Estimating the Cream Skimming Effect of Private School Vouchers on Public School Students[1] (Preliminary and Incomplete)

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Abstract

We examine whether a voucher program for private schools would lure the best students away from public schools, with negative consequences for those who remain behind. Given both heterogeneity in program types and limited data on entrance into voucher programs, one cannot answer this question directly. Instead, we study what the effect of vouchers would be on the students left behind if vouchers tend to attract students who are similar to those who currently go to private high schools. Using the NELS:88 data, we estimate a model of the private school entrance decision and estimate the importance of observable peer group effects on outcomes. We then combine these results to simulate the effects of a voucher program on outcomes of those left behind in public schools. We estimate the model using a number of specifications. Under completely general specifications, our results are quite imprecise. However, under stronger index type assumptions we obtain more precision and find that the consequences of cream skimming are negative but very small for high school graduation rates and also negative but small for college attendance.

1 Introduction

Dissatisfaction with the performance of the U.S. educational system, particularly in minority urban school districts, has led to a surge in interest in and experimentation with public vouchers for private schools. To assess the overall effect of a large scale voucher program on educational outcomes, one must address three questions. First, by how much do private schools benefit the children who choose to attend them? Second, will a voucher program for private schools lure the best students away from public schools, and if so, will this have negative consequences for those who remain behind? Third, does increased competition from private schools induce public schools to improve?

Most research on private schools measures the direct benefits from private school attendance, primarily in the context of Catholic schools. The results are mixed, but most of the recent research, including studies by Evans and Schwab (1995), Neal (1997), Grogger and Neal (2000) and Altonji, Elder and Taber (forthcoming) suggests that students who attend Catholic schools perform substantially better than they would have done in a public school. The evidence is strongest for urban minority students, and the main effects appear to be on high school graduation and college attendance rates rather than on achievement on standardized tests.

However, evidence that students benefit from attending a private school does not establish that it is in the public interest to expand school choice. One also needs to know the impact of movement of children out of public schools on the children who remain. Critics of school choice argue that vouchers will lead to the isolation of disadvantaged children in public schools. If the effectiveness of schools is largely determined by the characteristics of the students and their parents, then a decline in the quality of the public school student body may hurt those who remain behind. The debate on this point has been sharp, but there is relatively little evidence on the subject. As we discuss in Section 2, several researchers have examined who takes up vouchers in US voucher programs targeted at low income families and in universal voucher programs in New Zealand and Chile. The evidence suggests that cream skimming effects for targeted programs are relatively small, but may be more serious for universal voucher programs. We also discuss a series of recent studies that use general equilibrium models of residential choice and school choice to study the effects of vouchers on the make up of neighborhoods and public and private schools as well as who gains and who loses from vouchers.

In this paper, we evaluate the effect of a large scale voucher program on educational outcomes. We analyze the degree to which vouchers would change the performance of students by changing the characteristics of their classmates. The primary contribution of our project is to measure the effects of a voucher program on students who remain in public school. We consider both broad based voucher programs and programs that are targeted to low income students, low income neighborhoods, and/or students in low achievement schools.

The analysis uses data from the National Education Longitudinal Survey of 1988 (NELS:88) and proceeds in three stages. In stage one, we determine the effects of a voucher program on the composition of public school students. We estimate a discrete choice model of the probability of attending a public school as a function of characteristics of the student, the student's parents, the neighborhood, and in some specifications, the public school. We then use the school choice model to predict the average observed and unobserved characteristics of the population that will remain in public schools and the population who will attend private schools. To be more specific, we first estimate a probit model for public school choice that identifies the conditional probability that a student with specified observed characteristics chooses public school, given the status quo of no voucher program. Under the assumptions of the probit model we can identify the distribution of the error term in the school choice equations for students who attend public school in the absence of a voucher. We model the voucher as a shift in the index determining school choice for a given group of students. This allows us to compute the relative probability that public school students will remain in public school given the level of the voucher. Furthermore, the assumption implies the natural result that students who are currently in private schools continue to attend them after a voucher is put into place. This permits us to obtain the distribution of observed and unobserved characteristics of students who will remain in public school by using the relative probabilities of continued public school attendance to reweight the distribution for public school students under the status quo. By comparing reweighted means to the means of public school students one obtains estimates of how the mean family incomes, mean parental education, mean eighth grade test scores and other characteristics of high school peers will change for those who remain in public high schools. A big advantage of our approach is that we do not need variation in tuition or voucher levels to estimate which students are likely to respond to the voucher program.

The second stage is to estimate the extent of peer effects. We start with the reasonably standard procedure of estimating the direct effects of observed student characteristics by estimating regression models with high school fixed effects for our outcomes of interest. We then regress the fixed effects from these regressions on the peer effects variables. Three issues arise at this point. The first is that we observed only a few students from each school and therefore our estimates of school averages of characteristics are noisy. We deal with this problem through an instrumental variables scheme similar to that which has been used in a number of previous peer effects studies. Second, given sample sizes and collinearity among the peer effects of variables, it difficult to obtain precise estimates of peer effects without further restrictions. We address this issue by estimating peer effects models that impose the restriction that the relative important of average characteristics of students in the peer effects model is proportional to the relative importance of corresponding student specific variable in the school choice equation or in the outcome equation.

A third, particularly difficult problem stems from the fact that many important characteristics of students are not measured and thus will not be in our data. For example, the usual school level parental background measures, such as average family income and average parental education are only crude measures of the resources that parents provide to their children. Many of the characteristics of the students, their families, and the school are unmeasured. We wish to be able account for the effects of the tuition voucher not only on the observed characteristics of the student body but on the unobserved characteristics as well. We address the issue using methods developed in Altonji, Elder and Taber (2002) to deal with the problem of unmeasured peer characteristics. The basic idea of their work is that when studying outcomes that depend on many different variables (such as performance in school) it is reasonable to assume that the outcome determinants the social scientist gets to observe and the set of outcome determinants that he or she does not get to observe have similar properties. In the context of the current problem, Altonji, Elder and Taber (2002) provides a rational for assuming that the regression index of observed school level characteristics and the index of unobserved characteristics of the student body will have similar relationships with the probability that students from the attendance area of a given public school choose private school. The implication of this is that the shift in the observed and unobserved characteristics of the student body induced by the tuition voucher will have the same relationship with the outcomes of interest in a sense that we make precise below. Consequently, we use the effect of the shift in the index of observed student body characteristics on the outcomes to estimate the effect of the shift in the unobserved characteristics or to construct a bound for the effect of the shift in the unobservables.

In the final stage, we use our estimates of the peer effects models and estimates of the shift in both the observed and unobserved characteristics of the peers of students who remain in public school to estimate the effect of the voucher program on the students who are left behind in public school. We report results for a number of different model specifications. Our results are still preliminary. So far, they indicate that a large scale voucher program would have small effects on the high school graduation probabilities of those who remain in public school.

The paper continues in Section 2 with a brief review of lessons from past and current voucher programs and from simulation studies of the effects of vouchers. In Section 3, we present our school choice model and define the parameter of interest. In section 4 we discuss estimation in situations in which peer effects depend only on observed variables and in situation in which unobserved variables also matter. Section 5 discusses NELS:88 data and provides descriptive statistics. In Section 6 we briefly discuss the estimates of school choice model and models of the effects of a student level characteristics on outcomes. In Section 7 we estimate peer effects models and estimate the effects of school choice on students who remain in public school. In Section 8, we provide a brief discussion of an extension to consider Catholic and non-Catholic high schools as seperate options and in Section 9 we provide and implement a way to account for correlation among students in unobservables that influence school choice. In the conclusion we summarize our main results, which are still very preliminary, and provide a research agenda.

2 Prior Evidence on Cream Skimming Effects

In this section we provide background to our paper by summarizing existing evidence on the effects of vouchers on the composition of public schools and also on the consequences of selection. Section 2.1 summarizes the evidence on selection into voucher programs from studies of existing programs in the U.S. and abroad. The US evidence is almost exclusively for programs that target low income families. Section 2.2 summarizes evidence from simulation models of residential choice and school choice.

2.1 Studies of Existing Voucher Programs and Experiments

The literature on voucher programs in the US provides some evidence on the likely importance of cream skimming for programs that are targeted to low income families. Howell and Peterson (2002) summarize evidence from several programs describing the type of students who apply for vouchers, take up vouchers when they are offered, and continue to use them. Regarding who applies, they compare characteristics for a random sample of voucher applicants to the Children's Scholarship Fund (CSF) with a sample of the eligible population that they surveyed. Their sample of the eligible population consists of families with children in grades 1-8 with incomes below $40,000 a year in cities of more than 200,000 people. The CSF program is limited to families with incomes below 270 percent of the federal poverty level. Consequently, the comparison group has somewhat higher income than the sample of families who were eligible for a CSF fellowship. Howell and Peterson's Table 3.1 and 3.2 suggest that applicant families have a slightly higher percentage of mothers who are college graduates, are more likely to be two parent households, move less frequently, are more likely to be black and less likely to be Hispanic, and are more likely to attend church at least once a week. There is also evidence that applicant families are more likely to be involved in schools, as evidenced by attendance at parent teacher conferences and volunteering in the school. There is no significant difference in the fraction of students who have been diagnosed with a learning disability. For the most part, the differences are relatively modest. However, Howell and Peterson point out that the degree of positive selection in the applicants sample may be understated as a result of the fact that the comparison sample has higher income than the eligible sample.

Howell and Peterson present evidence from the New York City, Dayton, and Washington D.C. voucher program evaluations on who takes up a voucher. The percentages of families who are offered vouchers who actually use them in the first year is 82 percent for New York, 78 percent for Dayton, and 68 percent for Washington D.C.[1] However, it important to point out that these results are for the pool of families who apply for vouchers.

Their evidence suggests that students who used a voucher to attend the lower elementary grades have slightly higher reading scores than decliners. The only statistically significant

[1] Howell and Peterson present evidence that costs and transportation problems play an important role in the decision not to accept a voucher. The importance of costs suggests that there will be positive selection on income in programs that only partially cover tuition, books, and fees. Transportation difficulties are likely to be idiosyncratic and depend upon specific location and the details of the parents schedules.

and substantial difference is scores is for grades 6-8 in Washington D.C., although this is also the only site at which a large sample of students in the upper grades is available. For math they report modest, statistically significant negative selection on math scores in the case of the Dayton program, small, statistically insignificant positive selection in New York and Washington D.C. for grades 1 to 5, and a statistically significant positive difference of 6.3 percentile points for 6th to 8th graders in Washington D.C.. There is also evidence in all three cities that the percentage of children with a learning disability is lower among those who take vouchers. (The gaps are 2 percent in Dayton, 4.2 percent in Washington D.C., and 5 percent in New York City. Only the latter is statistically significant.) Howell and Peterson compare a number of family background variables for takers and decliners and conclude that the two groups closely resembled each other. Howell and Peterson's estimates for the national CSF program suggests to us that selection into the voucher program among eligibles is positive, but not dramatically so.

Howell and Peterson also discussed evidence from the large-scale voucher program in the Edgewood school district of San Antonio TX. The Edgewood voucher program is interesting because 90 percent of families in the district are low income. Math scores were 1.8 percentage points higher for vouchers students and 6.7 points higher for reading (only the latter is statistically significant). Those who participated in the voucher program had better educated parents, were less likely to have limited English proficiency, and were less likely to have participated in bilingual or ESL programs. They were also less likely to be economically disadvantaged. Overall, voucher participants exhibit a modest amount of positive selection.[2]

Howell and Peterson also present evidence on the likelihood that initial users of vouchers remained in voucher programs for two years. They do not find consistent patterns across New York, Washington D.C., and Dayton.

Howell and Peterson summarize their evidence on selection associated with school vouchers targeted to low-income populations by saying the "On the whole, these findings earn school vouchers a surprisingly positive grade on the selection line of the report card." They do not examine peer group effects on those who remain in public school, but these effects must be small if the those who take up vouchers are representative of those who do not.

There are no universal voucher programs to study in the U.S., but Ladd (2002) sum-

[2]Howell and Peterson also touch on the evidence from the Cleveland voucher program. The results for Cleveland do not show clear pattern of positive selection, but the vouchers were offered first to those with the lowest incomes, which gave them an advantage in finding a private school.

marizes the international evidence. Hsieh and Urquiola (2002) find that Chile's universal voucher program induced higher income and higher ability children to move to private sector schools. Ladd (2002) summarizes the evidence from her study of New Zealand's choice program as suggesting that selection worked in a direction similar to the Chilean program and that "the expansion of choice in that country exacerbated the problems of the schools at the bottom of the distribution and the reduced the ability of those schools to provide an adequate education."

The evidence on who makes use of charter schools is in principle highly relevant to the question of who would use a private school voucher. Bulkley and Fisler (2002) briefly review the evidence on the racial and socioeconomic composition of charter schools. RPP International (2001) found that the racial and ethnic composition of charter schools is similar to that of the school district. Given that the composition of charter schools is heavily influenced by the specific areas in which they were introduced and the missions of the schools, one cannot easily draw conclusions for a universal or a targeted voucher program from aggregate statistics on the composition of charter schools. Nevertheless, there is little indication that charter schools lead to a large exodus of the most advantage children from regular public schools.

2.2 General Equilibrium Models of Voucher Programs with Peer Group Effects

Our work is also related to a sizable literature on general equilibrium effects of voucher programs with peer effects. Peer effects are a key component of the school choice general equilibrium models of Manski (1992), Epple and Romano (1998, 2002, 2003), Epple, Newlon, and Romano (2002), and Caucutt (2002). Manski (1992) simulates a model with three different communities (poor, average, and wealthy) in which the fraction of students who are highly motivitated is valued by parents. In the other models school quality depends on average peer quality and private schools may price discriminate on the basis of ability. As a result of heterogeneity in ability and income, in equilibrium there is a strict hierarchy of school quality. They show that low income, high ability students would pay lower tuition and go to similar schools as low ability, high income children. These papers all include calibration exercises that simulate the general equilibrium effects of various voucher programs. Many of the simulations focus on the extent to which vouchers lead to cream skimming. Almost all of the simulations show cream skimming, although the magnitude vary with the details of the model specification and assumed parameter values. Nechyba's (1999, 2000, 2003) models abstract from price discrimination, but include housing location as part of the choice decision of the agents. He shows that migration can have a countervailing effect on low income households who remain in public school. Some high income families that use vouchers will move to lower tax districts, strengthening the tax base and thus the income available public schools in those districts.

To our knowledge, the only paper that explicitly estimates and simulates the extent of peer group effects with vouchers is Ferreyra (2003). She extends Nechyba's (1999) general equilibrium model by explicitly including household religious preferences. She estimates the parameters of a parsimonious version of the model using school district data from several large metropolitan areas. She then simulates the effects of vouchers in her model.

The above models share with our model the property that peer groups influence school quality (or human capital). However, in the above models the concept of school quality is intentionally left abstract and only matters in that it enters into the parent's utility function directly. In contrast, we directly estimate the effects of peer effects on particular outcomes. This distinction is quite important because at the abstract level, peer effects in these other models could influence school and location choices for a number of reasons, including: a) the possibility that they affect school outcomes and parents care about the school outcomes, b) the possibility that parent's care about outcomes and think that peer effects are important even though they may not be and c) the possibility that parents care about peer quality in and of itself. With this in mind our exercise is very different from Ferreyra's (2003). We look directly at the peer effects on particular outcomes and simulate the effects of cream skimming on those outcomes for public school students. Ferreyra (2003) does not have data on school quality, but infers the production function for it based on location and schooling decisions. Though these approaches are different, they are both important for evaluating vouchers. We view our work as complementary with the general equilibrium work. Incorporating all of the important aspects of vouchers into one paper is impossible so various papers focus on various aspects. Our focus here is on an element that is an important component of these models—the extent of cream skimming and its impact on student outcomes—but has not been directly examined before. Hopefully, our evidence will help inform the development of general equilibrium models.

3 An Econometric Model of School Choice and Definition of the Cream Skimming Effect

In this section, we begin by presenting the basic model for schooling and classmate effects that underlies our analysis of private school vouchers on students who remain in *public* school. We then define our parameter of interest—the cream skimming effect. While most work to date has focussed on the effect of vouchers on students who move students from public to private schools we focus on those who are left behind in public schools.

Let $\mathcal{S}$ be the set of all schools in the population. $\mathcal{S}$ can be partitioned into public schools $\mathcal{S}_p$ and private schools $\mathcal{S}_c$. Let X_i denote a random vector of covariates that is observable to the econometrician for individual i. For each individual, $S_i(\tau)$ indicates which school individual i would attend under a voucher program indexed by τ. We assume that each student i is assigned to a particular school district $d(i)$ with public school $P_{d(i)} \in \mathcal{S}_p$. We will usually refer to the public school option as P_i. However, we will sometimes refer to it as $P_{d(i)}$ or simply as P_d. The student must either attend this school or a private school. Thus the particular public school that is chosen does not depend on the voucher level. We are also assuming that the characteristics of the private schools options available to i are not affected by the voucher.[3] Formally for any $\tau, S_i(\tau) \in \{P_i, \mathcal{S}_c\}$.

Letting $V(s,\tau)$ be the utility an individual obtains from choosing school s under voucher program τ,we assume that

$$V(P_i,\tau) - \max_{s \in S_c} V(s,\tau) = X_i'\beta - \tau_i(\tau) + u_i \tag{1}$$

where X_i is observable, $\tau_i(\tau)$ is the voucher level that individual i would receive under program τ, and u_i represents unobservable factors that influence school choice and is independent of X_i. Thus the decision of student i facing voucher program τ, the public school

[3] Our assumption is consistent with an expansion of the private school sector to accomodate increased demand provided that attributes that influence choice do not change. We are assuming that any feedback from voucher induced changes in the peer characteristics of public and private schools to school choice is of a second order of importance. One can accomodate the likely possibility that average distance from private schools would decrease in the wake of a large scale voucher program, with an effect on the demand for private schools. To do so, one could redefine $\tau_i(\tau)$ to be an index capturing both the effect of the tuition subsidy and of a uniform reduction in distance resulting from the private school expansion. In some sense, the reduction in distance associated with private school entry acts as a multiplier on the effect of a voucher on demand for private school. In practice however, one might expect the size of the distance reduction to depend on the existing stock of private schools and to vary across households depending on precisely where they live. We would model this in our specification of $\tau_i(\tau)$.

decision can be written as

$$S_i(\tau) = P_i \text{ if } X_i'\beta - \tau_i(\tau) + u_i > 0. \tag{2}$$

The parameter vector β reflects the degree to which the relative costs and benefits to the student (broadly construed) of public school attendance vary with X_i. The error term u_i captures the many unobserved factors that influence school choice and are omitted from X_i. The private school voucher $\tau_i(\tau)$ enters as an intercept shift and decreases the value of public school relative to private school. As we shall see in a moment, (2) is consistent with variation by parental income, education, race, and other income in the effect of τ on $\Pr(S_i(\tau) = P_i)$. However, it is an important restriction. It says that the effect of $\tau_i(\tau)$ on the index driving the decision to attend public school is the same regardless of X_i and u_i In contrast, one might expect the effect to be smaller for persons near the very top of the income distribution. Also, to the extent that more educated persons are more proactive about school choice, one might also expect parental education to interact with $\tau_i(\tau)$.

Our simplest specification does not have heterogeneity in the voucher levels and treats $\tau_i(\tau) = \tau$. However, we also consider vouchers targeted at particular groups of people (such an individuals in urban areas or with low family income). In this case we model $\tau_i(\tau) = \tau$ for eligible students and $\tau_i(\tau) = 0$ for those that are not eligible.

We assume that school choice depends on individual aspects of the students (X_i, u_i) and on aspects of the public schools schools themselves. Fixed aspects of public schools, such as where they are located, are easy to handle by including them in X_i. One could also augment the X_i vector with other characteristics of P_i, including student body characteristics, and we plan to do so in the next version of the paper. Some difficult issues arise in estimating those characteristics from the NELS:88 data for use in a school choice model, because we only observe them for the subsample of students who choose P_i. We noted in a previous footnote that a dependence of school choice on student body characteristics means that initial cream skimming effects of the voucher will have feedback effects on school choice, which we are not addressing.

Because we do not have data on τ, we normalize $var(u_i) = 1$. This implicitly defines the scale of τ such that a unit change in τ has the same effect on school choice as a one standard deviation change in the u_i. As we noted in the introduction, a key strength of our approach is that we are able to side step the difficult problem of estimating the price elasticity of demand for private schools. We instead define the "size" of the voucher in terms of the number of people induced to attend private school by the voucher. For example, we can choose the value of τ so that it induces 10% of public school students to move.

Let $Y_i^p(\tau)$ be an outcome that individual i would achieve if they attended public school under voucher level τ. Examples of outcomes are high school completion, college attendance, test scores, or wage levels. The outcome of interest a student would receive if they attended public school can be written as

$$Y_i^p(\tau) = X_i'\gamma + \theta(P_i, \tau) + \varepsilon_i, \tag{3}$$

where $\theta(s, \tau)$ is a component that is common to all individuals who attend school s and ε_i represents unobservable individuals factors that are uncorrelated with all other components in the model. The school effect $\theta(s, \tau)$ depends on τ through peer effects that change as different students attend public school.[4] Note that Equation (3) rules out interactions between X_i and $\theta(P_i, \tau)$. We can easily relax this, at least for the observed component of θ. (If one were to relax it, it would only make sense to allow the effect of τ on choice to vary with X.)

We assume that there are currently no vouchers ($\tau = 0, \tau_i(0) = 0$). Our sample consists of individuals $i = 1, ..., N$ where $(X_i, S_i(0))$ represent i.i.d. random variables drawn from the model described above.

For individual i we define the treatment effect of vouchers conditional on staying in public school for individual i as

$$\begin{aligned}\pi_i^p(\tau) &\equiv Y_i^p(\tau) - Y_i^p(0) \\ &= \theta(P_i, \tau) - \theta(P_i, 0).\end{aligned}$$

Our goal is to measure the average value of this "cream skimming" effect for people who would stay in public school under a voucher system:

$$\pi^p(\tau) \equiv E(\pi_i^p(\tau) \mid S_i(\tau) = P_i).$$

For a given individual we observe X_i and $S_i(0)$. Thus we know whether they currently attend public school or not. If they attend public school we observe their outcome $Y_i^p(0)$

[4] We use the term "peer effects" to refer to the influence of the average values in a school of a variety of student body characteristics that are not changed by a voucher and are determined prior to high schools. These include parental education and income, race, gender, and performance in lower grader. We do not attempt to identify interactions between outcomes across students.

and school P_i because $P_i = S_i(0)$ in this case. We also assume that we observe at least two students from each public school in the data. A key to our identification strategy for $\pi^p(\tau)$ lies in the fact that under the choice model presented above or any model in which the criterion function that determines school choice is monotone in τ, if $S_i(\tau) = P_i$ then $S_i(0)$ must equal P_i, and if $S_i(0) \neq P_i$ then $S_i(\tau) \neq P_i$.

4 Estimating $\pi^p(\tau)$ Under Alternative Assumptions About Peer Effects

In this section we provide methods to estimate the effect of the voucher program on those who stay in public school under alternative assumptions about how peer effects are determined. We define a series of models that consist of a peer effects specification and an econometric strategy. In this section we focus on identification.

4.1 Observable Peer Effects Only [Model 1]

We first consider the case in which school quality $\theta(s,\tau)$ depends only on observable peer effects. For any school $s \in \mathcal{S}_p$ and any voucher level τ, we define the observable peer effects to be a linear function of

$$\overline{Z}(s,\tau) = E(Z_i \mid S_i(\tau) = s),$$

where Z_i is a known or estimable function of the X_i variables. An important special case is $Z_i = X_i$.

In general, the school fixed-effect can be expressed as

$$\theta(s,\tau) = \overline{Z}(s,\tau)'\delta + \overline{u}(s,\tau) + \xi_s, \tag{4}$$

where $\overline{u}(s,\tau)$ is an index of the unobservable characteristics of school s that are related to student body characteristics and thus are potentially influenced by the voucher and ξ_s captures other determinants of school quality that are not influenced by the voucher, such as the characteristics of the building, the principal, and the teachers.[5] In this subsection we abstract from unobservable school characteristics that are influenced by the voucher and set

[5] Note that we ignore the reflection problem discussed by Manski (1993). For the purposes of our simulation it does not matter for the final simulations whether the peer effects operate through covariates or outcomes. Thus we can interpret our model as estimates of the reduced form of a model with reflection. The reduced form is all that is needed.

$\overline{u}(s,\tau)$ to 0, in which case $\theta(s,\tau)$ is simply

$$\theta(s,\tau) = \overline{Z}(s,\tau)'\,\delta + \xi_s, \tag{5}$$

where ξ_s is uncorrelated with $\overline{Z}(s,\tau)$. We refer to estimation imposing (5) as Model 1_δ.

It is important to discuss the assumption that $\overline{Z}(s,\tau)'\,\delta$ is uncorrelated with ξ_s. Much of the literature on peer group effects tries to address this problem.[6] It seems likely that in fact $\overline{Z}(s,\tau)'\,\delta$ and $\xi_s$would be positively correlated. Given our empirical strategy for estimation of δ this is going to bias our estimates upward which will bias our final results upwards. Therefore, we interpret our estimates of the voucher effect as an upper bound on the true effect.

Under these conditions the key parameter can be written as

$$\pi^p(\tau) \equiv \left[E\left(\overline{Z}(P_i,\tau) \mid S_i(\tau) = P_i\right) - E\left(\overline{Z}(P_i,0) \mid S_i(\tau) = P_i\right)\right]'\delta.$$

It is fairly straight forward to identify γ, δ, and β, so we defer the discussion of their estimation and assume for now that they are known. To establish that $\pi^p(\tau)$ is identified conditional on γ, δ, and β, we first consider the term $E\left(\overline{Z}(P_i,\tau) \mid S_i(\tau) = P_i\right)$ and then turn to $E\left(\overline{Z}(P_i,0) \mid S_i(\tau) = P_i\right)$.

4.1.1 An Estimator for $E\left(\overline{Z}(P_i,\tau) \mid S_i(\tau) = P_i\right)$

First, notice that by the law of iterated expectations

$$\begin{aligned} E\left(\overline{Z}(P_i,\tau) \mid S_i(\tau) = P_i\right) &\equiv E(E(Z_i \mid S_i(\tau) = P_i) \,|S_i(\tau) = P_i) \\ &= E(Z_i \mid S_i(\tau) = P_i). \end{aligned}$$

Define $G(X_i \mid S_i(\tau) = P_i)$ as the distribution of X_i conditional on students who go to public school under voucher program τ. Keep in mind that Z_i is a function of X_i. By definition $E(Z_i \mid S_i(\tau) = P_i) = \int Z_i dG(X_i \mid S_i(\tau) = P_i)$. One complication is that we only observe the public school chosen if $S_i(0) = 1$, so we must condition on this event. Under the monotonicity assumption that $\Pr(S_i(0) = P_i \mid S_i(\tau) = P_i) = 1)$ we can condition on it. An application of Bayes theorem implies that

$$dG(X_i \mid S_i(\tau) = P_i) = \frac{\Pr(S_i(\tau) = P_i \mid S_i(0) = P_i, X_i) dG(X_i \mid S_i(0) = P_i)}{\int \Pr(S_i(\tau) = P_i \mid S_i(0) = P_i, X_i) dG(X_i \mid S_i(0) = P_i)}. \tag{6}$$

[6] See for example Moffitt(2001) for discussion.

Under our probit assumption

$$\Pr(S_i(\tau) = P_i \mid S_i(0) = P_i, X_i) = \frac{\Phi(X_i'\beta - \tau_i(\tau))}{\Phi(X_i'\beta)}$$

where $\Phi(.)$ is the standard normal cdf. Thus in our model

$$E(Z_i \mid S_i(\tau) = P_i) = \frac{\int Z_i \frac{\Phi(X_i'\beta - \tau_i(\tau))}{\Phi(X_i'\beta)} dG(X_i \mid S_i(0) = P_i)}{\int \frac{\Phi(X_i'\beta - \tau_i(\tau))}{\Phi(X_i'\beta)} dG(X_i \mid S_i(0) = P_i)}. \tag{7}$$

One may consistently estimate $E(Z_i \mid S_i(\tau) = P_i)$ using the sample analog to (7). Note that the X_i for the sample of public school students are drawn from $dG(X_i \mid S_i(0) = P_i)$.

Let N_p denote the number of individuals who attend public school in the sample ($S_i(0) = P_i$) and without loss of generality order the observations so that these individuals so that $i = 1, ..., N_p$ refers to the public school students only. Consequently, the sample analog to (7) is simply

$$\hat{E}\left(\overline{Z}(P_i, \tau) \mid S_i(\tau) = P_i\right) = \sum_{i=1}^{N_p} \psi(X_i'\widehat{\beta}, \tau_i(\tau)) Z_i$$

where we introduce the notation

$$\psi(X_i'\widehat{\beta}, v_i(\tau)) \equiv \frac{\frac{\Phi(X_i'\widehat{\beta} - \tau_i(\tau))}{\Phi(X_i'\widehat{\beta})}}{\sum_{i=1}^{N_p} \frac{\Phi(X_i'\widehat{\beta} - \tau_i(\tau))}{\Phi(X_i'\widehat{\beta})}}$$

for the weights. Basically, we obtain $\hat{E}\left(\overline{Z}(P_i, \tau) \mid S_i(\tau) = P_i\right)$ by reweighting the distribution of Z_i of the current sample of public school attendees by the relative probability that they will remain in public school following a voucher of τ.

4.1.2 An Estimator for $E\left(\overline{Z}(P_i, 0) \mid S_i(\tau) = P_i\right)$

Now consider the second part of $\pi^p(\tau)$, $E\left(\overline{Z}(P_i, 0) \mid S_i(\tau) = P_i\right)$. This can be written as

$$E\left(\overline{Z}(P_i, 0) \mid S_i(\tau) = P_i\right) = \int E\left(\overline{Z}(P_i, 0) \mid S_i(\tau) = P_i, X_i\right) dG(X_i \mid S_i(\tau) = P_i)$$

The model implies that the decision to enter private school is independent of which public school one was assigned to conditional on X_i (which include school characteristics), or that

$$\Pr(S_i(\tau) = s \mid X_i) = \Pr(P_i = s \mid X_i) \Pr(S_i(\tau) \in \mathcal{S}_p \mid X_i). \tag{8}$$

From the above equation it follows that

$$(9) \qquad E\left(\overline{Z}\left(P_i,0\right) \mid S_i\left(\tau\right)=P_i,X_i\right)=E\left(\overline{Z}\left(P_i,0\right) \mid X_i\right).$$

Consequently,

$$E\left(\overline{Z}\left(P_i,0\right) \mid S_i\left(\tau\right)=P_i\right)=\int E\left(\overline{Z}\left(P_i,0\right) \mid X_i\right)dG(X_i \mid S_i\left(\tau\right)=P_i)$$

where $dG(X_i \mid S_i\left(\tau\right)=P_i)$ is defined in (6). Thus, under the probit assumption,

$$(10) \qquad E\left(\overline{Z}\left(P_i,0\right) \mid S_i\left(\tau\right)=P_i\right) = \int E\left(\overline{Z}\left(P_i,0\right) \mid X_i\right)\frac{\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)}dG(X_i \mid S_i\left(0\right)=P_i)}{\int\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)}dG(X_i \mid S_i\left(0\right)=P_i)}.$$

Define

$$(11) \qquad \overline{Z}_{P_{-i}}=\frac{\sum_{j=1}^{N_p}Z_j 1\left(S_j\left(0\right)=P_i,i\neq j\right)}{\sum_{j=1}^{N_0}1\left(S_j\left(0\right)=P_i,i\neq j\right)}.$$

We use the subscript $-i$ to denote the fact that $\overline{Z}_{P_{-i}}$ is the average value of Z for other sample members who attended the same school with i excluded. $\overline{Z}_{P_{-i}}$ is an unbiased estimator of $\overline{Z}\left(P_i,0\right)$.[7] Using this fact, (10), and the fact that the density of X_i of those for whom $S_j\left(0\right)=P_i$ is $dG(X_i \mid S_i\left(0\right)=P_i)$, we arrive at the following consistent estimator for $E\left(\overline{Z}\left(P_i,0\right) \mid S_i\left(\tau\right)=P_i\right)$ for the case in which u is assumed to be normal:

$$(12) \qquad \hat{E}\left(\overline{Z}\left(P_i,0\right) \mid S_i\left(\tau\right)=P_i\right)=\frac{\sum_{i=1}^{N_p}\overline{Z}_{P_{-i}}\frac{\Phi(X_i'\widehat{\beta}-\tau_i(\tau))}{\Phi(X_i'\widehat{\beta})}}{\sum_{i=1}^{N_p}\frac{\Phi(X_i'\widehat{\beta}-\tau_i(\tau))}{\Phi(X_i'\widehat{\beta})}}.$$

To establish consistency, notice that

$$\begin{aligned}\sum_{i=1}^{N_p}\overline{Z}_{P_{-i}}\frac{\Phi(X_i'\widehat{\beta}-\tau_i(\tau))}{\Phi(X_i'\widehat{\beta})} \xrightarrow{p} & \quad E\left(\overline{Z}_{P_{-i}}\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)} \mid S_i\left(0\right)=P_i\right)\\ &= E\left(E\left(\overline{Z}_{P_{-i}} \mid S_i\left(0\right)=P_i,X_i\right)\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)} \mid S_i\left(0\right)=P_i\right)\\ &= E\left(\overline{Z}\left(P_i,0\right)\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)} \mid S_i\left(0\right)=P_i\right).\end{aligned}$$

[7] We leave X_i out because random variation in X across students from the same high school makes the correlation between X_i and the mean including X_i stronger than the correlation between X_i and $\bar{Z}(P_i,0)$.

Thus a consistent estimator of the treatment effect is

$$(13) \qquad \widehat{\pi}^p(\tau) = \frac{\sum_{i=1}^{N_p} \left(Z_i - \overline{Z}_{P_{-i}}\right)' \delta \frac{\Phi(X_i'\beta - \tau_i(\tau))}{\Phi(X_i'\beta)}}{\sum_{i=1}^{N_p} \frac{\Phi(X_i'\beta - \tau_i(\tau))}{\Phi(X_i'\beta)}} = \sum_{i=1}^{N_p} \psi(X_i'\beta, \tau_i(\tau)) \cdot \left(Z_i - \overline{Z}_{P_{-i}}\right)' \delta$$

after substitution of consistent estimators for β and δ.

The above equation shows that the cream skimming effect $\widehat{\pi}^p(\tau)$ depend on three factors. To see this, notice that for a universal voucher ($\tau_i(\tau) = \tau$) there are three separate ways in which $\widehat{\pi}^p(\tau)$ can be zero.

First, if $\beta = 0$, then there is no variation in the weights $\psi(X_i'\beta, \tau_i(\tau))$ across individuals. In this case the students who move in response to τ are more or less a random sample and the characteristics of the peers of students who remain in public school do not change. There would be no cream skimming. As a result, $\widehat{\pi}^p(\tau)$ is potentially more negative the greater degree to which $\psi(X_i'\beta, \tau_i(\tau))$ varies with $X_i'\beta$.

Second, suppose there is no heterogeneity in observables within a school. In this case $(Z_i - \overline{Z}_{P_{-i}})$ is zero for all i and $\widehat{\pi}^p(\tau)$ will be zero. Following this logic, the more heterogeneity within a school, the more negative the treatment effect.

Finally, $\widehat{\pi}^p(\tau)$ will be zero if there are no peer group effects ($\delta = 0$). More generally, the larger the magnitude of the peer effects, the more important the cream skimming effect will be (assuming that better and more advantaged students from a given school are more likely to move).

4.1.3 Estimation of the Public School Attendance Parameter β and the Outcome Parameter γ.

In most of the empirical analysis below we estimate coefficient vector β on X_i in school choice model (2) by MLE probit, with $\tau_i(\tau)$ set to 0.

We estimate γ and the fixed school effects θ_s using a standard OLS regression of $Y_i(0)$ on X_i and school fixed effects. There are well known problems with this strategy when Y_i is a binary variable such as high school graduation or college attendance.

Although the estimates of γ are not our main focus, bias in the estimator for γ could spill over into bias in the estimation of the link between θ_s and $\bar{Z}_s$. Consequently, a discussion is in order even though we do not have a way to address the issue. Measurement error is likely to lead to underestimation of γ (in absolute value) and bias δ in the opposite direction to the extent that school level averages are less affected by measurement error and a substantial component of the true variation in X_i is across school. This is likely to lead to an overestimate of the importance of the average level of eighth grade test scores (which have a random component to them), parental education, income, etc in high school performance. Within school variation in omitted factors that influence education outcomes and income and are correlated with the within school variation in X_i will also lead to bias in γ. The effect of this latter source of bias on δ is harder to determine.

4.1.4 Estimation of the School Quality Parameter δ

One may rewrite (5) as

$$\hat{\theta}(s_i, 0) = Z_i'\delta + \nu_{\theta i} \tag{14}$$

where $\hat{\theta}(s_i, 0)$ is the estimate of the school fixed effect for the school s_i attended by person i and the error term $\varepsilon_{\theta i} = [\overline{Z}(s_i, 0)' - Z_i']\delta + \xi_s + [\hat{\theta}(s_i, 0) - \theta(s_i, 0)]$. We estimate δ by instrumental variables regression. For each individual i and each covariate, we form the instrument set $\overline{Z}_{p_{-i}}$ as in (11). We obtain $\widehat{\pi}^p(\tau)$ by plugging $\hat{\beta}$ and $\hat{\delta}$ into (13).

The estimator is consistent as the number of schools gets large holding the distribution of the number of students sampled per school constant under the assumption that after appropriate weighting the students in our sample are a random sample of the students who attend P_i.

4.1.5 Observable Peer Effects Restricting δ to be proportional to β or γ.

Below we find that it is difficult to estimate δ accurately. Consequently, we estimate models with two alternative restrictions on (5). The first, which we refer to as Model 1_β, is that

$$\overline{Z}(s, \tau)'\delta = c + \delta_{X'\beta}\overline{X}(s, \tau)'\beta. \tag{15}$$

This says that up to a factor of proportionality peer effects depend on average student characteristics in the same way that the school choice does. Even if this restriction is false the fact that the cream skimming effect of the voucher has to work through $X_i'\beta + \tau$ implies that one can think of (15) as a "reduced form" that is a first order approximation to the effect.

The second and perhaps more natural assumption is that

$$\overline{Z}(s,\tau)'\delta = \delta_{X'\gamma}\overline{X}(s,\tau)'\gamma.$$

We refer to Model 1 with the above restriction as Model 1_γ. The restriction imposes that up to a factor of proportionality peer effects depend on the mean of X_i of the students in schools in the same way the outcome Y_i depends on X_i.

In the case of Model 1_β we estimate $\delta_{X'\beta}$ by instrumental variables regression of $\hat{\theta}(s,0)$ on $X_i'\hat{\beta}$ using $\overline{X}'_{S_i-i}\hat{\beta}$ as the instrumental variable. In the case of Model 1_γ we estimate $\delta_{X'\gamma}$ by instrumental variables regression of $\hat{\theta}(s,0)$ on $X_i'\hat{\gamma}$ using $\overline{X}'_{S_i-i}\hat{\gamma}$ as the instrumental variable. In the case of Model 1_β, $\widehat{\pi}^p(\tau)$ is

$$\widehat{\pi}^p(\tau) = \sum_{S_i(0)=P_i} \psi(X'\hat{\beta},\tau_i(\tau))\hat{\delta}_{X'\beta}(X_i - \overline{X}_{S_{-i}})'\beta. \tag{16}$$

In the case of Model 1_γ one obtains $\hat{\pi}(\tau)$ by substituting $\hat{\delta}_{X'\gamma}$ for $\hat{\delta}_{X'\beta}$ in the above equation.

4.2 Allowing for Observable and Unobservable Peer Effects [Model 2]

We now augment the model to allow for unobservable peer effects. The key addition is that we now address peer effects that are unobserved to the econometrician ($\overline{u}(s,\tau)$). The problem is that unobservables raise tricky issues for identification. Our strategy uses the assumption that the relationship between $\overline{Z}(P_i,\tau)'\delta$ and τ is the same as the relationship between ξ_s and τ in a sense that we make precise below. We consider 3 cases. Model 2_β assumes that $Z_i = X_i$ and that δ is proportional to β. Model 2_γ assumes that $Z_i = X_i$ and that δ is proportional to γ. Model 2_δ places no restrictions on δ.

We begin with Model 2_β because it is the simplest case. Using notation similar to before define

$$\overline{X}(s,\tau) = E(X_i'\beta \mid S_i(\tau)=s) \text{ and } \overline{u}(s,\tau) = E(u_i \mid S_i(\tau)=s)$$

where u_i is the error term in the selection equation (2).

The crucial assumption of Model 2_β is that we can write $\theta(s,\tau)$ as

$$\theta(s,\tau) = \alpha_0 + \alpha_1\overline{X}(s,\tau)'\beta + \alpha_1\overline{u}(s,\tau) + \xi_s \tag{17}$$

where as before ξ_s is independent of everything else. The essence of the "unobservables are like observables" assumption is that in (17) the coefficient on the school mean of the index that determines school choice, $\overline{X}(s,\tau)'\beta$, is the same as the school mean of the error in the choice equation. Altonji, Elder, and Taber (2002) provide a model that justifies this restriction under some strong assumptions.

A key result that simplifies the analysis is

$$\begin{aligned}\overline{u}(s,\tau) &= E(u_i \mid S_i(\tau)=s) \\ &= E(E(u_i \mid S_i(\tau)=s, X_i) \mid S_i(\tau)=s) \\ &= E(\lambda(X_i'\beta) \mid S_i(\tau)=s).\end{aligned}$$

where $\lambda(X_i'\beta)$ is the inverse Mills ratio and the last equation follows from our assumption of normal error terms.[8] Since this is just a function of X_i, we can apply the line of analysis used in Model 1 after defining Z_i appropriately. Let

$$\begin{aligned}Z_i^* &= X_i'\beta + \lambda(X_i'\beta) \\ \overline{Z}^*(s,\tau) &= E(Z_i^* \mid S_i(\tau)=s).\end{aligned}$$

Then (17) may be rewritten as

$$\theta(s,\tau) = \alpha_0 + \alpha_1 \overline{Z}^*(s,\tau) + \zeta_s. \quad (18)$$

Now the analysis is equivalent to the analysis of the previous case with Z_i^* substituted for Z_i. We can write

$$\begin{aligned}\pi^p(\tau) &= E(\theta(P_i,\tau) \mid S_i(\tau)=P_i) - E(\theta(P_i,0) \mid S_i(\tau)=P_i) \\ &= \alpha_1 E[\overline{Z}^*(P_i,\tau) - \overline{Z}^*(P_i,0) \mid S_i(\tau)=P_i]\end{aligned}$$

Everything goes through as before. Following the same line of argument, we have

$$\widehat{E}\left(\overline{Z}^*(P_i,\tau) \mid S_i(\tau)=P_i\right) = \sum_{i=1}^{N_p} \psi(X_i'\widehat{\beta}, \tau_i(\tau))\widehat{Z}_i^*$$

where $\widehat{Z}_i^* = X_i'\widehat{\beta} + \lambda\left(X_i'\widehat{\beta}\right)$.

[8] The above derivation assumes that there are no unobserved school specific variables that are common to all students with P_d as their public school alternative. We relax this assumption in Section 9 below.

Now consider the second part of $\pi^p(\tau)$, $E\left(\overline{Z}(P_i,0) \mid S_i(\tau)=P_i\right)$. This can be written as

$$E\left(\overline{Z}^*(P_i,0) \mid S_i(\tau)=P_i\right) = \frac{E\left(\overline{Z}^*(P_i,0)\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)} \mid S_i(0)=P_i\right)}{E\left(\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)} \mid S_i(0)=P_i\right)}.$$

Thus

$$\begin{aligned}(19) \qquad \pi^p(\tau) &= \alpha_1 E[\overline{Z}_0(P_i,\tau) - \overline{Z}_0(P_i,0) \mid S_i(\tau)=P_i] \\ &= \alpha_1 \frac{\int\left(Z_i^* - \overline{Z}_0(P_i,0)\right)\frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)} dG(X_i \mid S_i(0)=P_i)}{\int \frac{\Phi(X_i'\beta-\tau_i(\tau))}{\Phi(X_i'\beta)} dG(X_i \mid S_i(0)=P_i)}.\end{aligned}$$

We estimate β and γ using the approach described above. We estimate α_1 by instrumental variables regression after substituting Z_i^* for $\overline{Z}^*(s,\tau)$ in (18), where both variables are redefined so that they are constructed using $\hat{\beta}$ rather than β. We use 2 alternative sets of instrumental variables. The instrumental variables set IV1a is $\overline{Z}_{P_{-i}}$ and $\bar{\lambda}(X_i'\hat{\beta})_{P_{-i}}$. The instrumental variables set IV1b is $\overline{Z}^*_{P_{-i}}$ where $\overline{Z}^*_{P_{-i}} = \frac{\sum_{j=1}^{N_{P_i}} Z_i^* 1(S_j(0)=P_i, i\neq j)}{\sum_{j=1}^{N_{P_i}} 1(S_j(0)=P_i, i\neq j)}$ and N_{P_i} is the number of sample members who attended $i's$ high school.

The estimator $\widehat{\pi}^p(\tau)$ is the sample analog to (19):

$$\widehat{\pi}^p(\tau) = \sum_{i=1}^{N_p} \alpha_1 \left(\widehat{Z}_i^* - \widehat{\overline{Z}}^*_{P_{-i}}\right)\psi(X_i'\hat{\beta}, \tau_i(\tau))$$

where

$$\widehat{\overline{Z}}^*_{P_{-i}} = \frac{\sum_{j=1}^{N_{P_{-i}}} \widehat{Z}_i^* 1\left(S_j(0)=P_i, i\neq j\right)}{\sum_{j=1}^{N_{P_{-i}}} 1\left(S_j(0)=P_i, i\neq j\right)}.$$

4.2.1 Model 2_δ and Model 2_γ

We now relax the assumption that θ is directly a function of $X'\beta$ and u_i and assume as in Model 1_δ that

$$\theta(s,\tau) = \overline{Z}(s,\tau)'\delta + \overline{u}(s,\tau) + \xi_s.$$

We will maintain the assumption that unconditionally ξ_s is uncorrelated with the mean of Z_i in a school.

The "observables are like unobservables" assumption (17) together with unconditional independence between X_i and u_i implies that

$$
\begin{aligned}
(20) \qquad \text{Proj}\left(\theta(s,\tau) \mid \overline{Z}(s,\tau), \overline{u}(s,\tau)\right) &= \alpha_0 + \overline{Z}(s,\tau)'\delta + \alpha_1 \overline{u}(s,\tau) \\
\text{Proj}\left(\overline{Z}(s,\tau)'\delta \mid \overline{X}(s,\tau)'\beta\right) &= \alpha_0^x + \alpha_1 \overline{X}(s,\tau)'\beta
\end{aligned}
$$

In this case

$$
\begin{aligned}
\pi^p(\tau) &= E\left(\theta(P_i,\tau) \mid S_i(\tau) = P_i\right) - E\left(\theta(P_i,0) \mid S_i(\tau) = P_i\right) \\
&= E[\overline{Z}(P_i,\tau)'\delta - \overline{Z}(P_i,0)'\delta + \alpha_1\left(\overline{u}(P_i,\tau) - \overline{u}(P_i,0)\right) \mid S_i(\tau) = P_i]
\end{aligned}
$$

Applying the same argument as in Method 1, one arrives at the estimator $\pi^p(\tau)$

$$
(21) \qquad \widehat{\pi}^p(\tau) = \sum_{i=1}^{N_p} \psi(X_i'\widehat{\beta}, \tau_i(\tau)) \left(Z_i'\widehat{\delta} + \alpha_1 \lambda(X'\widehat{\beta} - \tau_i(\tau)) - \overline{Z}'_{P_{-i}}\widehat{\delta} - \alpha_1 \widehat{\overline{\lambda}}_{P_{-i}}\right).
$$

after obtaining consistent estimators β, δ, and α_1.

One can see from the equations above that the parameter α_1 is overidentified. One can identify it as the coefficient on $\lambda(X_i'\beta)$ from the IV estimation of the equation relating $\theta(s,\tau)$ to Z_i and $\lambda(X_i'\beta)$. However, with this approach identification comes from functional form only (unless one is willing to exclude some of the elements of X_i from Z_i.) If $Z_i'\delta$ were completely nonparametric and we did not impose exclusion restrictions this would not work. The essence of the assumption about observables and unobservables is contained in the second equation of (20) for the projection of $\overline{Z}(s,\tau)$ on $\overline{X}(s,\tau)'\beta$. We prefer to force identification of α_1 to come from this expression and do so by using an exactly identified GMM system to estimate $(\alpha_o, \delta, \alpha_1, \alpha_o^x)$. Specifically, we estimate β, γ and the school effect θ_s as described in section 3.1.3. We then estimate $(\alpha_o, \delta, \alpha_1, \alpha_o^x)$ using the moment conditions

$$
\begin{aligned}
E\left[\theta(S_i(0), 0) - \alpha_0 - Z_i'\delta - \lambda(X_i'\beta) \mid S_i(0) = P_i\right] &= 0 \\
E\left[\left(\theta(S_i(0), 0) - \alpha_0 - Z_i'\delta - \alpha_1 \lambda(X_i'\beta)\right)\overline{Z}_{s_i - i} \mid S_i(0) = P_i\right] &= 0 \\
E\left[Z_i'\delta - \alpha_0^x - \alpha_1 X_i'\beta\right] &= 0 \\
E\left[\left(Z_i'\delta - \alpha_0^x - \alpha_1 X_i'\beta\right) X_i'\beta\right] &= 0
\end{aligned}
$$

Note that the first two sets of moment conditions use the public school sample only while the last two use the full sample.

We estimate π using (21).

Model 2_γ is estimated using the same methodology with $Z_i = X_i'\gamma$ and using our estimate of γ in estimation.

4.3 Targeted Programs

When we examine targeted programs, (i.e. programs in which $\tau_i(\tau)$ may vary across people), our estimator to evaluates the impact of the program on all students who remain in public school following the introduction of a voucher that is targeted to a subgroup within schools, not just the eligible population. It is not straightforward to use our approach to estimate the impact on members of the targeted subgroup, such as low income students, who remain in public schools unless either there is no heterogeneity in the targeted group within schools or the samples of students from each public high school are large. For example, we examine vouchers targeted at low income students and another targeted at students who go to urban public schools. In the low income example, we estimate the effect of the low income voucher program on all public students-not just low income students. In a future draft we will extend our methods to estimate outcomes for the targeted group. However, in the urban example we can just condition on the population of kids who go to urban schools, so we can estimate the effect on students in urban high schools. (Note that the effect of the urban program on kids in nonurban high schools is zero by construction).

5 Data

5.1 NELS:88

NELS:88 is a National Center for Education Statistics (NCES) survey that began in the Spring of 1988. A total of 1032 schools contributed as many as 26 eighth grade students to the base year survey, resulting in 24,599 eighth graders participating.[9] Subsamples of these individuals were reinterviewed in 1990, 1992, 1994 and 2000. The NCES only attempted to contact 20,062 base-year respondents in the first and second follow-ups, and only 14,041 in the 1994 survey. Additional observations are lost due to attrition. A subsample consisting of 15,623 individuals were re-interviewed in 2000, when most respondents were 26 years old. We use information on income from this wave.

[9] This description draws heavily from Altonji, Elder and Taber (2003).

Parent, student, and teacher surveys in the base year provide information on family and individual background and on pre-high school achievement and behavior. Each student was also administered a series of cognitive tests in the 1988, 1990, and 1992 surveys to ascertain aptitude and achievement in math, science, reading, and history. We use the 8th grade test scores as person specific control variables and peer measures. They have the advantage of being determined prior to high school. We use 12th grade reading and math tests as one of our outcome measures.

Our main outcome measures are high school graduation (HS_i), college attendance ($COLL_i$), and the log of labor income (INC_i). HS_i is one if the respondent graduated high school by the date of the 1994 survey, and zero otherwise. $COLL_i$ is one if the respondent was enrolled in a four-year university at the time of the 1994 survey and zero otherwise. The indicator variable for Catholic high school attendance, CH_i, equals one if the current or last school in which the respondent was enrolled was Catholic as of 1990 (two years after the eighth grade year) and zero otherwise.[10] INC_i is the logarithm of labor income in 1999. Notice that many respondents were still in school and not working full time. Hence, we set INC_i to missing if the respondent attended a postsecondary school in 1999. Unless noted otherwise, the results reported in the paper are weighted.[11]

The explanatory variables used in the analysis are listed in Table 1. Missing values for key explanatory variables are replaced by their respective unweighted average values and we include missing value dummies in the school choice and outcome models. These variables includes the family income, father's education, and mother's education. However, observations with missing values of the school ID or the school type are dropped. In addition, some variables contains only a small proportion of missing values. We decided to drop those observations rather than create additional dummy variables to indicate missing values.[12]

[10] A student who started in a Catholic high school and transferred to a public school prior to the tenth grade survey would be coded as attending a public high school ($CH = 0$). AET present evidence that this issue is of minor importance.

[11] The sampling scheme in the NELS:88 is complicated and explained in more detail in Altonji, Elder and Taber (2002) and in Grogger and Neal (2002). The weights depend in part on school choice and on outcomes, so it is important to weight. We use the 3rd follow-up panel weights for all analyses except that of INC_i. When analysing INC_i we use the 4rth follow-up panel weights ($4pnlwt$).

[12] These variables include religious background, race, family composition, marital status of the parents, 8th grade test scores, and urbanicity of the school.

6 Descriptive Statistics

6.1 Student Outcome and Characteristics

Table 1A presents weighted means and standard deviations for the variables we use in the analysis. The main point to be made from the table is that children who attend either Catholic high school or other private high schools are advantaged relative to students in public schools. For example, they come from families with higher incomes, have better educated parents, are more likely to have both father and mother present, and have higher 8th grade achievement scores. They also have a .27 advantage in log income (10.29 versus 10.02). Using the estimates of the standard deviation of the school specific and student specific components of family income that are reported in Table A1-A one may calculate that the income gap of .27 is equal to a .68 standard deviation shift in the component of parental income that varies across public high schools (Table A1-A) and to a .428 standard deviation shift in the student specific component of family income. The gap of 3.5 in eight grade math scores between Catholic high school students and public high school students is .65 of a standard deviation of the high school specific component of this variable. The gap between the observables for Catholic high school student and public school students is part of the cause for concern that vouchers will lead more advantaged students to leave public schools.

As previous work with NELS:88 has shown, students who attend Catholic high school are much more likely to graduate from high school than public high school students (.976 versus .873) and more likely to be attending college two years after the normal high school graduation year (.587 versus .301). The log income of students at non-Catholic private high schools are very similar to those of public high school students, but high school graduation rate is .04 higher and college attendance is .29 higher.

Tables 1B and 1C present summary statistics for students in urban areas and for urban minorities (blacks and Hispanics). The private school/public school gaps in parental education, family income, and 8th grade achievement tend to be larger in the urban subsample.

6.2 Sample Sizes By High School and Eighth Grade

Because of the complexity of the estimator of $\pi^p(\tau)$ and its components, we use the bootstrap method to compute standard errors, confidence intervals, and bias corrections for most of the parameters. The question of how to treat dependence across observations arises. We assume that peer effects depend on the students that one goes to high school with. However, there is likely to be correlation in the error terms among students who attend the same eighth grade and among the students who attend the same high school that must be taken into account when estimating confidence intervals. We allow for error correlation across students by using a block bootstrap procedure. The blocks consist of students from each set of eight grades who sent at least one student to a common high school. For example, suppose that eighth grade A sent students to high school 1, 2, and 3, eighth grade B sent students to high school 1 and 3, and no other eighth grades represented in NELS:88 sent students to high school 1, 2, or 3. Then the students from eight grade A and eight grade B constitute a block for purposes of constructing bootstrap replication samples. In practice, we obtain similar confidence interval estimates if we treat students from each high school as a block.

Figure 1A shows that 0.86 of the high schools have students from only 1 eighth grade. This is as expected given the sample design. The sampling process in the original survey used the eighth grade schools as strata. Among 39,000 schools containing the eighth grade in the U.S., 1,052 schools were selected. Since students usually go to a nearby high school, it is not very common in the sample for students from different eighth-grade schools to attend the same high school. Figure 1B shows that about 58% of the eighth grades have sample members in only 1 high school. About 28% have sample members in 2 high schools and 10% in 3 high schools, with a small fraction sending sample members to 4 or more high schools.

Figure 2 shows the distribution of observations per resampling block. The distribution is concentrated between 6 and 30, but there are a few blocks with larger numbers of students. The largest block contains 105 students when we exclude non-Catholic private schools from the analysis. If future work we will experiment with breaking up the blocks of no more than 50 students into a separate block for each high school involved on pragmatic grounds.

Figure 3 reports the distribution of N_s, the number of sample members in each high school. This distribution is relevant to estimation of γ via the high school fixed effects regression and especially to the sizes of the samples used to construct $\bar{Z}_{-i}$. The distribution is concentrated between 6 and 18 observations. For a small number of high schools we have fewer observations and for a small number we have more, with a maximum of 32.

7 Basic Results

We begin with a discussion of the school choice model and the effects of a student's own characteristics on outcomes. We then turn to the effects of student body characteristics on outcomes. Finally, we present estimates of the effects of a voucher program on the characteristics of those who remain in public school as well as estimates of the $\pi^p(\tau)$. Most of the results only consider Catholic schools, but in Section 8 we extend the analysis to incorporate Catholic schools and non-Catholic schools as distinct choices.

7.1 Estimates of the School Choice Model

Table 2 presents MLE-probit estimates of β from the public high school attendance (2) for the full sample and the urban subsample.[13] The dependent variable is one if the student attended public school and zero if the student attended Catholic school. Not surprisingly, there is a large negative coefficient on Catholic in the equation. Because religious preference has very special role in the decision to attend a Catholic high school, Catholic is set to 0 when we evaluate the indices $X'\beta$ and $X'\gamma$ for the purpose of imposing index restrictions on the peer effect parameters δ.

Having both parents present and having married parents both reduce the probability of attending public school but are not statistically significant. Students with better-educated mothers and fathers are less likely to attend public school. Parental income is negative and significant. Reading and math both enter with negative coefficients. Students in urban areas are much less likely to attend public school. The same is true of suburban students. These results are heavily influenced by the fact that Catholic schools are concentrated in urban and suburban areas. The region dummies are relative to the West. All three are negative.

One can also see that the average derivatives are consistently higher for the urban subsample than the full sample, often by as much as a factor of four. This is not surprising as families with high socioeconomic characteristics who live in the suburbs are more likely to send their children to public schools.

[13] Standard errors in Table 2 are based on 100 bootstrap replications.

7.2 The Effect of a Student's Own Characteristics on High School Graduation

Table 3A presents estimates of γ, the effect of student's own characteristics on high school graduation, holding high school characteristics common to all students constant. The estimates are the coefficients from a linear probability model with high school fixed effects included. Block bootstrap standard errors are included in parentheses. We are well aware of the limitations of the linear probability model with fixed effects, but fixed effects probit or logit estimators are unattractive for a variety of reasons. However, we will explore them in future drafts.

The results for most of the variables are consistent with the literature. We obtain positive coefficients on mother's and father's education and family income. Not surprisingly, the test scores enter positively. The largest coefficient is on math. A 10 point increase in the math score, which is 1 standard deviation in the full NELS:88 sample, is associated with a .04 increase in the probability of graduation. The positive coefficient on Black is consistent with other studies of educational attainment that control for test scores and family background.

7.3 Effects of Student Body Characteristics on Outcomes

In Table 4A we report estimates of the coefficient vector δ from the model (5) relating the estimated school fixed effects for high school graduation to the average characteristics of the student body and a set of location variables. Beneath each coefficient we report confidence intervals. These are based upon 500 bootstrap replications and in future work we will investigate whether this number is adequate. Unfortunately, given the degree of dependence among the covariates and the noise in $\hat{\theta}_s$ none of the variables are individually statistically significant.

If we impose the Model 1-β restriction that δ is proportional to β, our estimate of the coefficient $\delta_{X'\beta}$ on $\bar{X}'\hat{\beta}$ is .0056 with a confidence interval from -.0003 to .0075. The positive point estimate suggests that holding religion constant, having peers who are more likely to attend public school based on observed characteristics leads to slightly higher graduation rates rather than lower rates. If instead we impose the restriction that δ is proportional to $\bar{X}'\hat{\gamma}$ our estimate of $\hat{\delta}_{X'\gamma}$ is .2924 with a 95% confidence interval of -.103 to .556. Given that $\bar{X}'\hat{\gamma}$ and Y are in the same units, the point estimate says that the contribution of an increase in $X_i'\hat{\gamma}$ equal to $\Delta X_i'\hat{\gamma}$ for student i in a high school to graduation rate of that high school is the sum of $\Delta X_i'\gamma$, the direct effect of $\bar{X}_i'\hat{\gamma}$ on i plus $.29\Delta X_i'\gamma$. Consequently the fraction $.226 = .29/(.29 + 1)$ of the effect of $X_i'\hat{\gamma}$ on the graduation rate for a given high school operates through peer effects. However, this is a noisy estimate, given that the confidence interval for $\hat{\delta}_{X'\gamma}$ is (-.1026, .5564).

The nature of our data leads to one complication of our results. We measure peer groups in terms of high schools, but our data begins as a sample of individuals from the same eighth grade. The fact that some high schools have more than one feeder school will create problems to the extent that the mean of Z_i varies across feeder schools for a given high school unless the sample is representative of the mix of students from the various schools. In practice, we usually only have students from one feeder school. In this situation, the component $[\overline{Z}(s_i, 0)' - Z_i]$ will be negatively correlated with $\overline{Z}_{p-i}$,the average in the high school. This effect biases the estimate of δ downward. On the other hand, these students were peers during eighth grade as well, so since δ is defined to be the effect of high school peers, this aspect will tend to bias δ upward since it will pick up eighth grade peer effects as well.

7.3.1 Effects of Unobserved Student Body Characteristics

Table 4A also presents estimates of α_1, which is the coefficient linking θ_s to the school mean of the unobserved attributes that determine school choice. For Model 2-δ, which does not restrict δ, the point estimate of α_1 is 0.0003 and the 95% confidence interval estimate is -.0134 to 0.0463. When we restrict δ to be proportional to γ (Model $2-\gamma$), the point estimate is -.0036 with a confidence interval of -.0040 to .0006. Once again, imposing the index restriction not only improves the precision of the estimates of the effects of the observed characteristics, but also increases the precision of the estimated coefficient on the unobserved index.

7.4 The Effects of the Voucher Program on the Characteristics of Who Attends Public School and on Outcomes

7.4.1 Results When Catholic Schools are the Only Private School Option

We begin by comparing the mean characteristics of public school stayers and movers for our base model which is a universal voucher $\tau_i(\tau) = \tau$. For each bootstrap replication the value of τ is set to a level that is sufficient to induce 10% of the public school students to switch to private school. The mean value is .9059. This value is equivalent to a .9059 standard deviation change in the index of unobservables that determines school choice. (The implied value of τ varies across bootstrap simulations because of variation in the sample and variation in $\hat{\delta}$. The 5th and 95th percentiles of the simulation values are .802 and 1.15.) The value of 10% is about 3 times the combined effect of a 4 year increase in both father's education and mother's education and a .30 increase in log income.

Point estimates and 95% confidence interval estimates of the means of X_i for stayers and for movers are displayed in columns (1) and (2) of Table 5. The results show that the mean for movers is larger for two parent family, parents married, father's education, mother's education, income, and all four test scores. It is interesting to note that the difference in the means for movers and stayers are statistically significant for a number of variables for which the corresponding elements of $\hat{\beta}$ in the choice model are not statistically significant. For example, in the full sample choice model the coefficient on father's education is -.039 (.022), while the coefficient on mother's education is -.053 (.026). Given the key role of $\hat{\beta}$ in calculating the relative odds that an individual will remain in public school in response to a voucher, one might think that the difference in means would be larger for the education of the mother but not the father. In fact, the difference in means between movers and stayers is .64 for mother's education and .90 for father's education. The reason the connection between the stayer-mover difference in the elements of X and the corresponding elements values of $\hat{\delta}$ is only weak is that the stayer-mover difference for a particular variable may be positive if that variable is positively correlated with other variables that lower the odds of choosing in public school. A similar pattern shows up in results for test scores.

The fourth column of the table also reports the change in the average value of $\bar{Z}$, the average value of Z of the peers of those who stay in public schools. The changes are small. There is little change in race/ethnic composition of peers. The prevalence of two-parent households drops by only -.01, and there is little change in the percentage of children with married parents. Father's and mother's education drop by -.037 and -.024, respectively and the log of parental income drops by -.015. The math test score declines by -.15, which is only .015 standard deviations at the individual level and only .029 standard deviations of the distribution of average math scores across public schools.[14]

[14]Not surprisingly, the means for movers of urban and suburban are larger than the means for stayers. In part, this reflects the fact that Catholic schools, the only alternative considered in the analysis leading to Table 3, are much more prevalent in urban and suburban areas. Movers are more likely to be in the Northeast and somewhat less likely to be in the south.

Overall, the results suggest that a universal voucher program of the magnitude that we consider is unlikely to have a very large effect on the peers of the children who remain in public school. Consequently, unless outcomes are very sensitive to peers, the voucher program is not likely to have the substantial negative effect on how public school stayers do. However, one must be careful in thinking about what is large and what is small because one needs to compare the impact on the stayers to the gain of the movers. Since only 10% of the students move, the stayers are nine times more numerous than the movers. We will return to this issue momentarily.

Table 6A presents the point estimates and the 95% confidence intervals for the school means of $X'\beta$, $\bar{X}'\beta$ $X'\gamma$, $\bar{X}'\gamma$, $\lambda(X'\beta - \tau)$ and $\bar{\lambda}(X'\beta - \tau)$ by mobility group status. For purposes of this table we exclude Catholic from X. Not surprisingly, the mean of $X'\beta$ is much higher for stayers than for movers than (3.84 versus 1.96). (Recall the school choice model is normalized so that β is the probit coefficient relating X to the decision to choose public school.) The point estimate of the average change in the peer variable $\bar{X}'\beta$ for stayers is .0130, with a confidence interval that runs between .0086 and .0239. These values translates into very small shifts in the probability of choosing public school when the voucher is 0.

The second row of the table reports the point estimates and confidence intervals of $X'\gamma$. The point estimate for public school stayers is .878 with a confidence interval of .723 to 1.05. The point estimate for movers is .918. Thus, the difference in the characteristics of the stayers and movers implies a difference in graduation rates of about .04, which is quite large relative to the mean graduation rate for public school students. However, the point estimate of the mean change in the peer variable $\bar{X}'\gamma$ for stayers is only -.0023 with a confidence interval between -.0030 and -0.0016.

The third row reports the point estimate of λ, the expected value of the error term in the school choice equation. Not surprisingly, it is larger for movers than for stayers. The estimate of the mean change in the peer variable $\bar{\lambda}$ for stayers is 0.1539. This is quite a bit larger than the point estimate of the mean change in the peer variable $\bar{X}'\beta$ for stayers. This reflects the fact that aside from the variable Catholic, the other variables in our choice model have only limited explanatory power.

7.4.2 Estimates of the Cream Skimming Effect $\pi^p(\tau)$

We are now ready to turn to the estimates of the main parameter of interest— the cream skimming effect $\pi^p(\tau)$. Row 4 of Table 6A reports estimates of the means of $Z'\delta$ by mobility status, and the level and change in the average value of the peer effect $\bar{Z}' \delta$ based on Model 1-δ. Recall that this model does not restrict δ but assumes away the effects of unobservables. The point estimate of $Z'\delta$ for stayers is -.0332, but the 95% confidence interval estimate is -.152 to .179. The point estimate of $\bar{Z}' \delta$ for stayers before the voucher is imposed is -.0107, but again with a fairly wide confidence interval. The estimate of $\pi^p(\tau)$, the change in the mean peer effect for stayers, is -.023. The point estimate says that the graduation rate of those who would remain in public school would decline by about .023, a large effect. However, the range is too wide for the results to be of interest. Further restrictions are needed.

The results in the row labeled Model 1-β are comparable to those in row 4, except that we impose the restriction that δ is proportional to β. The estimates are much more precise. The point estimate $\pi^p(\tau)$ is essentially 0 and the confidence interval is very tight—.0000 to .0001. The lower bound estimate implies no negative effect on stayers.

When we impose the restrictions of model 1-γ, the point estimate of the change in the peer effect for stayers is -.0007 and the lower bound to the confidence interval is -.0015. To put these numbers in perspective, it is helpful compare the direct benefits to students who are induced to move to the harm for students who are left behind after weighting by the size of the groups. Suppose that moving from public school to private school leads to an increase in the graduation rate by .06 for those who move. This estimate is in the range of what one obtains using single equation methods based on NELS:88 and is in the range of the lower bound estimates that Altonji, Elder and Taber (2003) obtain when they address the problem of selection on unobservables. The voucher program induces 10% of public school students to move, leaving 9 students in public school for everyone who moves. The lower bound estimate of -.0007 implies that for each student who moves to private school the overall graduation rate for students who were in public school prior to the voucher rises by $.06 - .0007 \times 9 = .054$. The gain of .06 for each student who moves is partially offset by a decline of .006 in the expected number of graduates among students who remain, an offset of about 10% of the direct benefit received by the child who switches to private school. Using the lower bound estimate of -.0015, the negative impact on the number of stayers who graduates is .014 and the expected number of graduates among the pool of students who were in public school rises by .046 for each student who take up the voucher.

When we use Model 2-δ, which allows for both observables and unobservables and does not restrict δ, we obtain very imprecise results. For Model 2-β the point estimate of the effect of the change in the peers of stayers is .0007 and the lower bound is 0. These results indicate that the cream skimming effect is basically 0. When we use Model 2-γ, the point estimate is -.0011 and the lower bound estimate is -.0019. The point estimate implies that about 18% of the direct benefits to the graduate rate resulting from the move to private school is offset by $\pi^p(\tau)$.[15]

7.4.3 Sensitivity Checks

To guage the sensitivity of our results to possible mispecification of our model of school choice or of peer effects, we have performed a number of simulations under extreme assumptions. The assumptions concern the strength of peer effects, the amount of heterogeneity within schools, and the extent to which school choice is driven by the same factors that determined outcomes. Our discussion of (13) emphasizes that the size of the cream skimming effect is increasing in all three of these factors. The first experiment is to fix the peer effect coefficient on $X'\gamma$ to be unity ($\delta = 1$) in model $1-\gamma$ and $2-\gamma$. In this case, our point estimate $\pi^p(\tau)$ is -0.0023 for Model 1-γ and -0.0027 for Model 2-γ, which are about three times the size of the corresponding estimates in Table 6a. Next we consider a case with no sorting into schools ex-ante so that schools are completely heterogenous. In this case the point estimates of the cream skimming effects are -0.0011 and -0.0015 for Models 1 and 2 respectively. Consequently, even under an extreme assumption about heterogeneity, the point estimate of the cream skimming effect is very modest. Finally, we simulate a model in which sorting into new voucher schools is determined exclusively by the observable index $X'\gamma$. In this case we find an effect of -0.0045. This is a substantial effect relative to the private benefit of attending private school, but the assumption that the response to the voucher will be based entirely the same index that determines peer effects is extreme.

[15] It should be kept in mind that when student characteristics that influence choice affect θ linearly, as we assume, then the change in θ for public school stayers is offset by a change in θ for private school students such that overall mean of θ is not affected. The reduction in θ for stayers is offset by the combined effect of the increase in θ for movers and a possible decrease in θ of private school stayers. If θ is a nonlinear function of $\bar{X}_i$ or Y is a nonlinear function of θ (as in probit model for high school graduation), then the net effect of the shift in θ for public school stayers, movers, and private school stayers might be to increase graduation rates. This is in fact a likely outcome given that dropping out is a very rare event for more advantaged students. A given shift in θ will have a smaller impact on graduation for the advantaged than for the disadvantaged. We hope to investigate this in future work, but since the shift in peer quality is relatively small for stayers, any overall reduction in graduation rates is likely to be very small.

7.4.4 Results for Urban Students

We now turn to estimates of the peer effects on high school graduation of a voucher program that is targeted to urban families. The voucher is calibrated so that 10% of the urban children currently in public school would move to private schools in response. We use the estimates of the school choice model parameters β estimated on the urban sample. (Table 2, column 2). We estimate γ using the full sample. To increase sample size we also estimate the peer effects models using the full sample but in the case of model $1-\beta$, $2-\delta$, $2-\beta$, and $2-\gamma$ the estimates of β used in forming $X'\beta$ and $\lambda(X'\beta)$ depend on whether the school is in an urban area. Furthermore, in model $2-\delta$ and $2-\gamma$ we allow the α parameters to depend on whether the school is urban. The peer effects model estimates (Table 7) are identical to those in Table 4A for model $1-\delta$, $1-\gamma$, and $2-\delta$, although the confidence intervals differ because the bootstrap replication samples differ. In the case of models $2-\delta$ and $2-\gamma$, only the estimate of α for the urban schools enters into our estimates of $\pi^p(\tau)$. The estimates α for the urban schools are much noisier than the estimates for the nonurban schools. The result is substantially reduce the precision of our estimates of $\pi^p(\tau)$ based on model $2-\gamma$.

Table 8 reports estimates of the change in peer characteristics of stayers and urban voucher program. The point estimates very similar to those for a universal voucher and are small. For example, father's education would decline by .05 years and the 8th grade math score would decline by .135. The changes in the observables suggest that any negative impact on the voucher on those who remain in urban public schools will be small.

Rows 4-9 of Table 9A reports estimates of $\pi^p(\tau)$ for the various model specifications. Once again, the estimates based on Model $1-\delta$ and $2-\delta$ which does not impose index restrictions on the peer effects equation, are extremely noisy. The restricted models $1-\beta$, $1-\gamma$, and $2-\beta$ lead to small, precise point estimates with small, negative lower bound estimates. However, model $2-\gamma$ lead to a large point estimate that is very imprecisely measured. The imprecision seems to arise from the large sampling variability in the case of urban schools for α_1, the coefficient relating λ to the estimates of the school fixed effects in (20). At this point we are not sure why the sampling variance of α_1 is so much higher in the urban schools case and hope to resolve the issue for a future draft of the paper.

7.4.5 Results for Low Income Students

Tables 10 and 11 present the results for a voucher targeted at low income students. Only families whose income is in the lowest 20% of our sample is eligible for the voucher. We again calculate the value of the voucher that would move 10% of the eligible population to attend public school. The results are qualitatively similar to the results in Tables 5 and 6 in the sense that effects are small. However, because of the targeting, the peers of stayers become more slightly more advantaged as a result of the voucher. Programs that target all students in low income school districts regardless of income would have a different selection effect.

It is important to emphasize that we are estimating the effects on the full population of public school stayers on a voucher that moves 10% of the eligible population, which is only 2% of the full population. In this case instead of multiplying by 9 as in the previous example, one should multiply by 49. However, given the small magnitude of the effects, even after taking this product, one is left with a small number. As we have noted, it is also interesting to look at the effect of the targeted voucher on the targeted population we hope to do so in a subsequent draft.

7.4.6 Results for Non-Catholics

In view of the large effect of religious preference on Catholic school attendance, variation among non-Catholics in the probability of Catholic school attendance might be more driven by academic advantages of Catholic schools versus the available public school and provide a better indication of the degree of cream skimming that might arise from a universal voucher program. This line of reasoning suggests that a simulation in which only non-Catholics receive vouchers might provide a better indication of what the cream skimming effect of a general voucher program would be. While one would not expect to see a voucher program targeted in such a way, the simulation provides a check on whether movement of Catholics in response to the voucher is driving our results. Table 12 reports the effects of the program on peers and Table 13A reports the cream skimming effect. The estimates of the cream skimming effects are remarkably close to those in Table 6A.

7.5 Results for 12th Grade Test Scores and College Attendance

Tables 3B and 3C report high school fixed effect estimates of the effects of student's own characteristics on college attendance and 12th grade math scores. Tables 4B and 4C report peer effects models for these outcomes. The unrestricted estimates of δ are very imprecise. Tables 10B and 10C report the differences between moyouvers and stayers in peers as well estimates of the cream skimming effect. The results based on the restricted models indicate that cream skimming effects are likely to small for these outcomes as well.

8 Catholic and Other Private High Schools as Separate Alternatives

Our methods generalize in a natural way to the case of Catholic and non-Catholic private schools. Partition the set of all school $\mathcal{S}$ into public schools $\mathcal{S}_p$, Catholic schools $\mathcal{S}_c$ and non-Catholic private schools $\mathcal{S}_n$. Continue to assume that the characteristics of the private schools options available to i are not affected by the voucher. Formally for any τ, $S_i(\tau) \in \{P_i, \mathcal{S}_c, \mathcal{S}_n\}$.

Letting $V_i(s,\tau)$ be the utility an individual obtains from choose s under voucher program τ and continuing to suppress the i subscript, we assume that

$$V(P_i,\tau) - \max_{s\in S_c} V(s,\tau) = X_i'\beta_c - \tau_i(\tau) + u_{ci} \tag{22}$$

$$V(P_i,\tau) - \max_{s\in S_n} V(s,\tau) = X_i'\beta_n - \tau_i(\tau) + u_{ni} \tag{23}$$

where u_{ci} and u_{ni} represents unobservable factors that influence the relative the relative attractiveness of Catholic schools and other private schools relative to public schools. Both are assumed independent of X_i. Student i facing voucher program τ chooses $S_i(\tau)$ according to

$$S_i(\tau) = \begin{cases} P, & \text{if } X_i'\beta_c - \tau_i(\tau) + u_{ci} > 0, \text{and } X_i'\beta_n - \tau_i(\tau) + u_{ni} > 0; \\ C, & \text{if } X_i'\beta_c - \tau_i(\tau) + u_{ci} < 0, \text{and } X_i'\beta_c + u_{ci} < X_i'\beta_n + u_{ni}; \\ N, & \text{if } X_i'\beta_n - \tau_i(\tau) + u_{ni} < 0, \text{and } X_i'\beta_n + u_{ni} < X_i'\beta_c + u_{ci}. \end{cases} \tag{24}$$

Assume (u_{ci}, u_{ni}) are bivariate standard normal random variables with correlation ρ. Let $F(.,.)$ denote the cdf of (u_{ci}, u_{ni}). Then the probability of attending a public school is

$$F(X_i'\beta_c - \tau_i(\tau), X_i'\beta_n - \tau_i(\tau); \rho).$$

In the trinomial case, the ratio ψ_i of the probability that student attend will stay in public school if a voucher τ is introduced relative to the probability that the student is in public school under that status quo in which τ is 0

$$\psi_i = \frac{F(X_i'\beta_c - \tau_i(\tau), X_i'\beta_n - \tau_i(\tau); \rho)}{F(X_i'\beta_c, X_i'\beta_n; \rho)}.$$

Define

$$Pc^* \equiv \frac{(-X_i'\beta_c + \tau_i) - \rho(-X_i'\beta_n + \tau_i)}{\sqrt{1-\rho^2}},$$
$$Pn^* \equiv \frac{(-X_i'\beta_n + \tau_i) - \rho(-X_i'\beta_c + \tau_i)}{\sqrt{1-\rho^2}}.$$

The means of u_{ci} and u_{ni} conditional on attending a public school are

$$\lambda_{ci}(\tau) = \frac{\phi(-X_i'\beta_c + \tau_i)[1-\Phi(Pn^*)] + \rho\phi(-X_i'\beta_n + \tau_i)[1-\Phi(Pc^*)]}{F(X_i'\beta_c - \tau_i(\tau), X_i'\beta_n - \tau_i(\tau); \rho)}$$

and

$$\lambda_{ni}(\tau) = \frac{\phi(-X_i'\beta_n + \tau_i)[1-\Phi(Pc^*)] + \rho\phi(-X_i'\beta_c + \tau_i)[1-\Phi(Pn^*)]}{F(X_i'\beta_c - \tau_i(\tau), X_i'\beta_n - \tau_i(\tau); \rho)},$$

respectively. (See Maddala (1983), p. 368)).

8.1 Model 1-δ

In the case of model $1-\delta$, there are no unobserved peer characteristics. The variable $\overline{u}(s,\tau) \equiv 0$, so

$$\theta(s,\tau) = \overline{X}(s,\tau)'\delta + \zeta_s.$$

Let $D_i = (X_i - \overline{X}_{S_{-i}})'\hat{\delta}$. $\hat{\pi}(\tau)$ is the weighted average of D_i with weights $\hat{\psi}_i$.

8.2 Model 1-β

Assume δ is a linear combination of β_c and β_n with weights a_1 and a_2. Then

$$\theta(s,\tau) = a_0 + a_1\overline{X}(s,\tau)'\beta_c + a_2\overline{X}(s,\tau)'\beta_n + \zeta_s.$$

We estimate a_1 and a_2 by IV regression of $\hat{\theta}(s,0)$ on $X'\beta_c$ and $X'\beta_n$. The instruments are $\overline{X}'_{S_{-i}}\hat{\beta}_c$ and $\overline{X}'_{S_{-i}}\hat{\beta}_n$.

Define $D_i = \hat{a}_1(X_i - \overline{X}_{S_{-i}})'\hat{\beta}_c + \hat{a}_2(X_i - \overline{X}_{S_{-i}})'\hat{\beta}_n$. $\hat{\pi}(\tau)$ is the weighted average of D_i with weights ψ_i.

8.3 Model 1-γ

Conditional on estimates of the trinomial school choice model and the associated weights ψ_i, estimation of the other parameters and cream skimming effect is the same in the binomial case.

8.4 Model 2-δ

We replace (20)

$$\text{(25)}\qquad \text{Proj}\left[\theta(s,\tau)|\overline{X}(s,\tau),\overline{u}_c(s,\tau),\overline{u}_n(s,\tau)\right] = \alpha_0 + \overline{X}(s,\tau)'\delta + \alpha_1\overline{u}_c(s,\tau) + \alpha_2\overline{u}_n(s,\tau),$$

$$\text{(26)}\qquad \text{Proj}\left[\overline{X}(s,\tau)'\delta|\overline{X}(s,\tau)'\beta_c,\overline{X}(s,\tau)'\beta_n\right] = \alpha_0^* + \alpha_1\overline{X}(s,\tau)'\beta_c + \alpha_2\overline{X}(s,\tau)'\beta_n.$$

The above equations imply

$$E\left[\begin{array}{c} Z_1^{pub\prime}\left[\theta - X^{pub}\delta - \alpha_1\lambda_c(0) - \alpha_2\lambda_n(0)\right] \\ Z_2'\left[X\delta - \alpha_1 X'\beta_c - \alpha_2 X'\beta_n - \alpha_0^*\mathbf{1}\right] \end{array}\right] = \left[\begin{array}{c} \mathbf{0} \\ \mathbf{0} \end{array}\right],$$

where the first equation holds only for those attending a public school while the second one holds for all observations. Z_1^{pub} and Z_2 are the instruments.

Therefore, we have

$$E\left[\begin{array}{c} Z_1^{pub\prime}\theta \\ \mathbf{0} \end{array}\right] = E\left[\begin{array}{cccc} Z_1^{pub\prime}X^{pub} & Z_1^{pub\prime}\lambda_c(0) & Z_1^{pub\prime}\lambda_n(0) & \mathbf{0} \\ -Z_2'X & Z_2'(X'\beta_c) & Z_2'(X'\beta_n) & Z_2'\mathbf{1} \end{array}\right]\left[\begin{array}{c} \delta \\ \alpha_1 \\ \alpha_2 \\ \alpha_0^* \end{array}\right].$$

The parameters can be estimated by the sample analog.

$$\left[\begin{array}{c} \hat{\delta} \\ \hat{\alpha_1} \\ \hat{\alpha_2} \\ \hat{\alpha_0}^* \end{array}\right] = \left[\begin{array}{cccc} Z_1^{pub\prime}X^{pub} & Z_1^{pub\prime}\lambda_c(0) & Z_1^{pub\prime}\lambda_n(0) & \mathbf{0} \\ -Z_2'X & Z_2'(X'\beta_c) & Z_2'(X'\beta_n) & Z_2'\mathbf{1} \end{array}\right]^{-1}\left[\begin{array}{c} Z_1^{pub\prime}\hat{\theta} \\ \mathbf{0} \end{array}\right],$$

where X^{pub} is the submatrix of X for those going to public schools. The instrument Z_1^{pub} consists of $\overline{X}_{S_{-i}}$ and a constant term. Z_2 consists of $\overline{X}_{S_{-i}}\hat{\beta}_c$ and $\overline{X}_{S_{-i}}\hat{\beta}_n$.

Note that the condition (25) can by estimated only from the sample moments of the public school subsample while the condition (26) can be estimated by the entire sample.

8.5 Model 2-β

This model restricts $2-\delta$ by imposing that δ is a linear combination span of β_c and β_n, which leads to

$$\theta(s,\tau) = \alpha_0 + \alpha_1[\overline{X}(s,\tau)'\beta_c + \bar{u}_c(s,\tau)] + \alpha_2[\overline{X}(s,\tau)'\beta_n + \bar{u}_n(s,\tau)] + \zeta_s.$$

Let $\overline{X_{0c}}(s,\tau) \equiv \overline{X}(s,\tau)'\beta_c + \bar{u}_c(s,\tau)$ and $X_{0ci}(\tau) \equiv X_i\beta_c + \lambda_{ci}(\tau)$. Define $\overline{X_{0n}}(s,\tau)$ and $X_{0ni}(\tau)$ similarly. Hence, $\theta(s,\tau) = \alpha_0 + \alpha_1\overline{X_{0c}}(s,\tau) + \alpha_2\overline{X_{0n}}(s,\tau) + \zeta_s$. We have $\bar{u}_c(s,\tau) = E[\lambda_{ci}(\tau)|S_i(\tau) = s]$ and $\bar{u}_n(s,\tau) = E[\lambda_{ni}(\tau)|S_i(\tau) = s]$. Hence, $\theta(s,0) = \alpha_0 + \alpha_1\overline{X}(s,0)'\beta_c + \alpha_1 E[\lambda_{ci}(0)|S_i(0) = s] + \alpha_2\overline{X}(s,0)'\beta_n + \alpha_2 E[\lambda_{ni}(0)|S_i(0) = s] + \zeta_s$.

We estimate α_1 and α_2 by IV regression of $\hat{\theta}(P_i,0)$ on $X_{0ci}(0)$, $X_{0ni}(0)$ and a constant using the public school subsample with instruments $\overline{X}_{S_{-i}}$, $\overline{\lambda}_{c,S_{-i}}(0)$ and $\overline{\lambda}_{n,S_{-i}}(0)$. The term $\alpha_1[(X_{0ci}(\tau) - \overline{X}_{c0}(P_i,0)] + \alpha_2[X_{0ni}(\tau) - \overline{X}_{n0}(P_i,0)]$ can be estimated consistently by

$$D_i \equiv \hat{\alpha}_1[X_i'\hat{\beta}_c + \lambda_{ci}(\tau) - \overline{X}_{S_{-i}}'\hat{\beta}_c - \overline{\lambda}_{c,S_{-i}}(0)] + \hat{\alpha}_2[X_i'\hat{\beta}_n + \lambda_{ni}(\tau) - \overline{X}_{S_{-i}}'\hat{\beta}_n - \overline{\lambda}_{n,S_{-i}}(0)].$$

The estimate $\hat{\pi}(\tau)$ is the weighted average of D_i with weights ψ_i.

8.6 Model 2-γ

We assume δ is proportional to γ. The specification in Model 2-δ can be modified as

$$\text{(27)} \qquad \text{Proj}\left[\theta(s,\tau)|\left(\overline{X}(s,\tau)\gamma\right),\overline{u}(s,\tau)\right] = \alpha_0 + a\left(\overline{X}(s,\tau)'\gamma\right) + \alpha_1\overline{u}_c(s,\tau) + \alpha_2\overline{u}_n(s,\tau),$$

$$\text{(28)} \qquad \text{Proj}\left[a\left(\overline{X}(s,\tau)'\gamma\right)|\overline{X}(s,\tau)'\beta_c, \overline{X}(s,\tau)'\beta_n\right] = \alpha_0^* + \alpha_1\left[\overline{X}(s,\tau)'\beta_c\right] + \alpha_2\left[\overline{X}(s,\tau)'\beta_n\right].$$

Similar to Model $2-\delta$, we have

$$E\begin{bmatrix} Z_1^{pub\prime}\left[\theta - \alpha_0\mathbf{1} - a\left(\overline{X}(s,\tau)^{pub}\gamma\right) - \alpha_1\lambda_{ci}(0) - \alpha_2\lambda_{ni}\right] \\ Z_2'\left[a\left(\overline{X}(s,\tau)\gamma\right) - \alpha_1 X'\beta_c - \alpha_2 X'\beta_n - \alpha_0^*\mathbf{1}\right] \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix},$$

Therefore, the parameters can be estimated by the sample moments.

$$\begin{bmatrix} \hat{\alpha_0} \\ \hat{a} \\ \hat{\alpha_1} \\ \hat{\alpha_2} \\ \hat{\alpha_0}^* \end{bmatrix} = \begin{bmatrix} Z_1^{pub\prime}\mathbf{1} & Z_1^{pub\prime}X^{pub}\hat{\gamma} & Z_1^{pub\prime}\lambda_c(0)^{pub} & Z_1^{pub\prime}\lambda_n(0)^{pub} & \mathbf{0} \\ \mathbf{0} & Z_2'X\hat{\gamma} & -Z_2'X'\beta_c & -Z_2'X'\beta_n & -Z_2'\mathbf{1} \end{bmatrix}^{-1} \begin{bmatrix} Z_1^{pub\prime}\hat{\theta} \\ \mathbf{0} \end{bmatrix}.$$

The instrument Z_1^{pub} is $\overline{X}_{S_{-i}}^{pub}\hat{\gamma}$ and a constant term. The instrument Z_2 is $\overline{X}_{S_{-i}}\hat{\beta}_c$, $\overline{X}_{S_{-i}}\hat{\beta}_n$, and a constant term. Similar to Model $2-\delta$, the condition (27) is estimated using public school subsample while condition (28) is estimated using the full sample.

Let $D_i = \hat{\alpha_1}(\lambda_i(\tau) - \overline{\lambda}_{S_{-i}}(0)) + \hat{a}[(X_i - \overline{X}_{S_{-i}})'\hat{\gamma}]$. $\hat{\pi}(\tau)$ is the weighted average of D_i with weights ψ_i.

8.7 Results

We have estimated versions of models $1-\delta$, $1-\gamma$, $1-\beta$, $2-\delta$, $2-\gamma$, and $2-\beta$ generalized to the trinomial case. Estimates of the cream skimming effect based on model $1-\delta$ and $2-\delta$ are too noisy to be informative. However, but we continue to find a relatively small cream skimming effect on high school graduation for the models with index restrictions on how student body characteristics influence outcomes. We omit the results to save space.

9 Allowing for Unobserved School Effects in the School Choice Model

In this section, we generalize the model to allow for the possibility that the attractiveness of the public school relative to the available private school options depends on unobserved characteristics of the school and community. We assume that unconditionally (as opposed to conditional on school choice),

$$u_i = \nu_d + \omega_i,$$

and

$$X_i'\beta = \mu_d + \eta_i.$$

where μ_d and ν_d are the components of the observed and unobserved indices of school choice determinance $X_i'\beta$ and u_i that are common to students assigned to school district d. We assume ω_i is orthogonal to ν_d, and η_i is orthogonal to μ_d. One's first thought on how to approach this problem might be to simply specify that ν_d and ω_i are jointly normal and then use of a random effects probit estimator (or perhaps to specify ν_d as a discrete random variable). However, this approach will not work because our data set is clustered at the eighth grade level, and the choice of whether to attend a private eighth grade is in part influenced by high school plans. The use of random effects probit would tend to overstate the relative importance of ν_d

We take an alternative approach that permits us to deal with selection. We make the key assumption that the ratio of the common component.

$$(29) \qquad r \equiv \frac{Var(\omega_i)}{Var(u_i)} = Var(\omega_i) = q \cdot \frac{Var(\eta_i)}{Var[X_i'\beta]};$$

$$(30) \qquad q = 1$$

(Recall that $Var(u_i) = 1$.) The restriction $q = 1$ says that the fraction of the total variance in the unobserved school choice determinants that is between students assigned to the same public school optoin is the same as the fraction of the variance in $X_i'\beta$ that is between students assigned to the same option. To the extent that the observables are representative of the factors that influence school choice, this is a reasonable assumption. However, in a future draft we will examine the sensitivity of our results to varying q in a range around 1.

We estimate $E(X_i'\beta)$ and $Var(X_i'\beta)$ from the entire sample given $\hat{\beta}$. Denote them by $\hat{\mu}_{X'\beta}$ and $\hat{\sigma}^2_{X'\beta}$, respectively. Conditional on $q = 1$, the ratio r is estimated by Monte Carlo method. It is identified from the ratio of within school variation in $X_i'\beta$ to the total variation:

$$\frac{E\left[Var\left[X_i'\beta|S_i(0) = s\right]|s \in \mathcal{S}_p\right]}{Var\left[X_i'\beta|S_i(0) \in \mathcal{S}_p\right]}. \tag{31}$$

It is obvious that the ratio in (31) lies in the interval $[0, 1]$ and it is increasing in r. The denominator is estimated by the sample variance for public school students.[16]

$$\frac{1}{\#(S_i(0) \in \mathcal{S}_p) - 1} \sum_{S_i(0) \in \mathcal{S}_p} [X_i\hat{\beta} - \overline{X'\beta}_p]^2,$$

where $\overline{X'\beta}_p$ is the sample mean of $X_i\hat{\beta}$ among public school students. A consistent estimator of the numerator in (31) is to take the weighted average[17] over all public schools $s \in \mathcal{S}_p$ of the conditional sample variances,

$$\frac{1}{\#(S_i(0) = s) - 1} \sum_{S_i(0) = s} [X_i\hat{\beta} - \hat{\mu}_s]^2,$$

where $\hat{\mu}_s$ is the sample mean of $X_i\hat{\beta}$ among students attending school s.

[16] In our NELS data, there are weights for the observations. We need to modify the sample variance formula to account for the weights. Suppose w_i is the weight for X_i with $\sum_i w_i = 1$,

$$S_i \sim N\left(0, \frac{\sigma^2}{N^2 w_i^2}\right).$$

An unbiased estimator of σ is

$$\hat{\sigma}^2 \equiv \frac{\sum_i w_i (X_i - \hat{X})^2}{\frac{1}{N^2}\sum_i \frac{1}{w_i} - \frac{1}{N}},$$

where $\bar{X} = \sum_i w_i X_i$.

[17] The weight for school s is the sum of individual weights w_i with $S_i(0) = s$.

For a given value of r, we generate

$$\begin{aligned}
\mu_d &\sim N(\hat{\mu}_{X'\beta}, (1-r)\hat{\sigma}^2_{X'\beta}) \\
\eta_i &\sim N(0, r\,\hat{\sigma}^2_{X'\beta}) \\
\nu_d &\sim N(0, (1-r)) \\
\omega_i &\sim N(0, r)
\end{aligned}$$

and construct draws of $X_i'\beta = \mu_d + \eta_i$ and $u_i = \nu_d + \omega_i$. We then simulate the school choice decision using $S_i(0) = P_d$ if and only if $X_i'\beta + u_i > 0$. (We now use P_d rather than P_i to denote the public school option available to i to make explicit that students assigned to d face the same choice.) For the students who are predicted to choose public school we compute the ratio of within-school variation (31). We then search for an $\hat{r}$ that equates the simulated ratio to the sample ratio.

It is then straightforward to obtain estimates of the variances using the equations $\hat{\sigma}^2_\mu = (1-\hat{r})\hat{\sigma}^2_{X'\beta}$, $\hat{\sigma}^2_\eta = (\hat{r})\hat{\sigma}^2_{X'\beta}$, $\hat{\sigma}^2_\nu = 1-\hat{r}$, and $\hat{\sigma}^2_\omega = \hat{r}$.

We have

$$\begin{aligned}
E[u_i|S_i(\tau) = P_d] &= \nu_d + E[\omega_i|S_i(\tau) = P_d] \\
&= \nu_d + E[\omega_i|\omega_i + \eta_i > -\mu_d - \nu_d + \tau_i(\tau)] \\
&= \nu_d + \frac{\sigma^2_\omega}{\sqrt{\sigma^2_\omega + \sigma^2_\eta}}\lambda\left(\frac{\mu_d + \nu_d - \tau_i(\tau)}{\sqrt{\sigma^2_\omega + \sigma^2_\eta}}\right)
\end{aligned}$$

For each public school P_d, the mean of the unobservable characteristics $E[u_i|S_i(0) = P_d]$ can be estimated by the sample average of the inverse Mills ratio $\lambda(X_i'\beta)$ over all individuals i with $S_i(0) = P_d$. Denote it by $\hat{E}[u_i|S_i(0) = P_d]$. (Although u_i are correlated within a school due to the common component ν_d, the sample mean still converges to the population mean by the Law of Large Numbers.) An estimate of the common error term ν_d is obtained from the equation.

$$\hat{E}[u_i|S_i(0) = P_d] = \hat{\nu}_d + \frac{\hat{\sigma}^2_\omega}{\sqrt{\hat{\sigma}^2_\omega + \hat{\sigma}^2_\eta}}\lambda\left(\frac{\hat{\mu}_d + \hat{\nu}_d}{\sqrt{\hat{\sigma}^2_\omega + \hat{\sigma}^2_\eta}}\right)$$

In model 2, $\bar{u}(s,\tau) = E[u_i|S_i(\tau) = P_d]$. Therefore, a consistent estimator of $\bar{u}(s,\tau)$ is

$$\hat{E}[u_i|S_i(\tau) = P_d] = \hat{\nu}_d + \frac{\hat{\sigma}^2_\omega}{\sqrt{\hat{\sigma}^2_\omega + \hat{\sigma}^2_\eta}}\lambda\left(\frac{\hat{\mu}_d + \hat{\nu}_d - \tau_i(\tau)}{\sqrt{\hat{\sigma}^2_\omega + \hat{\sigma}^2_\eta}}\right).$$

Our approach to allowing for correlation in school choice determinants at the public school district level generalizes to the case when Catholic and non-Catholic private schools are treated as distinct options similar to the binomial choice case, but is considerably more complicated. We leave the details to a future draft.

9.1 Results

We have estimated versions of ours models that allow for correlation in the unobserved derminants of school choice using the procedure presented above. The estimates of the cream skimming effect for models $1-\delta$ and $2-\delta$ are quite noisy. In the case of model $1-\beta$, $2-\beta$, $1-\gamma$ and $2-\gamma$, the point estimates and .025 lower bound to the confidence interval estimate are quite close to those in Table 6a. Consequently, we conclude that accounting for correlation in the unobserved factors that influence school choice seems to make very difference in the context of our basic model.

10 Conclusions

Under the assumption that a voucher program influences school choices by shifting the intercept in the school choice equation, we estimate the relative odds that students in public school would shift to private school. Essentially, we estimate the change in the peers of the students who will remain in public school by reweighting the distribution of the characteristics of students currently in public school by the relative odds that they will stay after of voucher is put in place. We estimate the relationship between outcomes and peer characteristics using an instrumental variables scheme that addresses the fact that we only have estimates of peers. We use the coefficient estimates and our estimates of changes in peer characteristics to arrive at estimates of the cream skimming effect. With some additional admittedly strong assumptions, we are able to deal with unobserved fixed characteristics of schools that influence school choice. In our base model, we only consider Catholic schools, but our findings are robust to treating Catholic schools and other private schools as distinct choices.

The specific parameter estimates vary with the details of the econometric specification and the voucher program specified. However, the point estimates and the .025 lower bound to the confidence interval estimate of the cream skimming effect of a voucher program on high school graduation rates are typically small in absolute value. The same is true for college attendance, although the lower bound estimates are a bit more negative. The exception to this is that our estimates for the urban sample are very noisy when we allow unobserved heterogeneity.

Taken together, they suggest that the effects of vouchers on the productivity of public schools, either through perform in response to competitive pressure or through the financial resources available in public schools, may be more important than cream skimming. However, we wish to stress our results are still preliminary. In future drafts, we will make use a much richer set of observed school characteristics in our school choice and outcome equations, and will extend our methodology to allow peer effects to influence school choice as well as outcomes.

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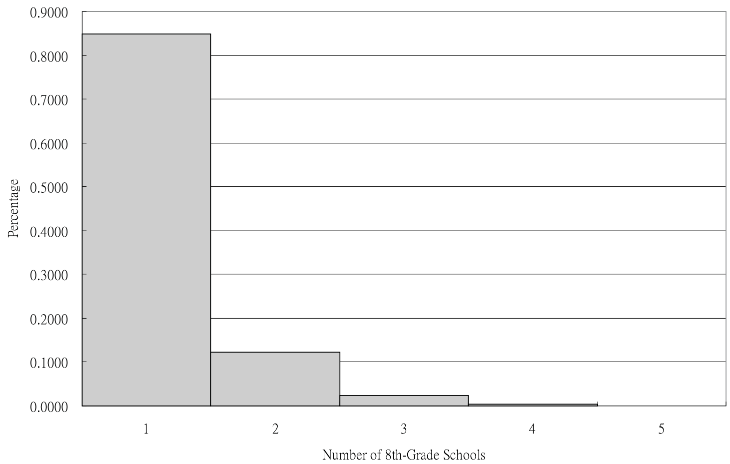

Figure 1a: The histogram of the number of 8th-grade schools attended for each high school

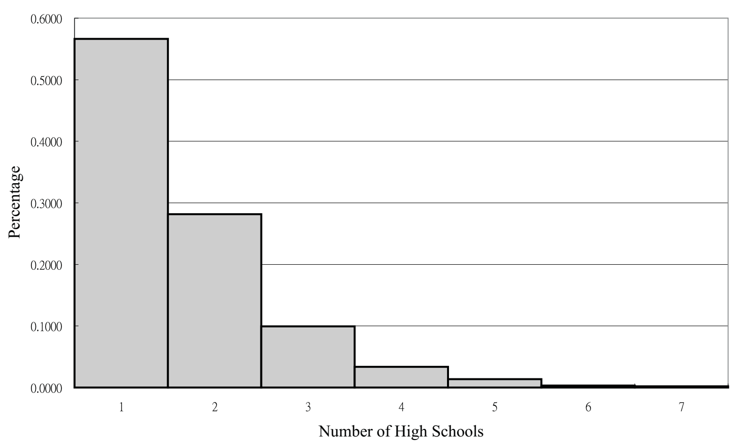

Figure 1b: The histogram of the number of high schools attended for each 8th-grade school

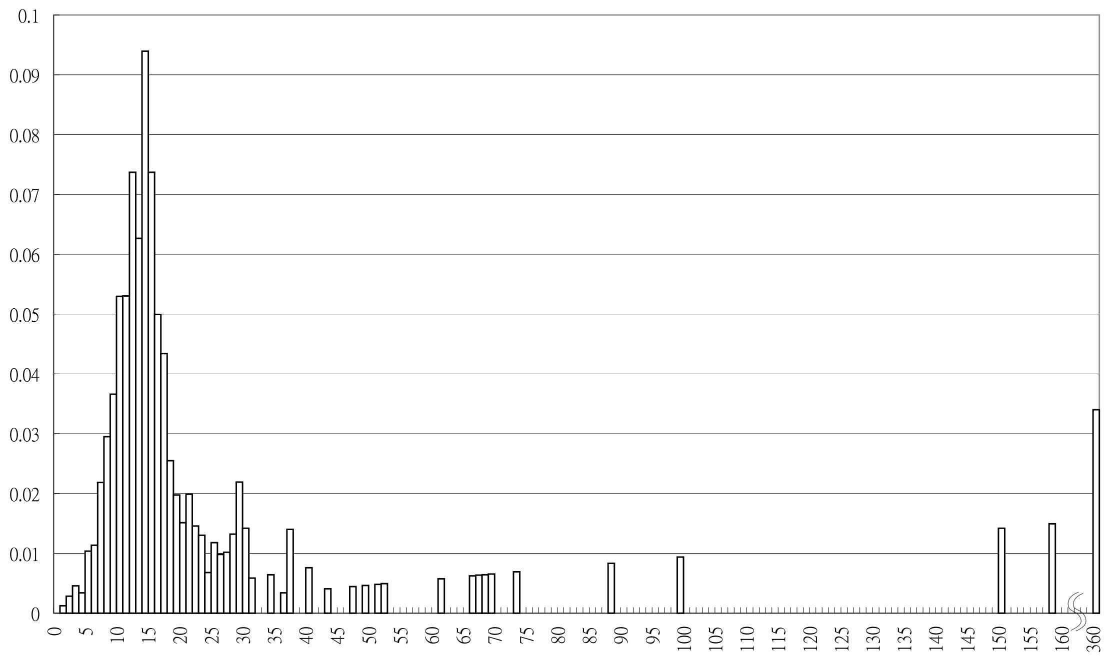

Figure 2: The histogram of the size of a re-sampling block.

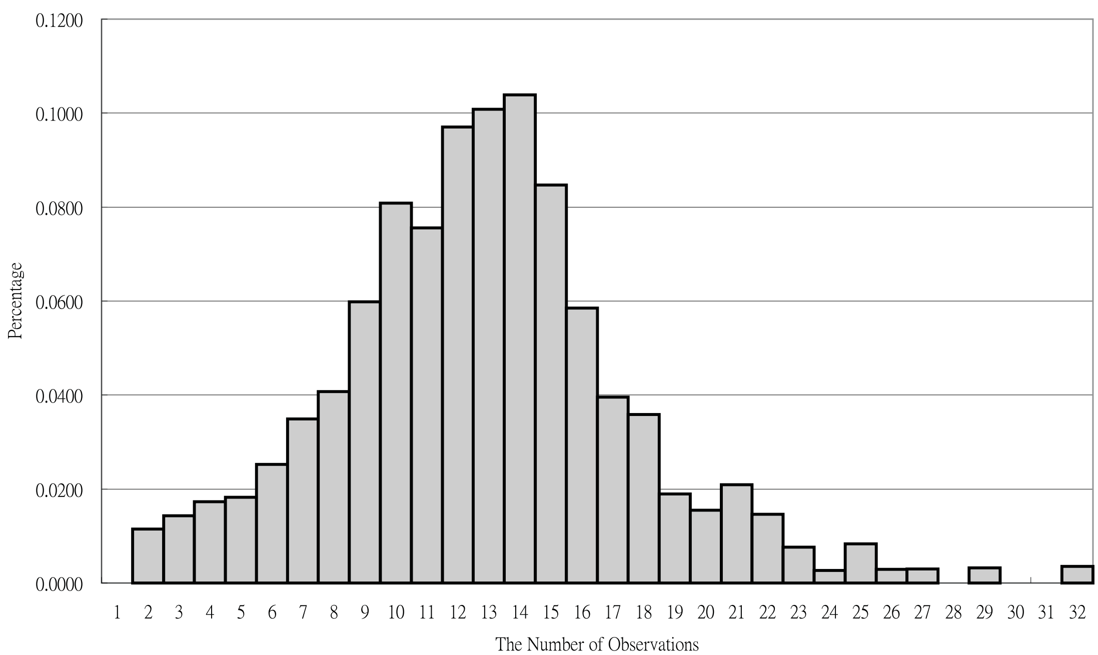

Figure 3: The histogram of the sample size used in the fixed-effect estimation for each public school

Table 1A

Descriptive Statistics: Full Sample by School Type

Variable	Full Sample (N=10579)	Public School (N=9265)	Catholic School (N=697)	Non-Catholic private (N=617)
HS	0.8811	0.8732	0.9768	0.9145
	(0.3237)	(0.3328)	(0.1505)	(0.2799)
COLL	0.3298	0.3011	0.5870	0.5926
	(0.4702)	(0.4588)	(0.4927)	(0.4917)
MATH	51.4066	50.9309	55.4217	55.9642
	(9.7405)	(9.7178)	(8.4551)	(9.5425)
INCOME	10.0332	10.0179	10.2920	9.9866
	(0.7673)	(0.7728)	(0.5745)	(0.8302)
Catholic	0.3122	0.2867	0.7982	0.1284
	(0.4634)	(0.4522)	(0.4016)	(0.3348)
female	0.5002	0.5050	0.4487	0.4701
	(0.5000)	(0.5000)	(0.4977)	(0.4995)
Asian	0.0343	0.0341	0.0442	0.0866
	(0.1819)	(0.1744)	(0.2056)	(0.2815)
Hispanic	0.0942	0.0962	0.0946	0.0452
	(0.2921)	(0.2949)	(0.2928)	(0.2079)
Black	0.1187	0.1229	0.1116	0.0301
	(0.3235)	(0.3284)	(0.3151)	(0.1709)
White	0.7528	0.7495	0.7496	0.8381
	(0.4314)	(0.4333)	(0.4335)	(0.3686)
both parents present	0.6637	0.6797	0.7970	0.8239
	(0.4673)	(0.4725)	(0.4025)	(0.3812)
parents married	0.7973	0.7866	0.8807	0.9185
	(0.4020)	(0.4097)	(0.3244)	(0.2738)
father's education	13.5095	13.3216	14.5889	16.2397
	(2.7923)	(2.7234)	(2.6881)	(2.7643)
mother's education	13.0224	12.9013	13.8179	14.6189
	(2.2262)	(2.2038)	(2.1008)	(2.0748)
log income87	10.2042	10.1753	10.4878	10.4296
	(0.7784)	(0.7914)	(0.5950)	(0.5740)
reading score	51.3227	50.8700	54.5650	56.8465
	(9.9983)	(9.9357)	(9.5912)	(9.5206)
math score	51.4086	51.0141	54.2474	56.1996
	(10.0376)	(10.0244)	(9.0381)	(9.9395)
science score	51.3149	51.0187	53.2319	55.2631
	(9.9763)	(9.9973)	(9.0794)	(9.7004)
history score	51.2271	50.7381	54.9476	56.8360
	(9.9723)	(9.8480)	(9.4259)	(10.7833)
urban	0.2689	0.2194	0.8588	0.4871
	(0.4434)	(0.4139)	(0.3485)	(0.5002)
suburban	0.4210	0.4433	0.1412	0.3453
	(0.4937)	(0.4968)	(0.3485)	(0.4758)
rural	0.3101	0.3373	0.0000	0.1676
	(0.4626)	(0.4728)	(0.0000)	(0.3739)
northeast	0.1907	0.1816	0.2864	0.2521
	(0.3929)	(0.3855)	(0.4524)	(0.4346)
north central	0.2723	0.2769	0.2953	0.1262
	(0.4452)	(0.4475)	(0.4565)	(0.3323)
south	0.3516	0.3542	0.2794	0.4072
	(0.4775)	(0.4783)	(0.4485)	(0.4917)
west	0.1854	0.1873	0.1400	0.2145
	(0.3886)	(0.3902)	(0.3472)	(0.4108)

Note: (1) The standard deviations are in the parentheses. (2) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (3) *INCOME* is the log wage income in 1999 based on the 4th follow-up. NELS:88 base-year to 4th follow-up panel weights are used for this row. The sample sizes are 8887, 7738, 599, and 550, respectively.

Table 1B
Descriptive Statistics: Urban Subsample by School Type

Variable	Full Sample (N=2870)	Public School (N=1991)	Catholic School (N=568)	Non-Catholic private (N=311)
HS	0.8814	0.8472	0.9819	0.9599
	(0.3234)	(0.3599)	(0.1333)	(0.1965)
$COLL$	0.3608	0.2808	0.5799	0.5790
	(0.4803)	(0.4495)	(0.4940)	(0.4945)
$MATH$	51.5062	50.0575	55.3788	55.0073
	(9.9790)	(10.0311)	(8.3809)	(9.8801)
$INCOME$	9.9720	9.9193	10.2745	10.0476
	(0.7414)	(0.7878)	(0.3801)	(0.5412)
Catholic	0.4123	0.3418	0.7868	0.0911
	(0.4923)	(0.4744)	(0.4100)	(0.2882)
female	0.5085	0.5238	0.4356	0.5535
	(0.5000)	(0.4996)	(0.4963)	(0.4979)
Asian	0.0570	0.0529	0.0443	0.1379
	(0.2319)	(0.2239)	(0.2060)	(0.3453)
Hispanic	0.1653	0.1937	0.1000	0.0477
	(0.3715)	(0.3953)	(0.3003)	(0.2135)
Black	0.2026	0.2415	0.1249	0.0065
	(0.4020)	(0.4281)	(0.3309)	(0.0803)
White	0.5751	0.5119	0.7307	0.8079
	(0.4944)	(0.5000)	(0.4440)	(0.3946)
both parents present	0.6652	0.6172	0.7853	0.8354
	(0.4720)	(0.4862)	(0.4110)	(0.3714)
parents married	0.7711	0.7304	0.8745	0.9117
	(0.4202)	(0.4439)	(0.3315)	(0.2842)
father's education	13.6410	13.1338	14.5979	16.3461
	(2.9650)	(2.8687)	(2.6439)	(2.7146)
mother's education	13.1260	12.7582	13.8546	14.9880
	(2.3675)	(2.3416)	(2.0678)	(2.0828)
log income87	10.1638	10.0456	10.4799	10.5270
	(0.8139)	(0.8451)	(0.6116)	(0.6086)
reading score	51.1297	49.7178	54.6783	56.1092
	(10.2703)	(10.0976)	(9.5881)	(10.0341)
math score	51.0296	49.8270	53.9188	55.6547
	(10.2395)	(10.3643)	(8.7786)	(9.8475)
science score	50.0476	49.8965	53.1715	53.4422
	(10.0457)	(10.0822)	(9.1012)	(9.5907)
history score	50.7121	49.1908	54.8648	55.1272
	(10.2242)	(10.0118)	(9.3275)	(10.3947)
northeast	0.1938	0.1650	0.2915	0.2224
	(0.3954)	(0.3713)	(0.4548)	(0.4165)
north central	0.2138	0.1997	0.3076	0.0958
	(0.4101)	(0.3998)	(0.4619)	(0.2948)
south	0.3711	0.3894	0.2532	0.5146
	(0.4832)	(0.4877)	(0.4353)	(0.5006)
west	0.2212	0.2459	0.1477	0.1672
	(0.4151)	(0.4307)	(0.3551)	(0.3737)

Note: (1) The standard deviations are in the parentheses. (2) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (3) $INCOME$ is the log wage income in 1999 based on the 4th follow-up. NELS:88 base-year to 4th follow-up panel weights are used for this row. The sample sizes are 2119, 1517, 329, and 273, respectively.

Table 1C

Descriptive Statistics: Urban Minority Subsample by School Type

Variable	Full Sample (N=986)	Public School (N=862)	Catholic School (N=109)	Non-Catholic private (N=15)
HS	0.8297	0.8084	0.9693	1.0000
	(0.3761)	(0.3938)	(0.1733)	(0.0000)
COLL	0.2772	0.2309	0.6102	0.2460
	(0.4478)	(0.4217)	(0.4900)	(0.4458)
MATH	46.5972	45.8746	51.0542	58.0506
	(8.8838)	(8.6661)	(8.9044)	(6.1540)
INCOME	9.7923	9.7684	10.1036	9.9991
	(0.8459)	(0.8735)	(0.3446)	(0.3120)
Catholic	0.4063	0.3808	0.5543	0.8439
	(0.4914)	(0.4859)	(0.4993)	(0.3757)
female	0.5392	0.5494	0.4441	0.7956
	(0.4987)	(0.4978)	(0.4992)	(0.4174)
Asian	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Hispanic	0.4493	0.4450	0.4447	0.8804
	(0.4977)	(0.4973)	(0.4992)	(0.3358)
Black	0.5507	0.5550	0.5553	0.1196
	(0.4977)	(0.4973)	(0.4992)	(0.3358)
White	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
both parents present	0.5326	0.5266	0.6005	0.2385
	(0.4992)	(0.4996)	(0.4921)	(0.4411)
parents married	0.6355	0.6164	0.7490	0.9369
	(0.4815)	(0.4866)	(0.4356)	(0.2517)
father's education	12.2929	12.1243	13.4250	13.3354
	(2.6768)	(2.6580)	(2.5320)	(2.6800)
mother's education	12.2610	12.0877	13.4536	12.9839
	(2.3404)	(2.3213)	(2.1086)	(2.5096)
log income87	9.8134	9.7232	10.4230	10.3267
	(0.9304)	(0.9280)	(0.7137)	(0.4037)
reading score	46.9370	46.0602	53.2547	47.1753
	(9.0888)	(8.6435)	(9.7501)	(9.3730)
math score	46.1659	45.5203	50.2899	52.6651
	(8.2909)	(8.1753)	(7.8884)	(6.2128)
science score	45.3397	44.5656	50.6343	48.9408
	(8.2010)	(7.9450)	(8.1330)	(6.9251)
history score	46.6748	45.6495	53.8790	49.1462
	(9.6035)	(9.1383)	(9.8671)	(9.0584)
northeast	0.2046	0.2100	0.1751	0.0896
	(0.4036)	(0.4075)	(0.3818)	(0.2956)
north central	0.1607	0.1682	0.1158	0.0554
	(0.3675)	(0.3742)	(0.3215)	(0.2368)
south	0.4641	0.4626	0.4443	0.8265
	(0.4990)	(0.4989)	(0.4992)	(0.3920)
west	0.1706	0.1592	0.2648	0.0285
	(0.3675)	(0.3661)	(0.4443)	(0.1724)

Note: (1) The standard deviations are in the parentheses. (2) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (3) *INCOME* is the log wage income in 1999 based on the 4th follow-up. NELS:88 base-year to 4th follow-up panel weights are used for this row. The sample sizes are 662, 597, 50, and 15, respectively.

Table 2
Probit Model for Public School Attendance

Variable	Full Sample	Urban Subsample	Non-urban Subsample
constant	10.5205	8.1210	5.7669
	(0.9208)	(1.0301)	(1.1950)
Catholic	-1.3148	-1.4245	-1.2387
	(0.1024)	(0.1055)	(0.2153)
	[-0.1083]	[-0.3236]	[-0.0419]
female	0.1158	0.1921	-0.0620
	(0.0798)	(0.1003)	(0.1258)
	[0.0087]	[0.0390]	[-0.0016]
Asian	0.1018	0.1502	-0.1724
	(0.1635)	(0.2008)	(0.2850)
	[0.0073]	[0.0293]	[-0.0052]
Hispanic	0.4691	0.4693	0.2170
	(0.1211)	(0.1277)	(0.2263)
	[0.0306]	[0.0880]	[0.0048]
Black	-0.3001	-0.4324	-0.0927
	(0.1726)	(0.1922)	(0.2047)
	[-0.0244]	[-0.0917]	[-0.0026]
both parents present	-0.2216	-0.1409	-0.3451
	(0.1201)	(0.1628)	(0.1471)
	[-0.0160]	[-0.0283]	[-0.0076]
parents married	-0.0776	-0.1561	-0.0657
	(0.1445)	(0.1907)	(0.1740)
	[-0.0057]	[-0.0310]	[-0.0016]
father's education	-0.0386	-0.0621	-0.0101
	(0.0216)	(0.0278)	(0.0295)
	[-0.0029]	[-0.0126]	[-0.0004]
mother's education	-0.0528	-0.0767	-0.0147
	(0.0255)	(0.0323)	(0.0425)
	[-0.0039]	[-0.0156]	[-0.0003]
log income87	-0.2433	-0.3180	-0.0985
	(0.0785)	(0.0991)	(0.0897)
	[-0.0182]	[-0.0645]	[-0.0026]
reading score	-0.0092	-0.0156	0.0073
	(0.0061)	(0.0082)	(0.0080)
	[-0.0007]	[-0.0032]	[0.0002]
math score	-0.0036	0.0009	-0.0201
	(0.0064)	(0.0078)	(0.0112)
	[-0.0003]	[-0.0002]	[-0.0005]
science score	0.0148	0.0175	0.0146
	(0.0066)	(0.0075)	(0.0126)
	[0.0011]	[0.0036]	[0.0004]
history score	-0.0203	-0.0215	-0.0172
	(0.0065)	(0.0072)	(0.0124)
	[-0.0015]	[-0.0044]	[-0.004]
urban	-3.9192		
	(0.0809)		
	[-0.4468]		
suburban	-2.4064		
	(0.0689)		
	[-0.1802]		
northeast	-0.3193	-0.4430	-0.1445
	(0.1282)	(0.1522)	(0.2587)
	[-0.0256]	[-0.0973]	[-0.0040]
north central	-0.3301	-0.4922	0.0202
	(0.1140)	(0.1371)	(0.1980)
	[-0.0264]	[-0.1077]	[0.0005]
south	-0.2688	-0.1256	-0.6035
	(0.1191)	(0.1352)	(0.2137)
	[-0.0210]	[-0.0256]	[-0.0206]

Note: (1) The sample size is 9962 for the full sample and 2559 for the urban subsample. (2) Standard errors are in the parentheses. The correlation across students from the same eighth grade is taken into account. (3) Marginal effects are in brackets. These effects for dummy variables are calculated as the change from 0 to 1. The effects for other variables are evaluated at the mean value. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 3A
Effects of Students' Own Characteristics
on Public High School Graduation (γ)
Linear Probability Model with HS Fixed Effects

Variable	Coefficient
Catholic	0.0303
	(0.0089)
female	0.0260
	(0.0088)
Asian	0.0111
	(0.0245)
Hispanic	0.0194
	(0.0219)
Black	0.0803
	(0.0174)
both parents present	0.0391
	(0.0120)
parents married	0.0201
	(0.0162)
father's education	0.0075
	(0.0019)
mother's education	0.0060
	(0.0022)
log income87	0.0285
	(0.0076)
reading score	0.0006
	(0.0006)
math score	0.0040
	(0.0006)
science score	0.0008
	(0.0006)
history score	0.0013
	(0.0007)

Note: (1) Standard errors are in the parentheses. They are calculated from 500 bootstrap replications. (2) The sample size used in the calculation is 9260. Schools with only one sampled student are dropped. (3) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 3B
Effects of Students' Own Characteristics
on College Attendance (γ)
Linear Probability Model with HS Fixed Effects

Variable	Coefficient
Catholic	0.0433
	(0.0126)
female	0.0583
	(0.0101)
Asian	0.0622
	(0.0264)
Hispanic	0.0470
	(0.0204)
Black	0.1341
	(0.0208)
parents	0.0627
	(0.0136)
parents married	-0.0232
	(0.0188)
father's education	0.0231
	(0.0028)
mother's education	0.0239
	(0.0030)
log income87	0.0165
	(0.0072)
reading score	0.0030
	(0.0009)
math score	0.0110
	(0.0009)
science score	0.0016
	(0.0009)
history score	0.0032
	(0.0008)

Note: (1) Standard errors are in the parentheses. They are calculated from 500 bootstrap replications. (2) The sample size used in the calculation is 9185. Schools with only one sampled student are dropped. (3) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 3C
Effects of Students' Own Characteristics
on 12th-Grade Math Score (γ)
Linear Model with HS Fixed Effects

Variable	Coefficient
Catholic	0.2091
	(0.1791)
female	-0.6782
	(0.1703)
Asian	1.3138
	(0.3126)
Hispanic	-0.1445
	(0.3417)
Black	-0.5523
	(0.3653)
both parents present	0.6472
	(0.1952)
parent's married	-0.5536
	(0.2280)
father's education	0.1324
	(0.0335)
mother's education	0.0780
	(0.0356)
log income87	0.3931
	(0.1078)
reading score	0.0907
	(0.0113)
math score	0.6231
	(0.0121)
science score	0.0617
	(0.0140)
history score	0.0604
	(0.0133)

Note: (1) Standard errors are in the parentheses. They are calculated from 500 bootstrap replications. (2) The sample size used in the calculation is 7320. Schools with only one sampled student are dropped. (3) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 4A

Estimation of Peer Effects Model for Public High School Graduation

	model 1-δ	model 1-β	model 1-γ	model 2-δ	model 2-β	model 2-γ
Estimation of δ						
constant	-16.2605 (-26.8818, 37.3829)	-0.0318 (-0.1703, 0.1266)	-0.2693 (-0.5900, 0.0845)	-16.2621 (-26.1081, 36.2975)	-0.0348 (-0.1719, 0.1258)	-0.2703 (-0.5906, 0.0846)
female	1.4415 (-9.7754, 8.2353)			1.4416 (-9.8019, 8.6933)		
Asian	0.3349 (-5.4291, 5.9661)			0.3350 (-5.4248, 5.8791)		
Hispanic	-0.0155 (-2.0283, 1.8012)			-0.0156 (-2.0322, 1.7962)		
Black	-1.3959 (-3.1548, 6.4767)			-1.3961 (-3.1854, 5.8205)		
both parents present	5.6605 (-10.7342, 11.2792)			5.6611 (-10.3547, 11.3832)		
parents married	-2.0103 (-7.5408, 19.6625)			-2.0107 (-7.4656, 19.6178)		
father's education	-0.4543 (-1.4332, 1.1759)			-0.4543 (-1.3417, 1.1915)		
mother's educaiton	0.7287 (-2.2156, 1.7957)			0.7288 (-2.2153, 1.7914)		
log income87	1.4070 (-4.2582, 3.3267)			1.4072 (-4.2409, 3.3345)		
reading score	-0.0967 (-0.6809, 0.5026)			-0.0967 (-0.6509, 0.5013)		
math score	-0.1189 (-0.2305, 0.2718)			-0.1189 (-0.2312, 0.2734)		
science score	0.1442 (-0.3060, 0.4282)			0.1443 (-0.3050, 0.4320)		
history score	-0.0208 (-0.2268, 0.1161)			-0.0208 (-0.2272, 0.1161)		
urban	-0.0981 (-0.4193, 0.6786)			-0.0982 (-0.4207, 0.6325)		
suburban	-0.1570 (-0.6020, 0.4504)			-0.1570 (-0.5919, 0.4549)		
northeast	-0.5722 (-1.1223, 0.8397)			-0.5722 (-1.1628, 0.8468)		
north central	-0.4383 (-1.0751, 0.8083)			-0.4384 (-1.0741, 0.8133)		
south	0.0834 (-0.8544, 0.7674)			0.0834 (-0.8554, 0.7679)		
$X\beta$		0.0056 (-0.0001, 0.0074)				
$X\beta + \lambda$					0.0063 (0.0001, 0.0080)	
$X\gamma$			0.2924 (-0.0728, 0.6440)			0.2939 (-0.0729, 0.6451)
Estimation of α						
				0.0003 (-0.0184, 0.0365)		-0.0036 (-0.0049, 0.0004)

Note: (1) 95% confidence intervals are in the parentheses. They are calculated from 500 bootstrap replications. (2) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (3) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 4B

Estimation of Peer Effects Model for College Attendance

	model 1-δ	model 1-β	model 1-γ	model 2-δ	model 2-β	model 2-γ
constant	-10.7148 (-25.6527, 13.6161)	-1.5283 (-1.6822, -1.3867)	-1.5344 (-1.7972, -1.2585)	-10.7201 (-26.1227, 13.2711)	-1.5289 (-1.6833, -1.3872)	-1.5345 (-1.7975, -1.2583)
female	-0.1247 (-6.7919, 4.6557)			-0.1250 (-6.7803, 4.6235)		
Asian	0.4765 (-3.7259, 5.6295)			0.4768 (-3.8121, 5.6259)		
Hispanic	0.5380 (-1.5039, 2.2889)			0.5382 (-1.5286, 2.2820)		
Black	-1.4489 (-2.1683, 3.8575)			-1.4501 (-2.1784, 3.8549)		
both parents present	2.6722 (-4.3578, 5.2963)			2.6742 (-4.3467, 5.3460)		
parents married	-3.1361 (-8.0831, 10.6134)			-3.1393 (-8.1767, 10.6700)		
father's education	-0.4798 (-0.8923, 1.0527)			-0.4802 (-0.8911, 1.0407)		
mother's education	0.8948 (-1.4998, 1.7516)			0.8954 (-1.4915, 1.7430)		
log income87	0.8757 (-1.6400, 2.8532)			0.8763 (-1.6508, 2.8461)		
reading score	-0.0512 (-0.4288, 0.4905)			-0.0512 (-0.4379, 0.4945)		
math score	-0.0825 (-0.1885, 0.0981)			-0.0826 (-0.1887, 0.0973)		
science score	0.0609 (-0.2027, 0.2846)			0.0610 (-0.2012, 0.2844)		
history score	-0.0105 (-0.1348, 0.1119)			-0.0105 (-0.1339, 0.1112)		
urban	-0.0767 (-0.5885, 0.4224)			-0.0772 (-0.5999, 0.4242)		
suburban	-0.1137 (-0.6357, 0.3240)			-0.1138 (-0.6353, 0.3227)		
northeast	0.0565 (-0.5887, 0.6456)			0.0563 (-0.5955, 0.6554)		
north central	0.0166 (-0.5332, 0.5320)			0.0165 (-0.5185, 0.5292)		
south	0.3927 (-0.7335, 0.6022)			0.3929 (-0.7323, 0.6059)		
$X\beta$		0.0028 (-0.0026, 0.0074)				
$X\beta + \lambda$					0.0029 (-0.0027, 0.0076)	
$X\gamma$			0.0090 (-0.1617, 0.1677)			0.0091 (-0.1621, 0.1682)
Estimation of α						
				0.0015 (-0.0277, 0.0322)		-0.0003 (-0.0028, 0.0027)

Note: (1) 95% confidence intervals are in the parentheses. They are calculated from 500 bootstrap replications. (2) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (3) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 4C

Estimation of Peer Effects Model for 12th-Grade Math Score

	model 1-δ	model 1-β	model 1-γ	model 2-δ	model 2-β	model 2-γ
Estimation of δ						
constant	-6.2799 (-279.8633,474.9558)	1.4382 (-1.2863, 3.9639)	-1.2376 (-6.3977, 3.1942)	-6.4629 (-283.3887,478.3001)	1.3725 (-1.3193, 3.9685)	-1.2427 (-6.4082, 3.1938)
female	-11.9344 (-79.6656, 58.1799)			-11.9259 (-78.7071, 74.5732)		
Asian	8.7155 (-145.2022,201.5351)			8.6402 (-156.5912,217.8736)		
Hispanic	0.6934 (-48.1099, 57.9742)			0.6962 (-50.8932, 49.0470)		
Black	4.2414 (-72.0321,109.5314)			4.1957 (-77.9486, 96.9558)		
both parents present	10.3332 (-102.1621,157.2636)			10.2970 (-94.4659,183.0087)		
parents married	-8.7759 (-153.7476,185.2711)			-8.7137 (-168.6906,163.2149)		
father's education	-0.6050 (-12.1270, 14.8815)			-0.6094 (-11.8711, 15.9271)		
mother's educaiton	2.0091 (-25.1081, 22.6678)			2.0121 (-21.0474, 25.8513)		
log income87	0.8190 (-48.7541, 31.0816)			0.8317 (-50.9925, 31.2703)		
reading score	1.0160 (-6.8602, 6.0940)			1.0126 (-7.0601, 6.0413)		
math score	-0.4534 (-5.0468, 10.0968)			-0.4507 (-5.5011, 10.3403)		
science score	-0.3839 (-8.1550, 4.3289)			-0.3815 (-7.9738, 5.4550)		
history score	-0.3860 (-9.0854, 5.8691)			-0.3873 (-9.2839, 5.8725)		
urban	-0.8378 (-16.4132, 17.5066)			-0.7907 (-17.8483, 17.0464)		
suburban	-1.5577 (-13.8711, 24.2109)			-1.5465 (-14.5607, 21.2686)		
northeast	-1.9103 (-25.9501, 36.1785)			-1.8857 (-26.3157, 34.2113)		
north central	-0.7497 (-21.6195, 26.8337)			-0.7400 (-24.2477, 23.2194)		
south	-0.7573 (-24.0806, 38.7779)			-0.7445 (-27.4360, 30.5708)		
$X\beta$		-0.0221 (-0.1484, 0.1362)				
$X\beta + \lambda$					-0.0039 (-0.1415, 0.1430)	
$X\gamma$			0.0516 (-0.0344, 0.1588)			0.0517 (-0.0345, 0.1589)
Estimation of α						
				-0.1309 (-2.0958, 1.7533)		-0.0315 (-0.0583, 0.0102)

Note: (1) The 95% confidence intervals are in the parentheses. They are calculated from 500 bootstrap replications. (2) The sample size used in the calculation is 8947. Schools with only one sampled student are dropped. (3) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 5
Peer Effects on Covariates
Eligibility: All Students

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
Catholic	0.2558 (0.2331, 0.2788)	0.6132 (0.5518, 0.6697)	0.2824 (0.2605, 0.3042)	-0.0266 (-0.0318, -0.0215)	-0.0347 (-0.0411, -0.0288)
female	0.5105 (0.4979, 0.5233)	0.4834 (0.4465, 0.5258)	0.5091 (0.4970, 0.5208)	0.0014 (-0.0029, 0.0057)	0.0026 (-0.0017, 0.0067)
Asian	0.0311 (0.0250, 0.0407)	0.0464 (0.0316, 0.0621)	0.0325 (0.0265, 0.0429)	-0.0014 (-0.0036, 0.0006)	-0.0015 (-0.0028, -0.0002)
Hispanic	0.0942 (0.0732, 0.1158)	0.1199 (0.0770, 0.1641)	0.0948 (0.0756, 0.1168)	-0.0006 (-0.0043, 0.0025)	-0.0025 (-0.0068, 0.0018)
Black	0.1109 (0.0925, 0.1309)	0.1256 (0.0778, 0.1763)	0.1104 (0.0919, 0.1294)	0.0006 (-0.0025, 0.0046)	-0.0014 (-0.0066, 0.0037)
both parents present	0.6760 (0.6626, 0.6892)	0.7538 (0.7146, 0.7884)	0.6849 (0.6723, 0.6965)	-0.0089 (-0.0136, -0.0050)	-0.0075 (-0.0113, -0.0036)
parents married	0.7929 (0.7799, 0.8052)	0.8446 (0.8160, 0.8743)	0.7994 (0.7879, 0.8101)	-0.0064 (-0.0103, -0.0034)	-0.0050 (-0.0083, -0.0018)
father's education	13.2370 (13.1108, 13.3604)	14.1398 (13.8350, 14.4347)	13.2736 (13.1503, 13.3984)	-0.0366 (-0.0585, -0.0131)	-0.0876 (-0.1159, -0.0591)
mother's educaiton	12.8386 (12.7367, 12.9385)	13.4789 (13.2806, 13.6831)	12.8630 (12.7665, 12.9576)	-0.0244 (-0.0418, -0.0062)	-0.0621 (-0.0806, -0.0415)
log income87	10.1555 (10.1184, 10.1912)	10.3990 (10.3324, 10.4556)	10.1702 (10.1354, 10.2048)	-0.0147 (-0.0206, -0.0078)	-0.0236 (-0.0296, -0.0163)
reading score	50.7841 (50.4059, 51.1973)	53.2941 (52.3895, 54.1665)	50.9441 (50.5627, 51.3344)	-0.1600 (-0.2512, -0.0726)	-0.2435 (-0.3302, -0.1553)
math score	50.8944 (50.4734, 51.3785)	53.4495 (52.4112, 54.3896)	51.0444 (50.6387, 51.5128)	-0.1500 (-0.2340, -0.0683)	-0.2478 (-0.3380, -0.1417)
science score	51.1154 (50.6929, 51.5918)	52.4164 (51.5639, 53.2758)	51.2325 (50.8280, 51.6787)	-0.1171 (-0.2013, -0.0340)	-0.1262 (-0.2081, -0.0363)
history score	50.6038 (50.2065, 51.0309)	53.4570 (52.4619, 54.4002)	50.7961 (50.4214, 51.1984)	-0.1923 (-0.2833, -0.0832)	-0.2767 (-0.3697, -0.1663)
urban	0.1601 (0.1150, 0.1995)	0.6351 (0.5439, 0.7644)	0.1601 (0.1150, 0.1995)	0.0000 (0.0000, 0.0000)	-0.0461 (-0.0596, -0.0359)
suburban	0.4501 (0.4032, 0.5004)	0.3640 (0.2356, 0.4561)	0.4501 (0.4032, 0.5004)	0.0000 (0.0000, 0.0000)	0.0084 (-0.0024, 0.0218)
northeast	0.1769 (0.1395, 0.2143)	0.2643 (0.1777, 0.3453)	0.1769 (0.1395, 0.2143)	0.0000 (0.0000, 0.0000)	-0.0085 (-0.0154, -0.0012)
north central	0.2775 (0.2370, 0.3205)	0.2601 (0.1827, 0.3512)	0.2775 (0.2370, 0.3205)	0.0000 (0.0000, 0.0000)	0.0017 (-0.0070, 0.0090)
south	0.3557 (0.3050, 0.3997)	0.3007 (0.2231, 0.3925)	0.3557 (0.3050, 0.3997)	0.0000 (0.0000, 0.0000)	0.0053 (-0.0031, 0.0131)

Note: (1) 10% of the public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 500 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 6A
Peer Effects on High School Graduation
Eligibility: All Students

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
$X\beta$	3.8406	1.9581	3.8276	0.0130	0.0000
	(4.2268, 5.5766)	(1.7625, 2.2127)	(4.2078, 5.5565)	(0.0086, 0.0237)	(0.0000, 0.0000)
$X\gamma$	0.8783	0.9182	0.8807	-0.0023	-0.0039
	(0.7305, 1.0162)	(0.7621, 1.0673)	(0.7323, 1.0194)	(-0.0031, -0.0016)	(-0.0048, -0.0028)
$\lambda(X\beta - \tau)$	0.1539	0.7199	0.0606	0.0933	0.0783
	(0.1212, 0.1734)	(0.6471, 0.8809)	(0.0404, 0.0761)	(0.0798, 0.1008)	(0.0595, 0.0882)
model 1-δ					
$X\delta$	-0.0332	0.2035	-0.0107	**-0.0225**	-0.0230
	(-0.1897, 0.1679)	(-0.5365, 0.5547)	(-0.1837, 0.1592)	(-0.0814, 0.0830)	(-0.0564, 0.0559)
model 1-β					
$\delta_1(X\beta)$	0.0215	0.0109	0.0214	**0.0001**	0.0000
	(-0.0003, 0.0340)	(-0.0001, 0.0152)	(-0.0003, 0.0339)	(0.0000, 0.0001)	(0.0000, 0.0000)
model 1-γ					
$\delta_1(X\gamma)$	0.2568	0.2685	0.2575	**-0.0007**	-0.0011
	(-0.0613, 0.5513)	(-0.0641, 0.5773)	(-0.0615, 0.5529)	(-0.0015, 0.0002)	(-0.0023, 0.0003)
model 2-δ					
$X\delta + \alpha\lambda$	-0.0332	0.2036	-0.0107	**-0.0225**	-0.0229
	(-0.1913, 0.1684)	(-0.5356, 0.5763)	(-0.1837, 0.1592)	(-0.0839, 0.0837)	(-0.0561, 0.0591)
model 2-β					
$\delta_1(X\beta + \lambda)$	0.0251	0.0168	0.0244	**0.0007**	0.0005
	(0.0005, 0.0379)	(0.0003, 0.0220)	(0.0005, 0.0370)	(0.0000, 0.0008)	(0.0000, 0.0006)
model 2-γ					
$\delta_1(X\gamma) + \alpha\lambda$	0.2575	0.2672	0.2586	**-0.0010**	-0.0014
	(-0.0614, 0.5521)	(-0.0639, 0.5753)	(-0.0616, 0.5541)	(-0.0019, 0.0002)	(-0.0027, 0.0003)

Note: (1) 10% of the public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 500 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 6B
Peer Effects on College Attendance
Eligibility: All Students

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
$X\beta$	3.8406	1.9581	3.8276	0.0130	0.0000
	(4.3399, 5.6257)	(1.7603, 2.2107)	(4.3240, 5.6059)	(0.0081, 0.0257)	(0.0000, 0.0000)
$X\gamma$	1.8067	1.9009	1.8118	-0.0051	-0.0091
	(1.6656, 1.9480)	(1.7479, 2.0463)	(1.6713, 1.9534)	(-0.0069, -0.0033)	(-0.0114, -0.0069)
$\lambda(X\beta - \tau)$	0.1539	0.7199	0.0606	0.0933	0.0783
	(0.1245, 0.1718)	(0.6536, 0.8730)	(0.0392, 0.0769)	(0.0803, 0.1013)	(0.0610, 0.0895)
model 1-δ					
$X\delta$	-1.5238	-1.4364	-1.5221	**-0.0017**	-0.0085
	(-1.6700, -1.3716)	(-1.9116, -0.8986)	(-1.6664, -1.3753)	(-0.0671, 0.0518)	(-0.0577, 0.0428)
model 1-β					
$\delta_1(X\beta)$	0.0109	0.0055	0.0108	**0.0000**	0.0000
	(-0.0129, 0.0356)	(-0.0051, 0.0155)	(-0.0129, 0.0356)	(0.0000, 0.0001)	(0.0000, 0.0000)
model 1-γ					
$\delta_1(X\gamma)$	0.0163	0.0172	0.0164	**0.0000**	-0.0001
	(-0.3020, 0.2986)	(-0.3189, 0.3163)	(-0.3029, 0.2995)	(-0.0009, 0.0009)	(-0.0016, 0.0016)
model 2-δ					
$X\delta + \alpha\lambda$	-1.5236	-1.4356	-1.5221	**-0.0015**	-0.0083
	(-1.6697, -1.3713)	(-1.9048, -0.9260)	(-1.6664, -1.3765)	(-0.0733, 0.0513)	(-0.0594, 0.0444)
model 2-β					
$\delta_1(X\beta + \lambda)$	0.0117	0.0078	0.0114	**0.0003**	0.0002
	(-0.0138, 0.0374)	(-0.0072, 0.0220)	(-0.0135, 0.0367)	(-0.0003, 0.0008)	(-0.0002, 0.0005)
model 2-γ					
$\delta_1(X\gamma) + \alpha\lambda$	0.0164	0.0171	0.0164	**-0.0001**	-0.0001
	(-0.3024, 0.2990)	(-0.3174, 0.3144)	(-0.3036, 0.3002)	(-0.0011, 0.0012)	(-0.0019, 0.0018)

Note: (1) 10% of the public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 500 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 6C
Peer Effects on 12th-Grade Math Score
Eligibility: All Students

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
$X\beta$	3.8406	1.9581	3.8276	0.0130	0.0000
	(4.0874, 5.8169)	(1.7875, 2.2018)	(4.0694, 5.7997)	(0.0089, 0.0239)	(0.0000, 0.0000)
$X\gamma$	48.9136	51.2982	49.0577	-0.1442	-0.2313
	(46.7570, 51.3353)	(48.9701, 53.8104)	(46.9020, 51.4927)	(-0.2209, -0.0812)	(-0.3051, -0.1400)
$\lambda(X\beta-\tau)$	0.1539	0.7199	0.0606	0.0933	0.0783
	(0.1192, 0.1716)	(0.6435, 0.8916)	(0.0387, 0.0760)	(0.0778, 0.1019)	(0.0586, 0.0901)
model 1-δ					
$X\delta$	0.9249	2.4835	1.0375	**-0.1126**	-0.1512
	(-5.5692, 9.1842)	(-11.3540, 15.4992)	(-5.7591, 9.8202)	(-1.3023, 1.0198)	(-1.4469, 1.3154)
model 1-β					
$\delta_1(X\beta)$	-0.0848	-0.0432	-0.0845	**-0.0003**	-0.0000
	(-0.6536, 0.6948)	(-0.2725, 0.2701)	(-0.6508, 0.6930)	(-0.0024, 0.0024)	(0.0000, -0.0000)
model 1-γ					
$\delta_1(X\gamma)$	2.5221	2.6451	2.5296	**-0.0074**	-0.0119
	(-1.7356, 7.6159)	(-1.8150, 7.9841)	(-1.7407, 7.6407)	(-0.0253, 0.0049)	(-0.0386, 0.0072)
model 2-δ					
$X\delta+\alpha\lambda$	0.9130	2.4142	1.0374	**-0.1244**	-0.1630
	(-6.6245, 8.2531)	(-10.6307, 13.6972)	(-6.1267, 9.2417)	(-1.4420, 1.1491)	(-1.5208, 1.5826)
model 2-β					
$\delta_1(X\beta+\lambda)$	-0.0158	-0.0106	-0.0153	**-0.0004**	-0.0003
	(-0.6664, 0.7792)	(-0.3710, 0.3969)	(-0.6516, 0.7610)	(-0.0149, 0.0157)	(-0.0097, 0.0110)
model 2-γ					
$\delta_1(X\gamma)+\alpha\lambda$	2.5252	2.6307	2.5356	**-0.0104**	-0.0144
	(-1.7376, 7.6182)	(-1.8097, 7.9540)	(-1.7439, 7.6465)	(-0.0291, 0.0057)	(-0.0421, 0.0079)

Note: (1) 10% of the public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 500 bootstrap draws. (3) The sample size used in the calculation is 8947. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 7A
Estimation of Peer Effects Model for Public High School Graduation
Separate β's for Urban/Non-urban Samples

	model 1-δ	model 1-β	model 1-γ	model 2-δ	model 2-β	model 2-γ
			Estimation of δ			
constant	-16.2605 (-16.1512, 11.5330)	-0.0454 (-0.2012, 0.1618)	-0.2693 (-0.5221, 0.1107)	-16.6492 (-16.5992, 13.6746)	-0.0512 (-0.2167, 0.1323)	-0.2730 (-0.5243, 0.1132)
female	1.4415 (-5.3203, 8.4938)			1.4627 (-5.1754, 8.4501)		
Asian	0.3349 (-2.8372, 2.2978)			0.4282 (-2.9120, 2.2999)		
Hispanic	-0.0155 (-0.8738, 2.4329)			-0.0039 (-0.8480, 2.2744)		
Black	-1.3959 (-2.3476, 5.0905)			-1.4534 (-2.7678, 4.8267)		
both parents presnet	5.6605 (-8.1312, 3.9899)			5.8637 (-8.1299, 4.7724)		
parents married	-2.0103 (-7.4706, 13.8235)			-2.2654 (-6.8182, 14.9859)		
father's education	-0.4543 (-1.1021, 1.1177)			-0.4745 (-1.2069, 1.0686)		
mother's education	0.7287 (-0.9760, 1.4125)			0.7544 (-0.9583, 1.5337)		
log income87	1.4070 (-1.6017, 2.6686)			1.4538 (-1.8765, 2.4706)		
reading score	-0.0967 (-0.8895, 0.2037)			-0.0972 (-0.8940, 0.1963)		
math score	-0.1189 (-0.1513, 0.2334)			-0.1234 (-0.1355, 0.2469)		
science score	0.1442 (-0.2691, 0.2171)			0.1497 (-0.2998, 0.1971)		
history score	-0.0208 (-0.0753, 0.2101)			-0.0230 (-0.0735, 0.2540)		
urban	-0.0981 (-0.6902, 0.3023)			-0.1949 (-1.1095, 0.3343)		
Suburban	-0.1570 (-0.7850, 0.1958)			-0.1581 (-0.7763, 0.1977)		
northeast	-0.5722 (-0.3729, 1.1512)			-0.5965 (-0.3974, 0.8080)		
north central	-0.4383 (-0.4993, 0.6966)			-0.4539 (-0.5488, 0.6409)		
south	0.0834 (-0.5011, 0.4336)			0.0922 (-0.5100, 0.4983)		
$X\beta$		0.0119 (-0.0133, 0.0277)				
$X\beta + \lambda$					0.0136 (-0.0076, 0.0306)	
$X\gamma$			0.2924 (-0.0874, 0.6265)			0.2984 (-0.0889, 0.6357)
			Estimation of α			
urban				0.3384 (-0.5867, 0.5101)		0.3103 (-0.0851, 0.5200)
non-urban				-0.0129 (-0.1972, 0.1851)		-0.0258 (-0.0486, 0.0062)

Note: (1) 10% of eligible public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 100 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (5) Separate β's are estimated for urban subsamples and non-urban subsamples.

Table 8
Peer Effects on Covariates among Urban Students
Eligibility: Urban Families

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
Catholic	0.3127	0.5877	0.3414	-0.0287	-0.0274
	(0.2530, 0.3698)	(0.5127, 0.6610)	(0.2823, 0.3952)	(-0.0381, -0.0200)	(-0.0346, -0.0207)
female	0.5275	0.4896	0.5280	-0.0005	0.0038
	(0.4980, 0.5539)	(0.4392, 0.5481)	(0.5005, 0.5546)	(-0.0123, 0.0084)	(-0.0023, 0.0092)
Asian	0.0586	0.0495	0.0662	-0.0076	0.0009
	(0.0346, 0.0860)	(0.0309, 0.0678)	(0.0389, 0.1011)	(-0.0156, -0.0025)	(-0.0012, 0.0038)
Hispanic	0.2100	0.1339	0.2100	0.0000	0.0076
	(0.1555, 0.2681)	(0.0821, 0.1796)	(0.1598, 0.2631)	(-0.0098, 0.0104)	(0.0020, 0.0146)
Black	0.2140	0.1705	0.2139	0.0001	0.0043
	(0.1638, 0.2669)	(0.0970, 0.2423)	(0.1622, 0.2645)	(-0.0089, 0.0107)	(-0.0025, 0.0128)
both parents present	0.6205	0.7228	0.6302	-0.0097	-0.0102
	(0.5783, 0.6600)	(0.6749, 0.7781)	(0.5932, 0.6659)	(-0.0200, 0.0001)	(-0.0164, -0.0046)
parents married	0.7186	0.8287	0.7262	-0.0076	-0.0110
	(0.6820, 0.7529)	(0.7890, 0.8709)	(0.6943, 0.7554)	(-0.0174, 0.0007)	(-0.0169, -0.0062)
father's education	13.1151	14.0748	13.1705	-0.0553	-0.0955
	(12.7888, 13.4070)	(13.7488, 14.3874)	(12.8550, 13.4457)	(-0.1079, -0.0146)	(-0.1308, -0.0594)
mother's education	12.6655	13.5018	12.6793	-0.0137	-0.0832
	(12.4155, 12.9005)	(13.2292, 13.7620)	(12.4122, 12.9221)	(-0.0540, 0.0326)	(-0.1114, -0.0534)
log income87	10.0140	10.3647	10.0303	-0.0163	-0.0349
	(9.9373, 10.0907)	(10.2909, 10.4287)	(9.9510, 10.1087)	(-0.0389, 0.0109)	(-0.0434, -0.0264)
reading score	49.7153	53.3937	49.8580	-0.1427	-0.3660
	(48.6876, 50.7455)	(52.2214, 54.4003)	(48.8727, 50.8080)	(-0.3260, 0.0324)	(-0.4966, -0.2253)
math score	49.7434	52.9026	49.8789	-0.1355	-0.3144
	(48.5810, 50.9090)	(51.6577, 54.0281)	(48.7404, 51.0461)	(-0.2945, 0.0065)	(-0.4310, -0.1688)
science score	49.0557	52.1542	49.2640	-0.2082	-0.3083
	(47.9914, 50.1469)	(51.0257, 53.1989)	(48.1774, 50.3397)	(-0.3325, -0.0739)	(-0.4277, -0.1728)
history score	49.2163	53.3777	49.4544	-0.2380	-0.4141
	(48.2445, 50.2381)	(52.0776, 54.4131)	(48.5173, 50.3854)	(-0.4218, -0.0303)	(-0.5363, -0.2618)
northeast	0.1596	0.2394	0.1596	0.0000	-0.0079
	(0.0565, 0.2537)	(0.1402, 0.3203)	(0.0565, 0.2537)	(0.0000, 0.0000)	(-0.0166, 0.0008)
north central	0.1907	0.2505	0.1907	0.0000	-0.0059
	(0.1197, 0.2730)	(0.1753, 0.3680)	(0.1197, 0.2730)	(0.0000, 0.0000)	(-0.0153, 0.0001)
south	0.3856	0.3152	0.3856	0.0000	0.0070
	(0.2804, 0.4970)	(0.2074, 0.4329)	(0.2804, 0.4970)	(0.0000, 0.0000)	(-0.0033, 0.0174)

Note: (1) 10% of eligible public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 100 bootstrap draws. (3) The size of the urban subsample used in the calculation is 1898. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (5) The probability of staying in a public schools is estimated by using the urban subsample.

Table 9A

Peer Effects on High School Graduation among Urban Students

Eligibility: Urban Families

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
$X\beta$	1.9288	1.4808	1.9131	0.0157	0.0446
	(1.7330, 2.3641)	(1.2054, 1.7028)	(1.7124, 2.3458)	(0.0040, 0.0397)	(0.0346, 0.0861)
$X\gamma$	0.8712	0.9169	0.8739	-0.0027	-0.0046
	(0.7365, 1.0444)	(0.7733, 1.0986)	(0.7387, 1.0480)	(-0.0044, -0.0010)	(-0.0059, -0.0033)
$\lambda(X\beta - \tau)$	0.3345	0.6924	0.2473	0.0872	0.0791
	(0.2702, 0.3872)	(0.6347, 0.7987)	(0.1884, 0.3082)	(0.0738, 0.0951)	(0.0641, 0.0872)
model 1-δ					
$X\delta$	-0.0446	0.1354	-0.0811	**0.0366**	-0.0179
	(-0.2168, 0.1049)	(-0.6916, 1.0903)	(-0.2854, 0.1284)	(-0.1455, 0.1372)	(-0.1251, 0.0545)
model 1-β					
$\delta_1(X\beta)$	0.0229	0.0176	0.0227	**0.0002**	0.0005
	(-0.0224, 0.0698)	(-0.0164, 0.0485)	(-0.0221, 0.0689)	(-0.0003, 0.0010)	(-0.0006, 0.0020)
model 1-γ					
$\delta_1(X\gamma)$	0.2547	0.2681	0.2555	**-0.0008**	-0.0013
	(-0.0740, 0.4945)	(-0.0788, 0.5206)	(-0.0744, 0.4956)	(-0.0017, 0.0002)	(-0.0027, 0.0005)
model 2-δ					
$X\delta + \alpha\lambda$	-0.0175	0.2767	-0.0847	**0.0672**	0.0095
	(-0.2164, 0.1139)	(-0.4131, 1.0489)	(-0.2916, 0.1282)	(-0.1500, 0.2718)	(-0.1482, 0.1184)
model 2-β					
$\delta_1(X\beta + \lambda)$	0.0307	0.0295	0.0293	**0.0014**	0.0017
	(-0.0159, 0.0813)	(-0.0161, 0.0736)	(-0.0152, 0.0776)	(-0.0007, 0.0037)	(-0.0008, 0.0046)
model 2-γ					
$\delta_1(X\gamma) + \alpha\lambda$	0.3638	0.4885	0.3375	**0.0263**	0.0232
	(-0.1044, 0.6775)	(-0.1541, 0.8897)	(-0.0976, 0.6317)	(-0.0069, 0.0455)	(-0.0060, 0.0407)

Note: (1) 10% of eligible public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 100 bootstrap draws. (3) The size of the urban subsample used in the calculation is 1898. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (5) The probability of staying in a public schools (β) is estimated by using the urban subsample while other parameters (γ, δ, α) are estimated from the full sample.

Table 10
Peer Effects on Covariates among All Students
Eligibility: Family Income in the lower 20%

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
Catholic	0.2856	0.5561	0.2904	-0.0048	-0.0049
	(0.2662, 0.3129)	(0.4769, 0.6528)	(0.2730, 0.3168)	(-0.0087, -0.0027)	(-0.0092, -0.0035)
female	0.5081	0.4940	0.5102	-0.0020	0.0003
	(0.4969, 0.5182)	(0.4476, 0.5619)	(0.5000, 0.5194)	(-0.0047, 0.0000)	(-0.0014, 0.0011)
Asian	0.0325	0.0362	0.0337	-0.0012	-0.0001
	(0.0272, 0.0420)	(0.0183, 0.0596)	(0.0273, 0.0448)	(-0.0029, 0.0006)	(-0.0004, 0.0003)
Hispanic	0.0939	0.2448	0.0965	-0.0026	-0.0027
	(0.0721, 0.1121)	(0.1583, 0.3190)	(0.0742, 0.1160)	(-0.0045, -0.0005)	(-0.0054, -0.0014)
Black	0.1100	0.2379	0.1110	-0.0010	-0.0023
	(0.0964, 0.1287)	(0.1486, 0.3182)	(0.0975, 0.1292)	(-0.0031, 0.0009)	(-0.0046, -0.0007)
both parents present	0.6864	0.5287	0.6858	0.0006	0.0029
	(0.6714, 0.7017)	(0.4713, 0.6187)	(0.6733, 0.7006)	(-0.0020, 0.0026)	(0.0013, 0.0047)
parents married	0.8023	0.5631	0.7987	0.0036	0.0043
	(0.7890, 0.8160)	(0.5081, 0.6583)	(0.7858, 0.8124)	(0.0020, 0.0058)	(0.0026, 0.0064)
father's education	13.3242	13.3461	13.3131	0.0111	-0.0004
	(13.2078, 13.4491)	(12.5679, 13.8232)	(13.1979, 13.4364)	(-0.0041, 0.0224)	(-0.0092, 0.0196)
mother's education	12.9008	12.8980	12.8852	0.0156	0.0000
	(12.8208, 13.0071)	(12.2289, 13.2471)	(12.8051, 12.9899)	(0.0027, 0.0286)	(-0.0071, 0.0184)
log income87	10.1975	9.1849	10.1780	0.0195	0.0184
	(10.1553, 10.2328)	(9.1126, 9.3997)	(10.1349, 10.2119)	(0.0155, 0.0249)	(0.0165, 0.0235)
reading score	51.0389	50.4162	51.0130	0.0259	0.0113
	(50.6791, 51.6989)	(49.2214, 51.7474)	(50.6611, 51.6584)	(-0.0230, 0.0670)	(-0.0142, 0.0448)
math score	51.1537	50.5213	51.1302	0.0234	0.0115
	(50.7012, 51.6676)	(48.6758, 51.9008)	(50.6856, 51.6280)	(-0.0115, 0.0676)	(-0.0148, 0.0701)
science score	51.2766	49.3448	51.2511	0.0255	0.0350
	(50.8841, 51.7619)	(47.8214, 50.6422)	(50.8709, 51.7365)	(-0.0108, 0.0636)	(0.0140, 0.0866)
history score	50.8892	50.4122	50.8647	0.0245	0.0086
	(50.4927, 51.4456)	(48.9427, 51.7501)	(50.4755, 51.4176)	(-0.0289, 0.0789)	(-0.0207, 0.0411)
urban	0.1955	0.7864	0.1955	0.0000	-0.0107
	(0.1583, 0.2350)	(0.6949, 0.8778)	(0.1583, 0.2350)	(0.0000, 0.0000)	(-0.0172, -0.0092)
suburban	0.4460	0.2130	0.4460	0.0000	0.0042
	(0.4018, 0.4911)	(0.1220, 0.3051)	(0.4018, 0.4911)	(0.0000, 0.0000)	(0.0022, 0.0079)
northeast	0.1848	0.2168	0.1848	0.0000	-0.0006
	(0.1492, 0.2143)	(0.1208, 0.3423)	(0.1492, 0.2143)	(0.0000, 0.0000)	(-0.0041, 0.0010)
north central	0.2766	0.2348	0.2766	0.0000	0.0008
	(0.2347, 0.3131)	(0.1471, 0.3559)	(0.2347, 0.3131)	(0.0000, 0.0000)	(-0.0013, 0.0031)
south	0.3497	0.3876	0.3497	0.0000	-0.0007
	(0.3022, 0.3849)	(0.2324, 0.5180)	(0.3022, 0.3849)	(0.0000, 0.0000)	(-0.0037, 0.0019)

Note: (1) 10% of eligible public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 100 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 11A
Peer Effects on High School Graduation among All Students
Eligibility: Family Income in the lower 20%

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
$X\beta$	3.6840	2.2503	3.6922	-0.0082	0.0260
	(3.7965, 4.7771)	(2.0079, 2.5124)	(3.8051, 4.7825)	(-0.0106, -0.0035)	(0.0284, 0.0632)
$X\gamma$	0.8828	0.8507	0.8820	0.0008	0.0006
	(0.7186, 0.9822)	(0.6908, 0.9486)	(0.7178, 0.9812)	(0.0004, 0.0012)	(0.0003, 0.0012)
$\lambda(X\beta - \tau)$	0.0921	0.6667	0.0727	0.0194	0.0165
	(0.0725, 0.1143)	(0.6073, 0.8377)	(0.0537, 0.0920)	(0.0159, 0.0276)	(0.0132, 0.0241)
model 1-δ					
$X\delta$	0.0039	-0.7763	-0.0097	**0.0136**	0.0141
	(-0.1259, 0.1809)	(-2.8783, 1.8414)	(-0.1865, 0.1723)	(-0.0300, 0.1328)	(-0.0425, 0.0556)
model 1-β					
$\delta_1(X\beta)$	0.0206	0.0126	0.0206	**0.0000**	0.0001
	(-0.0043, 0.0355)	(-0.0024, 0.0197)	(-0.0044, 0.0356)	(-0.0001, 0.0000)	(0.0000, 0.0004)
model 1-γ					
$\delta_1(X\gamma)$	0.2581	0.2488	0.2579	**0.0002**	0.0002
	(-0.0484, 0.5684)	(-0.0461, 0.5542)	(-0.0484, 0.5679)	(0.0000, 0.0006)	(0.0000, 0.0005)
model 2-δ					
$X\delta + \alpha\lambda$	0.0039	-0.7762	-0.0097	**0.0136**	0.0141
	(-0.1259, 0.1808)	(-2.9010, 1.7668)	(-0.1862, 0.1723)	(-0.0297, 0.1456)	(-0.0413, 0.0553)
model 2-β					
$\delta_1(X\beta + \lambda)$	0.0237	0.0183	0.0237	**0.0001**	0.0003
	(-0.0020, 0.0396)	(-0.0015, 0.0285)	(-0.0020, 0.0395)	(0.0000, 0.0001)	(0.0000, 0.0006)
model 2-γ					
$\delta_1(X\gamma) + \alpha\lambda$	0.2591	0.2476	0.2589	**0.0002**	0.0001
	(-0.0485, 0.5698)	(-0.0460, 0.5513)	(-0.0485, 0.5694)	(0.0000, 0.0005)	(0.0000, 0.0004)

Note: (1) 10% of eligible public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 100 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 12

Peer Effects on Covariates among All Students

Eligibility: Non-Catholic Families

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
Catholic	0.3119	0.0000	0.2952	0.0167	0.0214
	(0.2904, 0.3318)	(0.0000, 0.0000)	(0.2751, 0.3146)	(0.0132, 0.0196)	(0.0200, 0.0225)
female	0.5094	0.4871	0.5094	0.0001	0.0015
	(0.4972, 0.5228)	(0.4371, 0.5367)	(0.4986, 0.5214)	(-0.0039, 0.0039)	(-0.0018, 0.0051)
Asian	0.0314	0.0480	0.0323	-0.0009	-0.0011
	(0.0245, 0.0366)	(0.0296, 0.0701)	(0.0258, 0.0381)	(-0.0026, 0.0010)	(-0.0025, 0.0001)
Hispanic	0.1016	0.0294	0.0993	0.0023	0.0050
	(0.0827, 0.1221)	(0.0139, 0.0439)	(0.0816, 0.1191)	(-0.0001, 0.0050)	(0.0032, 0.0065)
Black	0.1026	0.2445	0.1062	-0.0036	-0.0097
	(0.0883, 0.1204)	(0.1726, 0.3359)	(0.0928, 0.1239)	(-0.0070, 0.0004)	(-0.0165, -0.0044)
both parents	0.6797	0.7349	0.6868	-0.0071	-0.0038
present	(0.6652, 0.6936)	(0.6861, 0.7829)	(0.6740, 0.6993)	(-0.0112, -0.0042)	(-0.0072, -0.0005)
parents	0.7962	0.8222	0.7999	-0.0038	-0.0018
married	(0.7801, 0.8048)	(0.7762, 0.8734)	(0.7849, 0.8076)	(-0.0070, -0.0008)	(-0.0056, 0.0017)
father's	13.2356	14.5318	13.2760	-0.0405	-0.0890
educaiton	(13.1157, 13.3250)	(14.1157, 14.8743)	(13.1655, 13.3685)	(-0.0645, -0.0171)	(-0.1154, -0.0629)
mother's	12.8264	13.9084	12.8573	-0.0309	-0.0743
educaiton	(12.7294, 12.9117)	(13.6336, 14.1657)	(12.7573, 12.9413)	(-0.0505, -0.0105)	(-0.0934, -0.0582)
log income87	10.1637	10.3886	10.1725	-0.0088	-0.0154
	(10.1303, 10.1993)	(10.2901, 10.4582)	(10.1372, 10.2045)	(-0.0141, -0.0022)	(-0.0208, -0.0091)
reading score	50.8141	53.9233	50.9376	-0.1235	-0.2135
	(50.3407, 51.2008)	(52.4139, 54.9597)	(50.5311, 51.3141)	(-0.2065, -0.0466)	(-0.2891, -0.1104)
math score	50.9192	54.1675	51.0405	-0.1213	-0.2230
	(50.3608, 51.3364)	(52.3748, 55.6499)	(50.4999, 51.4044)	(-0.2027, -0.0517)	(-0.3324, -0.1166)
science score	51.1449	52.5537	51.2209	-0.0760	-0.0967
	(50.7494, 51.5246)	(50.7774, 53.5541)	(50.8077, 51.6001)	(-0.1464, -0.0139)	(-0.1833, 0.0128)
history score	50.6477	54.0380	50.7985	-0.1508	-0.2328
	(50.2683, 51.0245)	(52.6055, 55.1579)	(50.4176, 51.1762)	(-0.2475, -0.0560)	(-0.3233, -0.1454)
urban	0.1678	0.7269	0.1678	0.0000	-0.0384
	(0.1245, 0.2105)	(0.6202, 0.8655)	(0.1245, 0.2105)	(0.0000, 0.0000)	(-0.0482, -0.0300)
suburban	0.4542	0.2728	0.4542	0.0000	0.0125
	(0.4066, 0.4980)	(0.1344, 0.3798)	(0.4066, 0.4980)	(0.0000, 0.0000)	(0.0031, 0.0232)
northeast	0.1859	0.1780	0.1859	0.0000	0.0005
	(0.1489, 0.2153)	(0.1027, 0.2708)	(0.1489, 0.2153)	(0.0000, 0.0000)	(-0.0049, 0.0053)
north central	0.2782	0.2428	0.2782	0.0000	0.0024
	(0.2381, 0.3256)	(0.1839, 0.3440)	(0.2381, 0.3256)	(0.0000, 0.0000)	(-0.0041, 0.0066)
south	0.3474	0.3918	0.3474	0.0000	-0.0031
	(0.3079, 0.3973)	(0.2740, 0.5033)	(0.3079, 0.3973)	(0.0000, 0.0000)	(-0.0105, 0.0046)

Note: (1) 10% of eligible public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 100 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table 13A
Peer Effects on High School Graduation among All Students
Eligibility: Non-Catholic Families

	mean pub school stayers	mean movers	mean peer stayers (before)	change in peer for stayers	change in mean for pub school
$X\beta$	3.8021	1.7038	3.7890	0.0131	0.1441
	(3.8710, 4.7528)	(1.5248, 1.8833)	(3.8565, 4.7429)	(0.0089, 0.0225)	(0.1465, 0.2151)
$X\gamma$	0.8783	0.9342	0.8805	-0.0022	-0.0038
	(0.7531, 1.0228)	(0.8051, 1.0821)	(0.7550, 1.0255)	(-0.0030, -0.0015)	(-0.0048, -0.0030)
$\lambda(X\beta - \tau)$	0.1479	0.6426	0.0655	0.0824	0.0724
	(0.1134, 0.1677)	(0.5500, 0.8488)	(0.0449, 0.0813)	(0.0682, 0.0899)	(0.0552, 0.0820)
model 1-δ					
$X\delta$	-0.0233	0.1666	-0.0032	**-0.0201**	-0.0130
	(-0.1638, 0.1281)	(-0.6060, 0.6078)	(-0.1597, 0.1267)	(-0.0284, 0.0550)	(-0.0425, 0.0390)
model 1-β					
$\delta_1(X\beta)$	0.0212	0.0095	0.0212	**0.0001**	0.0008
	(-0.0005, 0.0383)	(-0.0002, 0.0151)	(-0.0005, 0.0382)	(0.0000, 0.0001)	(0.0000, 0.0017)
model 1-γ					
$\delta_1(X\gamma)$	0.2568	0.2732	0.2575	**-0.0006**	-0.0011
	(-0.0087, 0.6069)	(-0.0094, 0.6391)	(-0.0088, 0.6082)	(-0.0015, 0.0000)	(-0.0025, 0.0000)
model 2-δ					
$X\delta + \alpha\lambda$	-0.0233	0.1667	-0.0032	**-0.0201**	-0.0130
	(-0.1640, 0.1290)	(-0.5742, 0.5898)	(-0.1597, 0.1267)	(-0.0301, 0.0584)	(-0.0443, 0.0439)
model 2-β					
$\delta_1(X\beta + \lambda)$	0.0248	0.0147	0.0242	**0.0006**	0.0014
	(0.0011, 0.0429)	(0.0006, 0.0233)	(0.0011, 0.0420)	(0.0000, 0.0010)	(0.0001, 0.0024)
model 2-γ					
$\delta_1(X\gamma) + \alpha\lambda$	0.2576	0.2722	0.2585	**-0.0009**	-0.0014
	(-0.0088, 0.6081)	(-0.0094, 0.6377)	(-0.0088, 0.6098)	(-0.0020, 0.0000)	(-0.0029, 0.0001)

Note: (1) 10% of eligible public school students would move to a private school if they had received the voucher. (2) 95% confidence intervals are in the parentheses. They are estimated by the percentile of 100 bootstrap draws. (3) The sample size used in the calculation is 9029. Schools with only one sampled student are dropped. (4) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation.

Table A1-A
Decomposition of the Standard Deviations of Public School Students
Full Sample

	Standard Error	SD within schools	SD between schools
HS	0.3228	0.2946	0.1548
COLL	0.4588	0.4163	0.1928
MATH	9.7178	8.4163	4.8581
INCOME	0.7728	0.7196	0.2818
Catholic	0.4522	0.3737	0.2547
female	0.5000	0.4736	0.1602
Asian	0.1744	0.1577	0.0745
Hispanic	0.2949	0.2102	0.2067
Black	0.3284	0.2275	0.2368
White	0.4333	0.3065	0.3064
both parents present	0.4725	0.4311	0.1933
parents married	0.4097	0.3707	0.1746
father's education	2.7234	2.2990	1.4600
mother's education	2.2038	1.9332	1.0579
log income87	0.7914	0.6788	0.4069
reading score	9.9357	8.8018	4.6094
math score	10.0244	8.5968	5.1559
science score	9.9973	8.6379	5.0330
history score	9.8480	8.5674	4.8561
urban	0.4139	0.0000	0.4139
suburban	0.4968	0.0000	0.4968
rural	0.4728	0.0000	0.4728
northeast	0.3855	0.0000	0.3855
north central	0.4475	0.0000	0.4475
south	0.4783	0.0000	0.4783
west	0.3902	0.0000	0.3902

Note: (1) The sample size is 9265. (2) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (3) *INCOME* is the log wage income in 1999 based on the 4th follow-up. NELS:88 base-year to 4th follow-up panel weights are used for this row. The sample sizes is 7738.

Table A1-B

Decomposition of the Standard Deviations of Public School Students

Urban Subsample

	Standard Error	SD within schools	SD between schools
HS	0.3599	0.3008	0.1975
COLL	0.4495	0.3959	0.2128
MATH	10.0311	7.8352	6.2637
INCOME	0.7878	0.6173	0.4894
Catholic	0.4744	0.3758	0.2896
female	0.4996	0.4432	0.2306
Asian	0.2239	0.1886	0.1206
Hispanic	0.3953	0.2825	0.2764
Black	0.4281	0.2778	0.3258
White	0.5000	0.3319	0.3739
both parents present	0.4862	0.4230	0.2396
parents married	0.4439	0.3898	0.2124
father's education	2.8687	2.2281	1.8069
mother's education	2.3416	1.9233	1.3356
log income87	0.8451	0.6931	0.4834
reading score	10.0976	8.2878	5.7683
math score	10.3643	8.2578	6.2632
science score	10.0821	7.9449	6.2072
history score	10.0118	8.3543	5.5175
northeast	0.3713	0.0000	0.3713
north central	0.3998	0.0000	0.3998
south	0.4877	0.0000	0.4877
west	0.4307	0.0000	0.4307

Note: (1) The sample size is 1991. (2) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (3) *INCOME* is the log wage income in 1999 based on the 4th follow-up. NELS:88 base-year to 4th follow-up panel weights are used for this row. The sample sizes is 1517.

Table A1-C
Decomposition of the Standard Deviations of Public School Students
Urban Minority Subsample

	Standard Error	SD within schools	SD between schools
HS	0.3938	0.3297	0.2154
$COLL$	0.4217	0.3716	0.1992
$MATH$	8.6661	7.0523	5.0365
$INCOME$	0.8735	0.5795	0.6536
Catholic	0.4859	0.3315	0.3552
female	0.4978	0.4226	0.2631
Asian	0.0000	0.0000	0.0000
Hispanic	0.4973	0.3004	0.3962
Black	0.4973	0.3004	0.3962
White	0.0000	0.0000	0.0000
both parents present	0.4996	0.4208	0.2693
parents married	0.4866	0.4153	0.2535
father's education	2.6580	1.9528	1.8031
mother's education	2.3212	1.9543	1.2525
log income87	0.9280	0.7735	0.5126
reading score	8.6435	7.1847	4.8051
math score	8.1753	6.7526	4.6086
science score	7.9450	6.1779	4.9956
history score	9.1383	8.0137	4.3919
northeast	0.4075	0.0000	0.4075
north central	0.3742	0.0000	0.3742
south	0.4989	0.0000	0.4989
west	0.3661	0.0000	0.3661

Note: (1) The sample size is 862. (2) NELS:88 base-year to 3rd follow-up panel weights are used in the calculation. (3) $INCOME$ is the log wage income in 1999 based on the 4th follow-up. NELS:88 base-year to 4th follow-up panel weights are used for this row. The sample sizes is 597.