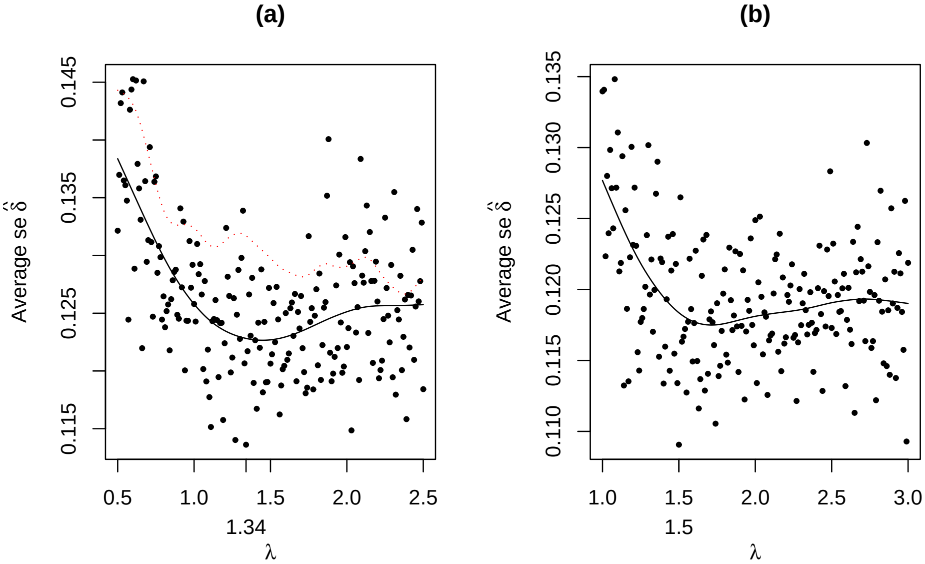


FIGURE 1. *Profile of the average standard error of the estimates of the effect of winning a voucher lottery. The continuous lines is $\hat{g}(\lambda)$, and the additional vertical line on the x-axis denotes $\hat{\lambda}$.*

the 0.1 quantile, and also estimates $\hat{\delta}(\tau)$'s fluctuating around a constant value beyond the neighborhood of $\tau = 0.1$. We observe that estimates of the effect of winning a voucher $\hat{\delta}(\tau)$ are positive and significant at the 0.1 quantile in models that include mathematics test scores, suggesting that lottery winners scored roughly 0.3 standard deviations higher in achievement tests. In general, the estimates $\hat{\delta}(\tau)$'s oscillates around a constant that is indistinguishable from zero beyond $\tau = 0.1$ (Figure 2).

The evidence seems to suggest that the effect of winning a voucher lottery is largest in the lower tail of the conditional educational attainment distribution, as conjectured by Angrist et al. (2002). (The sole exception is Reading and Writing test scores). We briefly investigated if the effect of winning a voucher on test scores at the 0.1

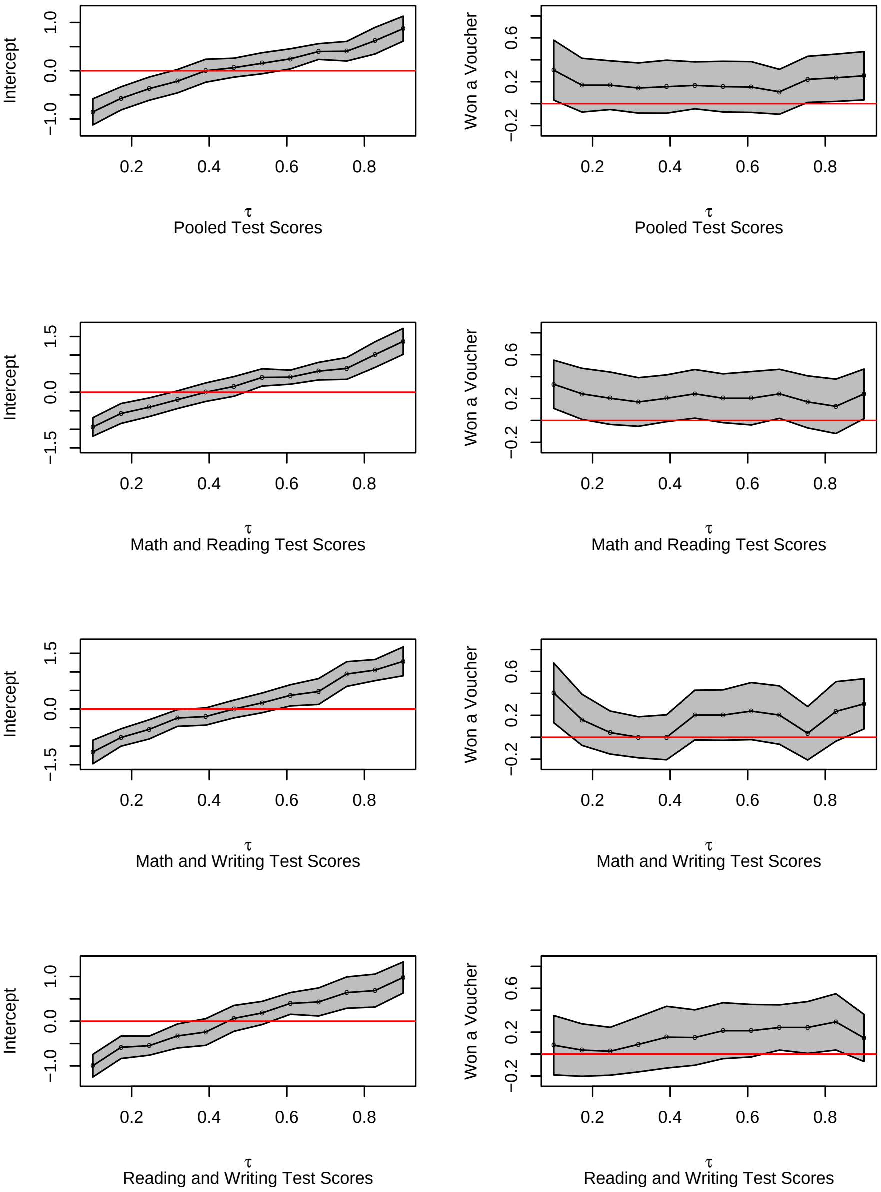
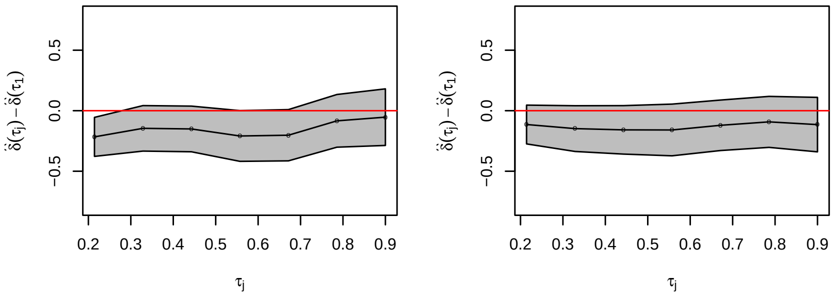
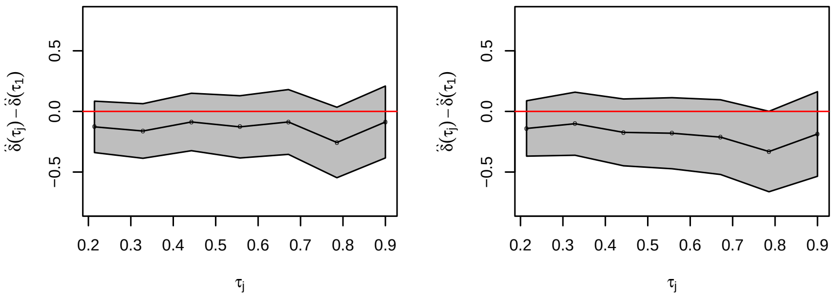


FIGURE 2. *Estimated Effects in Models without Covariates (only includes site dummies). The continuous lines with circles depicts the quantile estimates, and the shaded gray area denote a 90 percent confidence interval obtained after 1000 panel-bootstrap repetitions.*



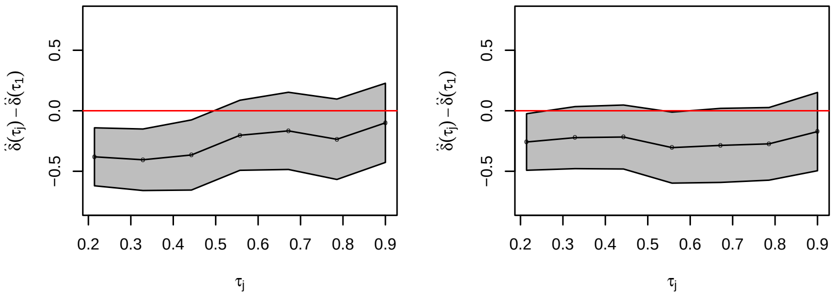
Pooled Test Scores (a)

Pooled Test Scores (b)



Math and Reading (a)

Math and Reading (b)



Math and Writing (a)

Math and Writing (b)

FIGURE 3. *Quantile Regression Plot Test Results. The continuous lines with circles depicts the quantile estimates, and the shaded gray area denote a 90 percent confidence interval obtained after 1000 panel-bootstrap repetitions. Letter 'a' indicates results obtained from a model without covariates, and 'b' from a model with covariates. The quantile* $\tau_1 = 0.1$.

quantile is significantly different across quantiles using Figure 3. In particular, we restricted attention to test the equality of the effect at the 0.1 quantile to every

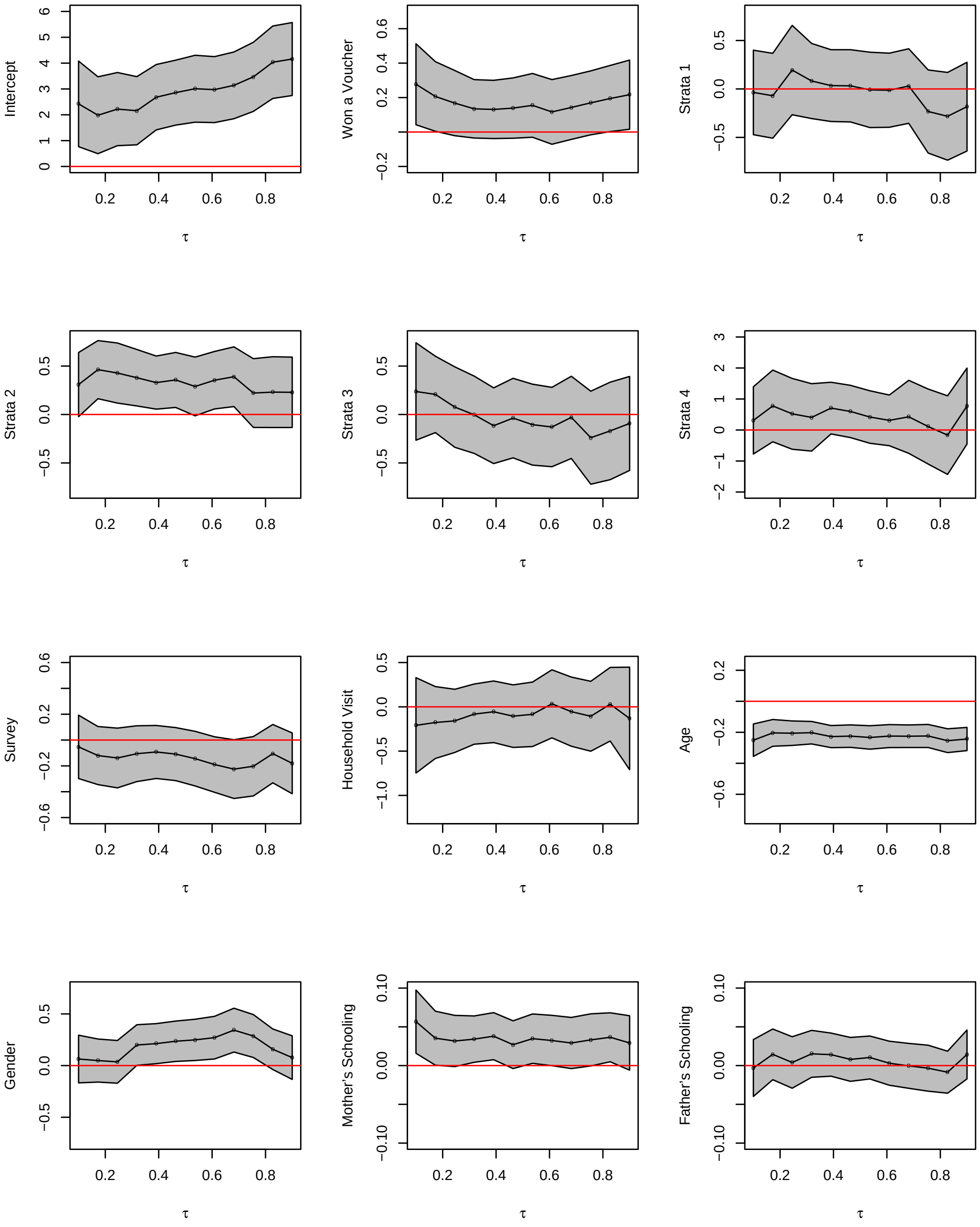


Figure 4. *Estimated effects in a model for Math, Reading and Writing. The continuous lines with circles depicts the quantile estimates, and the shaded gray area denote a 90 percent confidence interval obtained after 1000 panel-bootstrap repetitions.*

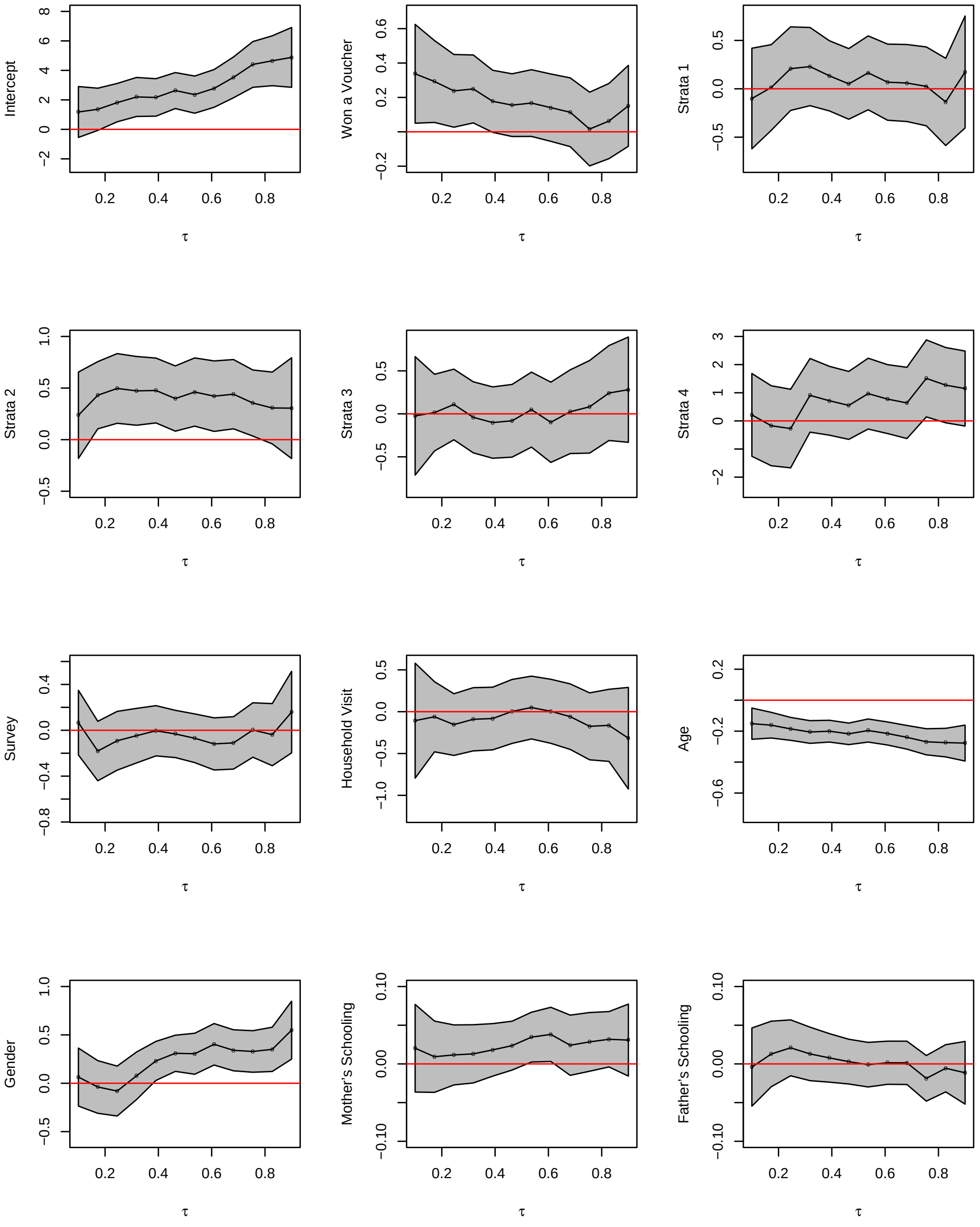


Figure 5. *Estimated effects in a model for Math and Reading. The continuous lines with circles depicts the quantile estimates, and the shaded gray area denote a 90 percent confidence interval obtained after 1000 panel-bootstrap repetitions.*

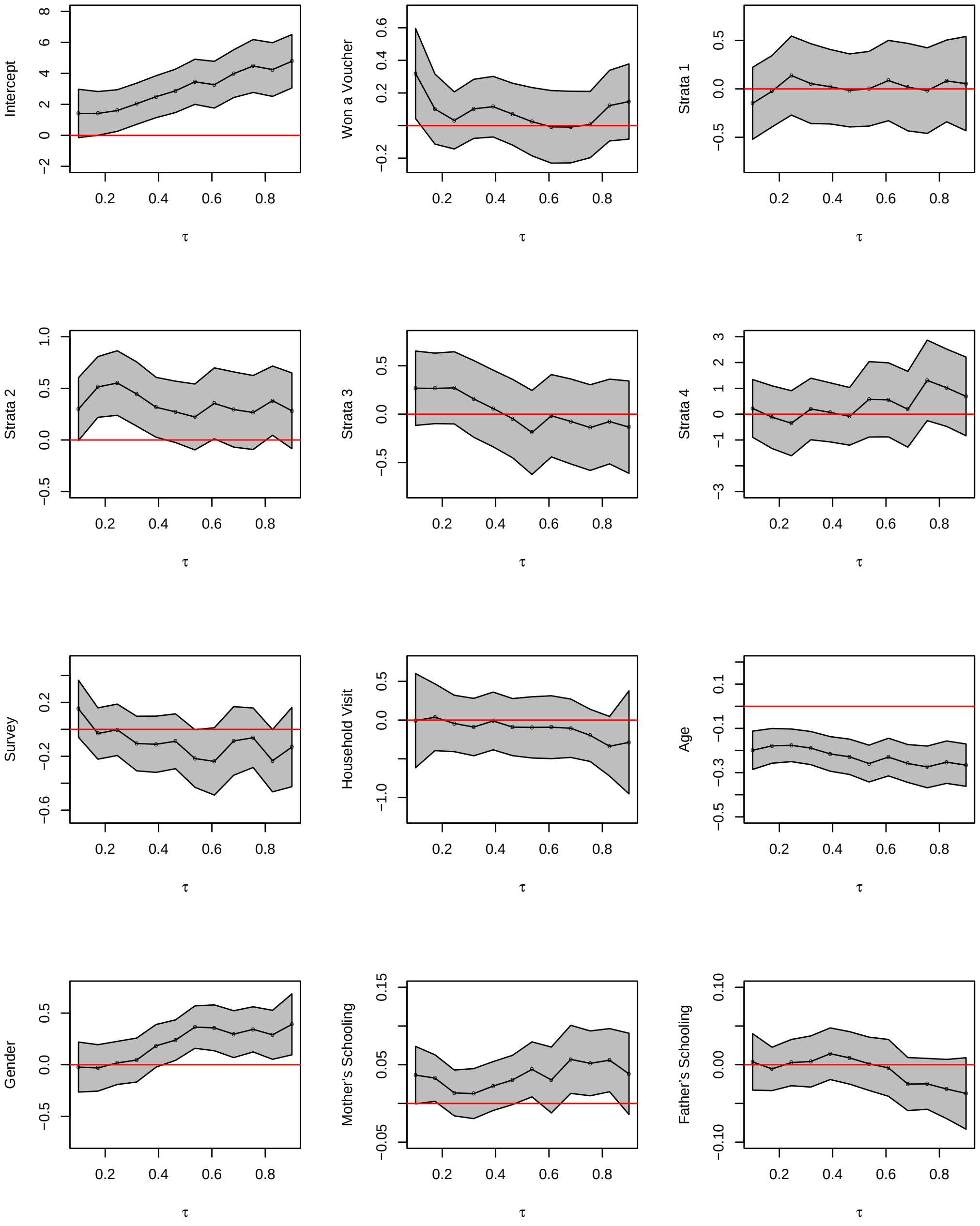


Figure 6. *Estimated effects in a model for Math and Writing. The continuous lines with circles depicts the quantile estimates, and the shaded gray area denote a 90 percent confidence interval obtained after 1000 panel-bootstrap repetitions.*

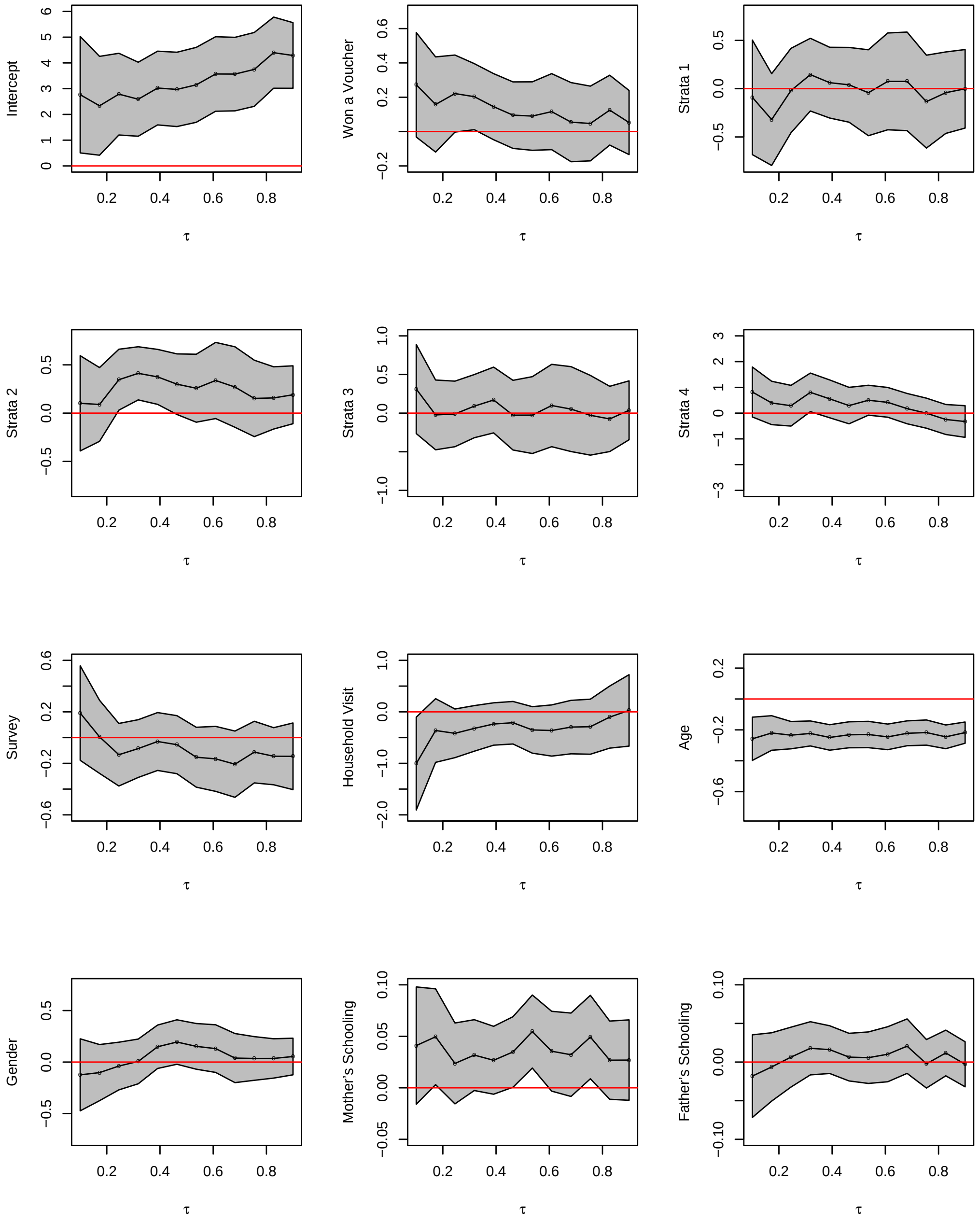


FIGURE 7. *Estimated effects in a model for Reading and Writing. The continuous lines with circles depicts the quantile estimates, and the shaded gray area denote a 90 percent confidence interval obtained after 1000 panel-bootstrap repetitions.*

pairwise combination of quantiles, $H_0 : \delta(0.1) = \delta(\tau_j)$, where $\tau_j$ is in the set of eight equally spaced quantiles ranging from $\{0.1, ..., 0.9\}$. We see that the difference between $\hat{\delta}(\tau_j)$ and $\hat{\delta}(0.1)$ is negative across the quantiles $\tau_j$'s in all the variants of the model. We also find that there are (weak) systematic differences between the effect of winning a voucher at the 0.1 quantile and quantiles beyond $\tau = 0.2$.

The estimated effects of winning a voucher in models with covariates are similar to the ones presented above, suggesting that adding covariates to the model does not alter the basic finding (Figures 4, 5, 6, and 7). The effect continues to be positive and significant at the 0.1 quantile, but insignificant beyond the 0.25 quantile. This suggests that upper-tail estimates could be partially influenced by gender composition, which turned out to be significant beyond the quantile $\tau = 0.4$[3]. The design of the experiment seems to eliminate both the possibility of confounding effects among the independent variables, and the interactions between the treatment and covariates included in the model.

4.3. **Robustness Checks.** A tentative, more simple approach for $\lambda$ selection in quantile regression may consider instead $\hat{\sigma}_u/\hat{\sigma}_\alpha$, but it could incorrectly estimate $\lambda$ because the estimator is not robust to departures from Gaussian conditions. In the case of classical random effects estimators, the standard procedure employs feasible

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[3] The survey covariates are not very interesting, with the exception of the second lowest socioeconomic strata of residence around the 0.2 quantile. While there is little evidence that parents' schooling affect test scores, older students seems to perform worse than younger students at any quantile of the conditional educational attainment distributions. The effect is significant and roughly constant over the quantiles.

GLS and maximum likelihood (MLE) to estimate the variances of $\alpha_i$ and $u_{it}$ obtaining the ratio $\hat{\sigma}_u^2/\hat{\sigma}_\alpha^2$. Moreover, we offer a third alternative for $\lambda$ selection that eliminates a potential scaling problem. We overcome this issue considering a variance minimizer strategy for one quantile (e.g., the median), using panel bootstrap described above. Given the previous evidence that gender composition affects educational attainment in the upper tail, we re-estimate the model for pooled test scores with covariates, and we present the results in Table 2. Considering alternatives methods for $\lambda$ selection, we find, again, the largest estimated effect at the 0.1 quantile. We also see that the panel bootstrap offers 6 percent variance reduction at the 0.5 quantile, a gain that could be explained by the robustness of the $\lambda$ selection procedure to departures from classical Gaussian conditions. Lastly, we observe that the panel-bootstrap estimate of $\lambda$ remains unchanged, suggesting that, after all, the scaling problem may not be an issue for the estimates showed in Table 1.

| Estimation Method | Estimates of $\lambda$ | Quantiles | | | | |
|---|---|---|---|---|---|---|
| | | 0.10 | 0.25 | 0.50 | 0.75 | 0.90 |
| Dependent Variable = Pooled Test Scores | | | | | | |
| Random Effects | 1.326 | $0.245^{\ddagger}$ | 0.141 | 0.133 | 0.124 | 0.191 |
| | | (0.137) | (0.112) | (0.106) | (0.108) | (0.121) |
| Maximum Likelihood | 1.385 | $0.247^{\ddagger}$ | 0.155 | 0.125 | 0.126 | 0.181 |
| | | (0.138) | (0.111) | (0.106) | (0.108) | (0.121) |
| Panel Bootstrap | 1.500 | $0.274^{\ddagger}$ | 0.157 | 0.114 | 0.077 | 0.158 |
| | | (0.141) | (0.111) | (0.103) | (0.107) | (0.116) |

TABLE 2. *Robustness checks. The table reports plug-in estimates of the effect of winning a voucher at several quantiles of the educational attainment distribution. The standard error (in parenthesis) are obtained after 1000 panel bootstrap repetitions.*

## 5. CONCLUSION

Angrist et al. (2002) studied the effects of the Colombian voucher program finding that lottery winners earned 0.2 additional standard deviations than lottery losers on achievement tests. Angrist and his coauthors conjectured that the vouchers provided incentives for lottery winners to work harder because they were renewable only conditional on good academic standing. While quantile regression estimates do not provide empirical support for this conjecture, random effects estimates are limited to the conditional mean effect. We overcome this issue employing a method to obtain quantile regression estimates in a panel data model of educational attainment. The results of this Comment suggest that the effect of winning a Colombian voucher is largest in the lower tail of the educational attainment distribution, a possibility conjectured by the original authors which could not be confirmed empirically using existing regression approaches. This finding supports the hypothesis that lottery winners' incentive to study harder could account for the impact of the vouchers, including lower repetition rate.

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