DOCUMENT RESUME

ED 400 237 SP 036 958

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TITLE	Why Don't Schools and Teachers Seem to Matter? Assessing the Impact of Unobservables on Educational Productivity.
PUB DATE	19 Jan 96
NOTE	35p.; Revised version of a paper presented at meetings of the Econometric Society (San Francisco, CA, January 1996).
PUB TYPE	Reports - Research/Technical (143) -- Speeches/Conference Papers (150)
EDRS PRICE	MF01/PC02 Plus Postage.
DESCRIPTORS	Educational Environment; Grade 10; High Schools; Longitudinal Studies; Mathematics Achievement; Scores; Secondary School Teachers; *Teacher Characteristics; *Teacher Effectiveness; *Teacher Qualifications
IDENTIFIERS	National Education Longitudinal Study 1988

ABSTRACT

Data from the National Educational Longitudinal Study of 1988 are used to link students with particular teachers and classes to estimate the impact of observable and unobservable schooling characteristics on student outcomes. A variety of models show some schooling resources, particularly teacher qualifications, to be significant in influencing tenth grade mathematics test scores. Teachers who are certified in mathematics, and those with bachelors or masters degrees in math are identified with higher test scores. Unobservable school, teacher, and class characteristics are important in explaining student achievement but do not appear to be correlated with observable variables in this sample. The results suggest that the omission of unobservables does not cause biased estimates in standard educational production functions. Six statistical tables are included. (Contains 38 references.) (JLS)

January 19, 1996

Why Don't Schools and Teachers Seem to Matter?
Assessing the Impact of Unobservables on Educational Productivity

by

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Abstract

In this paper, we use data drawn from the *National Educational Longitudinal Study of 1988*, which allows students to be linked to particular teachers and classes, to estimate the impact of observable and unobservable schooling characteristics on student outcomes. A variety of models show some schooling resources (in particular teacher qualifications) to be significant in influencing tenth grade mathematics test scores. Unobservable school, teacher, and class characteristics are important in explaining student achievement but do not appear to be correlated with observable variables in our sample. Thus, our results suggest that the omission of unobservables does not cause biased estimates in standard educational production functions.

I. Introduction

Over the past twenty five years the United States has significantly increased real per pupil expenditures on K-12 schooling. Despite this there is a widespread perception, based on unflattering international comparisons and time trends in standardized test scores, that the nation's public schools are failing.[1] The past decade, spurred by a spate of reports in the early 1980s, has seen numerous reforms scattered throughout the country, which have included new forms of student assessment, curriculum innovation and new classroom organization, as well as changes in school governance and financing. These reforms have been accompanied by increased research by economists, sociologists and others seeking to investigate the relationship between educational productivity and schooling expenditures. This literature, dating back to the 1966 Coleman report (Coleman et al., 1966), consists of literally hundreds of studies. Most have modelled standardized test scores across students, schools, or school districts, as a function of individual and family background characteristics and schooling variables such as expenditures per pupil and class size. This work concludes that individual and family background traits explain the vast majority of variation in student test scores. The effects of educational inputs such as per pupil spending, teacher experience, and teacher degree level have been shown to be relatively unimportant predictors of outcomes, and the impact of any particular input to be inconsistent across studies (Hanushek, 1986).

The results with regard to teachers are particularly puzzling. Few would deny that teachers play a central role in the education of our nation's children. Teaching is the largest profession in the United States, employing over three million adults (NCES, 1994, p. 71). An elaborate system of teacher education and certification is geared towards the preparation of those entering teaching, and there are significant professional development opportunities for those remaining in the profession. More than 40% of teachers have at least a Master degree and more than 25% have at least twenty years full-time teaching experience (NCES, 1994, p. 77). Over 60% of all schooling expenditures at the K-12 level are devoted to instructional costs which consist overwhelmingly of teacher salaries and benefits. Further, teacher salary incentives reward years of experience and degree levels, traits that do not appear to have a relationship to student achievement. What can explain the inconsistent

[1] This view is not unchallenged. See for example Berliner and Biddle (1995).

findings of the educational productivity literature with respect to educational resources, particularly teachers? In this paper we shed some light on this question by systematically exploring the relationship between student achievement and schooling inputs.

We utilize student level data from the *National Educational Longitudinal Study of 1988 (NELS)*, one of the most comprehensive nationally representative datasets available for educational productivity analyses. These data contain information on the background of 8th grade students in 1988, who were re-surveyed in 1990 and 1992. Unlike most other data, NELS links students to a specific class and teacher, and thus marks a significant improvement over most previous surveys. We start with a traditional model at the individual student level, modelling mathematics achievement as a function of individual and family background characteristics for our sample of public school students. We add a familiar set of schooling, teacher and classroom characteristics to our model. Following Murnane and Phillips (1981) we broaden the measured teacher characteristics by also focusing on a set of variables describing teacher behavior.

We then seek to determine the effect of omitting unobservable school or teacher or classroom traits on the estimated relationship between observable schooling characteristics and achievement. We estimate a variety of econometric models including those with fixed and random teacher effects, and auxiliary regressions in which consistent estimates of the effects of observable teacher characteristics on test scores are obtained by regressing estimated teacher fixed effects on these characteristics. We find that several teacher characteristics (in particular, teachers' math specific preparation) do appear to matter--that is, they are significant and influence student achievement in the expected direction. Further, there is little evidence that unobservable schooling characteristics omitted from standard educational production function models lead to systematic bias in the estimates of the coefficients of observable schooling variables.

II. Background: Previous Literature on Educational Productivity

In this section we briefly discuss the "educational productivity" literature. Over the past twenty five years a set of predominantly empirical studies conducted by economists have attempted to establish the relationship between schooling resources and student outcomes (Hanushek, 1986).[2] Outcomes have usually been measured by standardized test scores, although in recent years there has been a resurgence of academic interest in the relationship between school "quality" and other outcomes such as wages (Card and Krueger, 1992; Betts, 1995), graduation from high school and college attendance (Evans and Schwab, 1995).[3] Typically the outcome measure is regressed on a host of factors such as individual and family background variables, and measures of school inputs such as class size, teacher experience and education, and expenditures per pupil.[4]

In an often cited article, Eric Hanushek states that "differences in [school] quality do not seem to reflect variations in expenditures, class sizes, or other commonly measured attributes of schools and teachers" (Hanushek, 1986, p. 1142). To back this claim, he cites numerous studies which employ an educational production function methodology and show conflicting results as to the importance of schooling resources. He concludes that there is "no strong evidence that teacher-student ratios, teacher education, or teacher experience have an expected positive effect on student achievement" and that "there appears to be no strong or systematic relationship between school expenditures and student performance" (Hanushek, 1986, p. 1162). These mixed findings combined with the more robust result that individual and family background characteristics can explain the majority of variation in student test scores, has led some (but not necessarily Hanushek) to jump to the conclusion that schools and teachers may not matter, at least in the sense that additional monies spent on educational resources are wasted.

How can these results be explained? If we accept Hanushek's interpretation of the literature

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[2] The notion that there is an estimable education production function for a set of individuals within or across classes or teachers or schools or school districts is not unchallenged (Monk, 1992). Like any model, the education production function is certainly a simplification of reality, but it is a useful tool. This is particularly true for policy purposes because most applications focus on manipulable, measurable inputs rather than on intangible variables or amorphous constructs.

[3] The relationship between wages and test scores has recently been examined by Murnane, Willett, and Levy (1995).

[4] The focus of our discussion is on schooling inputs. It is quite likely, however, that there are unobservable student characteristics such as motivation which are typically omitted from educational production functions.

and methodology underlying the studies he reviewed, one possibility is that (public) schools have a suboptimal allocation of resources (allocative inefficiency) and/or do not operate on the production possibility frontier (technical inefficiency). In these cases additional teacher inputs or smaller class sizes would not necessarily imply higher output, ceteris paribus.[5] This result does not imply that schooling resources may never affect student achievement positively, simply that given the way public schools are organized additional resources do not make much systematic difference. This may also be due to lack of variation across school settings in variables like class size, making it difficult to identify the effects of such characteristics.

On the other hand, it may be premature to reach strong conclusions about previous research. It is possible to challenge Hanushek's "consensus" view of the literature. He reached his conclusions by noting the direction of estimated input effects on student achievement, along with whether they were statistically significant, and simply tallying ("vote counting") the number of statistically significant positive and negative coefficients. A recent "meta-analysis" by Hedges, Laine and Greenwald (1994) using the same set of studies reviewed by Hanushek reached a very different conclusion. Their basic argument was that the pattern of estimated coefficients is these studies suggested there were indeed systematic positive effects.[6] However, Hanushek (1994) in a reply to Hedges et al., effectively rejected most of their arguments.

A more compelling argument against accepting Hanushek's conclusion is that many of the studies he reviewed are "bad studies" and should not be given much weight; Hanushek made little attempt to separate out studies on the basis of quality save that they had been published. There are good reasons to believe that many educational production function studies, particularly those completed in the 1970s, had major deficiencies in empirical methodology and available data. If the methodological objections are reasonable then an indiscriminate review of the literature will not yield

[5] There is some evidence that public schools and school districts are in fact inefficient with regard to resource allocation (Callan and Santerre, 1990) and production technology (Grosskopf et al., 1995).

[6] A follow-up study using updated research reaches the same conclusion (Laine et al., 1995).

an accurate assessment of the effects of schooling inputs on student outputs.[7]

Data deficiencies imply several problems. The most important of these is that key variables may have been omitted from estimated test score models, potentially leading to biased estimated coefficients of the included variables. For example, many early studies were unable to control for prior achievement using a "pre-test" score to net out individual ability, as is now generally accepted to be important (Boardman and Murnane, 1979; Hanushek, 1979; Hedges et al., 1994). Variables representing school and teacher "quality" that are used in most production function studies are typically very crude. For example, teacher degree levels and years of experience may be only weakly related to teaching skill. Degree level alone does not distinguish between colleges of differing quality, nor when the degree was granted, nor does it convey any information about college major, certification requirements fulfilled, or subsequent professional development. Teacher motivation, enthusiasm, and skill at presenting class material are likely to influence students' achievement, but are difficult traits to accurately measure and are thus omitted from standard regression analyses.

Production function studies which have used more refined measures of teacher inputs have found more consistent results. Monk and King (1994) report that teacher subject matter preparation in mathematics and science does have some positive impact on student achievement in those subjects. Measures of the selectivity of teachers' colleges have also been shown to be positively related to student achievement (Ehrenberg and Brewer, 1994). The latter result most likely reflects the fact that the selectivity measure captures teacher ability. The few studies which have had measures of teacher (verbal) ability, for example in the form of a test score, have found a much more robust positive relationship to student achievement (Coleman et al., 1966; Ehrenberg and Brewer, 1995;

[7] With a few exceptions most educational production function studies use simple linear ordinary least squares (OLS) regression. However, schooling inputs may not be exogenous as OLS requires. For example, highly motivated teachers likely locate in a nonrandom manner across school districts, schools within a district, and classes within a school. Parents similarly self-select their children into school districts which most closely match their preferences, including willingness to pay for schooling (Goldhaber, 1995). There have been few attempts to control for this potential endogeneity (Ehrenberg and Brewer 1994, 1995; Akerhielm 1995) largely because it is extremely difficult to find suitable instruments for schooling inputs, so it is difficult to assess its importance.

Ferguson, 1991) than those using other teacher characteristics.

A further issue with regard to teaching "inputs" is that what actually takes place in the classroom (the process of teaching and learning) may not be captured by teacher characteristics alone (Murnane and Phillips, 1981). This includes both the specifics of the curriculum, the way in which material is conveyed to students by teachers, and the dynamics of student and teacher interaction in any classroom. There is a long tradition among education researchers investigating the relationship between teacher *behavior* and student outcomes (see Brophy and Good, 1986, for a review). Although this "process-product" research often uses a univariate approach (e.g., simple pairwise correlations) and small samples, it has produced some relatively strong results, particularly in regard to the importance of curricula exposure and some pedagogical strategies. If such variables are important predictors of student achievement and are not captured by included school and teacher characteristics, traditional educational production functions may again yield biased results.

Data deficiencies may also have led to significant measurement error problems in previous studies. For instance, it is possible that schooling inputs, particularly class size and expenditures per pupil, are measured with error. Some error likely arises from aggregation of variables to school level.[8] Rather than class size, studies often utilize total school enrollment divided by total number of teachers as an average pupil-teacher ratio. This can lead to dramatically different estimates of the effects of school resources on achievement (see, for instance, Akerhielm, 1995). Of particular concern is that "teacher characteristics" used in many studies are not in fact those of any individual teacher but rather a school level variable such as mean years of experience, percentage of teachers with at least a Masters degree, or mean teacher salary. Use of these measures ignores the considerable variation in teacher characteristics that may exist within a school, and makes it problematic to accurately access the impact of specific teacher characteristics on achievement.

The conventional view that observable school inputs, and teachers in particular, do not positively impact student achievement rests on somewhat shaky empirical grounds. The main problem is likely to be omitted variable bias arising from inadequate data and extremely crude proxies for teacher skill found in most educational production functions. In the absence of more refined

[8] For a discussion of aggregation bias in this context see Hanushek, Rivkin, and Taylor (forthcoming).

measures, it is important to establish whether the omission of unobservables biases the estimates of the variables that are included in the educational production functions. If this is the case it calls into serious question the usefulness of this approach for public policy. In the next section we lay out the problem and strategies for dealing with it.

III. Econometric Methodology

Traditional economic models of student achievement generally build upon the theoretical construct known as the educational production function (Hanushek, 1986). In these models the achievement of student i at school j, Y_{ij}, is regressed on a vector of individual and family background variables (including some measure of prior ability or achievement), X_{ij}, and a vector of schooling resources, S_j, which do not vary across students, and a random error term:

$$Y_{ij} = \beta X_{ij} + \gamma S_j + \epsilon_{ij} \tag{1}$$

For now, assume S_j may consist of school, teacher, or class specific variables. β is the return to individual and family background characteristics and γ is the return to schooling resources. If (1) is correctly specified, Ordinary Least Squares (OLS) estimation will yield consistent estimates of β and γ. The overall importance of schooling factors S_j can be ascertained by performing an F-test of the hypothesis that the coefficients of the schooling variables are jointly equal to zero.

As discussed in section II there are legitimate reasons for believing that standard educational production function models are subject to omitted variables bias. Assume, for example, that the vector of schooling resources S (dropping the subscripts) can be decomposed into two parts: observable characteristics, Z_1, such as class size, teacher experience, teacher degree level, or per pupil expenditure, which are included in the model; and unobservable characteristics, Z_2, such as teacher skill, behavior and motivation, and classroom peer effects, which are omitted from the model:

$$S_j = [Z_{1j}\ Z_{2j}] \tag{2}$$

Hence the true model is:

$$Y_{ij} = \beta X_{ij} + \gamma_1 Z_{1j} + \gamma_2 Z_{2j} + \epsilon_{ij} \tag{3}$$

but we estimate:

$$Y_{ij} = \beta^{*}X_{ij} + \gamma^{*}_{1}Z_{1j} + \upsilon_{ij} \tag{4}$$

where the error term now consists of unobservable schooling characteristics as well as a random component (where $\nu_{ij}=\gamma_2 Z_{2j}+\epsilon_{ij}$).

Thus the omission of Z_2 may cause two problems. First, the total effect of schooling resources on student outcomes could be understated because omitted factors (Z_2) will not be included in the explained portion of the variation in student achievement. Second, (4) may yield biased estimates of the effects of particular schooling resources on student outcomes, as shown in (5):

$$\begin{aligned} \beta^{*} &= \beta + \gamma_2(Z_2'Z_2)^{-1}(Z_2'X) \\ \gamma_1^{*} &= \gamma_1 + \gamma_2(Z_2'Z_2)^{-1}(Z_2'Z_1) \end{aligned} \tag{5}$$

The obvious solution to this problem is to utilize data which includes the relevant variables in Z_2, or at least good proxies for them. As noted in the discussion in section II, this might be done by adding measures of teacher behavior or teacher ability, or refined measures of peer effects. While recently available educational data have made this possible, it is unlikely that any dataset will contain sufficient information to adequately capture Z_2.

In the case in which individual and family background variables and included schooling resources are uncorrelated with excluded schooling resources $E(X'Z_2) = E(Z_1'Z_2) = 0$, OLS estimation of (4) will yield consistent and unbiased estimates of β and γ_1. However, OLS gives estimates of the variance of β and γ_1 which are biased upwards, thus preventing valid inferences about the estimated coefficients of either individual and family background variables or schooling variables.

Maintaining the assumption that Z_2 is uncorrelated with included regressors, one possible solution is to treat Z_2 as a random disturbance specific to a school. For example, suppose Z_2 contains school level predictors which do not vary across students, and can be reasonably assumed to be random across schools. In this case, denote the vector Z_2 by the random variable z_j. The model is then:

$$Y_{ij} = \beta X_{ij} + \gamma_1 Z_{1j} + z_j + \epsilon_{ij} \qquad (6)$$

This is a standard random effects model in which there are N groups (say schools) with T student observations per school (NT total observations). This model can be estimated by Generalized Least Squares (GLS) to yield consistent, efficient and unbiased estimates of the effect of observed schooling resources on student achievement Z_1. This model has the well known advantage that the desirable properties of the estimator does not rely on the number of student observations T being infinite. However, it is predicated on the orthogonality of the random effect with the included regressors, as well as requiring a distributional assumption about z_j.

Note that a version of this random effects model is possible in which observed schooling characteristics are omitted. In other words, treat the *total* effect of schools as constant across students but random across schools. Denote this random effect a_j.

$$Y_{ij} = \beta X_{ij} + a_j + \epsilon_{ij} \qquad (7)$$

In this model the schooling resource variables are assumed uncorrelated only with individual and family background variables, whereas in (6) unobservable schooling variables (treated as a random effect (z_j)) are assumed uncorrelated with both individual and family background variables (X) and observable schooling characteristics (Z_1). By explicitly incorporating the school specific variables which do not vary across students (Z_1) in (6) we eliminate or reduce the correlation between X and a_j; of course, if the omitted effect remains correlated with X or Z_1, the GLS random effects estimator is biased (Hsiao, 1986, p.52).

The assumption that either $E(X' Z_2) = 0$ or $E(Z_1'Z_2) = 0$ is a strong one; if it is violated standard OLS production functions will yield biased estimates of the effects of schooling resources on student outcomes. Similarly if a school specific random error component (z_j or a_j) is included in a production function but is correlated with included regressors (X or both X and Z_1) GLS will also yield biased and inconsistent estimates of the effects of schooling resources on student outcomes. For example, in (4), the direction of the bias will depend on the signs of γ_2 (the true effects of schooling unobservables), $E(X'Z_2)$ and $E(Z_1'Z_2)$. While it might be hypothesized that $\gamma_2 > 0$, the relationship between omitted schooling variables and the included regressors is an empirical issue.

Suppose that children from upper income families attend schools with more motivated teachers but that teacher motivation is unobservable, i.e., $E(X'Z_2) > 0$. In this case, assuming teacher motivation positively impacts student achievement, the estimation of the educational returns to increases in family income will be overstated. Similarly suppose that younger, more inexperienced teachers are the most motivated such that $E(Z_1'Z_2) < 0$. In this case the estimated effects of teacher experience on student achievement would be understated in (4).

If panel data are available, the standard technique to account for omitted variables bias is to estimate a fixed effects model. In this case let α_j be a schooling specific effect which does not vary across individuals but is specific to each school. In a sample of i =1...N schools with T observations per school, one can then estimate

$$Y_{ij} = \beta X_{ij} + \alpha_j + \epsilon_{ij} \qquad \textbf{(8)}$$

using ordinary least squares to obtain unbiased estimates of the effect of individual and family background variables (X) and the total effect of schooling resources (S) on student achievement. This model does not require the restrictive assumption that the unobservable schooling variables are uncorrelated with included variables since the effect of all school specific unobservables is captured by α_j. The estimates of β are also consistent. However, while the estimates of α_j, the schooling effects, are unbiased, their consistency relies on the number of observations being large (infinite). They also may not be fully efficient.

Determining whether a random effects model specification ((6) or (7)) or a fixed effects model (8) is the "correct" model depends partly on the relationship between the omitted effects and included regressors. If schooling effects are correlated with individual and family background variables then (7) is not appropriate. Similarly, (6) is not appropriate if observable schooling variables are correlated with unobservable schooling effects. Whether a fixed or random effects model is appropriate can easily be tested using a Hausman test. The null hypothesis is that the coefficient estimates from the fixed effects model (8) do not differ systematically from the estimates of the random effects specification of the model (7).

The difficulty with the fixed effects specification for our purposes is that while the total effect of schooling resources on achievement can be quantified, the effects of particular observable resources (Z_1) which are of interest for policy purposes cannot be ascertained since inclusion of Z_1 along with α_j would lead to perfect collinearity.[9] One possible solution is to estimate an auxiliary regression in which the estimates of α_j are regressed on observable schooling variables Z_1 to obtain consistent estimates of γ_1 (see, for example, Rauch, 1993, for an application of this methodology).[10] Since α_j is an estimate derived from (8), (9) must be a estimated by GLS to ensure the coefficient standard errors are unbiased.

$$\alpha_j = \gamma_1 Z_{1j} + \eta_j \tag{9}$$

IV. Data

The data used here are derived from the first two waves of the *National Educational Longitudinal Study of 1988* (NELS). This is a nationally representative survey of about 24,000 8th grade students conducted in the spring of 1988. 18,000 of these students were resurveyed in 10th grade (spring 1990). Students provided comprehensive information on themselves and their families (their race/ethnicity, sex, family structure), supplemented by a parental survey in 1988 (providing information on, for example, family income). At the time of each survey students took one or more subject based tests in mathematics, science, writing, and history. The data therefore permits the estimation of "value-added" or gain score production functions which control for previous knowledge or ability. In this paper, we confine our attention to those students who took the mathematics

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[9] One solution to this problem is an instrumental variables estimator developed by Hausman and Taylor (1981) which permits the efficient estimation of γ_1. They suggested estimating γ_1 using elements of X uncorrelated with α_j as instruments for Z_1. A necessary condition to implement this method is that the number of elements of X uncorrelated with α_j must be greater than the number of elements of Z_1 that are correlated with α_j.

[10] This method is a "weak" version of a the currently popular "hierarchical linear models" (HLMs) technique widely used within education (although rarely used by economists). HLMs estimate "within school" (typically slope) parameters which are used as outcomes in school level "between school" equations. See, for example, Bryk and Raudenbush (1988).

achievement test in the 8th and 10th grade, the 10th grade score being modelled as a function of the 8th grade score and other variables.[11] The tests were carefully designed by the Educational Testing Service to assess mathematics knowledge. While all students took the same test in the 8th grade, tests of varying difficulty were given to students in the 10th grade depending on their 8th grade score in order to guard against "ceiling" and "floor" effects. The tests were given a common scale using Item Response Theory (IRT).[12]

The unique feature of NELS is that it provides detailed teacher and class level information that is tied directly to individual students. In other words, the characteristics of each 10th grade mathematics teacher (sex, race/ethnicity, degree level, experience, certification, etc.) who taught students taking the 10th grade mathematics test is known. In addition, some characteristics of the classes which that teacher taught are also available (e.g. class size, track[13], class composition). This feature of the data makes NELS one of the most comprehensive and well designed studies available for conducting educational production function analyses. School administrators provided information on their schools: for example, in regard to the composition of the teaching staff (percentage with a Masters degree, percentage white, etc.) and school quality indicators (e.g. percentage of the school's graduates going on to four year colleges).

We confine our attention to a sample of 5,149 10th grade public school students. Public school students are examined because of the difficulties of controlling for the non-random assignment of students to public and private schools (Goldhaber, 1996). Further, any policy conclusions resulting from our analyses apply primarily to public schools. These students are drawn from 638 schools, with 2,245 individual mathematics teachers. The sampling frame of NELS is such that there are not only multiple students per school and per teacher, but there are also multiple classes per

[11] The 10th grade test was administered during the spring of 10th grade. Unfortunately no data are available on students' 9th grade experiences.

[12] IRT is a method that uses the pattern of right, wrong, and omitted responses to the questions actually administered on each test .and the difficulty, discriminating ability, and "guessability" of each question to place each student on a continuous scale regardless of the test he or she was given (see Rock and Pollock, 1991, for a discussion of IRT and the NELS data).

[13] A recent study of the effects of tracking on student achievement using the NELS data is Argys, Rees, and Brewer (1996).

teacher; there are 3,498 classes in our sample. This is also a unique advantage of the NELS data which, at least in principle, permits the estimation of a broader class of models than is usually the case. Means of all variables used in our analyses are found in Appendix Table 1

V. Results

Standard OLS Educational Production Functions

We begin by estimating standard educational production functions by ordinary least squares. Throughout our analyses, the dependent variable is the 10th grade mathematics test score. We group our explanatory variables into four sets: individual and family background variables (including sex, race/ethnicity, parental education, family structure, family income, and 8th grade math test score[14]), school variables (including urbanicity and regional dummies, school size, the percentage of students at the school who are white, the percentage of students at the school who are from single parent families, the percentage of students who typically go on to four year colleges, and the percentage of teachers at the school with at least a Masters degree), teacher characteristics variables (including sex, race/ethnicity, years of experience at the secondary level, whether the teacher is certified in mathematics, the teacher's degree level and whether his or her BA major or MA major are in math), and classroom variables (class size and percentage of minority students). As noted previously, a unique feature of our NELS data is that the teacher and classroom variables are specific to the students 10th grade mathematics class.

Table 1 contains the basic model results. We do not show the coefficients of individual and family background variables though they are included in each model. These variables alone explain approximately three quarters of the variation in the 10th grade math score. In our sample, most of the estimated coefficients of these variables are statistically significant in the expected direction. For example, years of parental education and family income are positively related to test scores, a result typical of the literature. Black and Hispanic students have lower predicted scores on average, as do

[14] Models were also run with a quadratic form of the base year test score. The estimated coefficient of this variable was negative and statistically significant, while the coefficient of the base year test score remained positive and significant, suggesting a nonlinear relationship between prior and current achievement. However, the inclusion of the quadratic term in the model did not change the estimated effects of other variables of interest, and the results are not shown here.

those from families with no mother in the household.

[Table 1 about here]

Column (1) of Table 1 adds the set of school characteristics to the model. Only two of the ten variables are statistically significant, though most coefficients are the expected sign. However, an F test of the hypothesis that the coefficients of the schooling variables are jointly equal to zero is rejected at the 1% level. Column (2) shows the results when teacher characteristics are added to the model. Here eight of the eleven teacher variables have statistically significant coefficients. An F test of the hypothesis that the coefficients of the teacher characteristics are jointly equal to zero is easily rejected at the 1% level. We find that students of more experienced teachers have higher scores. Female teachers are associated with higher test scores and black teachers with lower test scores; the relationship between teacher race, ethnicity and gender and student scores is likely more complex than this simple linear model allows but we do not explore the issue in here (for a more detailed analysis of this issue Ehrenberg, Goldhaber and Brewer, 1995).

Column (3) of Table 1 adds two classroom level variables to the production function: class size which is positively associated with achievement, and the percentage of minority students in the class which is negatively associated with achievement. The class size result is counterintuitive (though the magnitude of the estimated coefficient is small) but not atypical of production function results. As noted earlier, Akerhielm (1995) found a similar result with NELS data which she attributed to the nonrandom assignment of students to classes. Again an F test comparing the models in (2) and (3) easily rejects the hypothesis that the coefficients of these classroom variables are jointly equal to zero.

Before adding teacher behavior variables it is worth considering more closely the teacher characteristic results which contrast with many earlier studies which have found little relationship between such variables and student achievement. As shown in columns (2) and (3) of Table 1, the estimated coefficients of whether the teacher has a Bachelors degree and whether she has a Masters degree are negative (and in the case of BA, statistically significant) relative to the omitted category of no degree. This implies that teachers with Bachelors and Masters degrees are less effective than those without any degree, clearly a counterintuitive finding. The results for teacher certification are similar in that we find the coefficient on teacher certification to be statistically significant and negative. However, these models also include dummy variables indicating whether the teacher is certified in math, has a Bachelors in math, and has a Masters in math. These variables allow us to distinguish between teachers who are teaching mathematics classes and have a major in math (BA or MA), teaching mathematics classes and are certified in math, and those who are teaching mathematics but do not have specific math training. For example, the total effect of a teacher having a Bachelors degree in math is the sum of the coefficients of BA and BA major in math, whereas the effect of teacher who has a non-math BA is simply the coefficient of the BA variable.

Traditional education production functions do not include subject specific teacher degree and certification information. However, at least in our sample, the use of this more detailed data is critical in interpreting the effects of these teacher characteristics on student achievement. This can be seen in Table 2. Column (1) of Table 2 shows a model in which math specific degree and certification information is omitted. The results here would lead one to one to the conclusion that teacher degrees and certification have no impact on student achievement. This is in line with much of the previous literature. However, the results reported in column (3) of Table 2 (reproduced from column (3) of Table 1) would lead to a quite different conclusion. Here we show that a teacher with a BA in math or an MA in math has a statistically significant *positive* impact on students' achievement, while a teacher with a non-math BA or an MA has a negative impact on students' math achievement (all relative to the omitted category of no degree). We find similar results with teacher certification, when we estimate models with (columns (1) and (3) of Table 2) and without (columns (2) and (4) of Table 2) a set of state dummy variables indicating the location of the high school. We estimate models with state dummies to control for the differing certification requirements across states.

[Table 2 about here]

Adding "Teacher Behavior" Variables

As noted in the previous section, many education researchers have suggested that teacher characteristics do not begin to capture the ways in which teachers affect student achievement. In particular, teacher behavior is typically not included in educational production function analyses which treats the process of schooling as a "black box". Few attempts have been made to utilize such concepts in multivariate analysis, partly because measuring them is extremely difficult (Brewer and

Stasz, 1996), and partly because the choice of variables for inclusion is somewhat arbitrary. One useful effort to do this with data on elementary schools is Murnane and Phillips (1981). They include, in production functions explaining vocabulary test scores, variables such as the percentage of time the teacher uses subgroups, demonstrations, individualized work, and whether the teacher views their job as explaining subject matter. The authors find that these behavior variables explain a larger proportion of test score variance than teacher characteristics alone, although a model including *both* characteristics and behavior measures best fits the data.

Similar information on teacher behavior is included in NELS. This includes the percentage of the teacher's time in class devoted to small groups and individualized instruction, the percentage of time maintaining order and doing administrative tasks, whether the teacher uses oral questions frequently and emphasizes problem solving, whether the teacher has no control over curriculum content, teaching technique and disciplinary policy, and whether the teacher feels well prepared.[15] We selected these items partly to replicate the Murnane and Phillips analysis at the secondary level and partly to capture newer conceptions of mathematics teaching (small groups, problem solving) as reflected in the National Council of Teachers of Mathematics (NCTM, 1991) standards.

Column (4) of Table 1 shows a model including teacher behavior but not teacher characteristics; column (5) includes both sets of variables. The model with teacher behavior variables is marginally better at explaining test scores than the characteristics model, but including both sets of variables together provides for the best fit of the data, as was the case in Murnane and Phillips (this is confirmed by F-tests of the hypotheses that the added coefficients are jointly equal to zero). However, the estimated coefficients of the teacher characteristics variables do not change much when the behavior variables are added; the reverse is also true. This suggests that there my be no strong relationship between our set of teacher characteristics and any teacher behavior variable. We

[15] These items are based on teacher survey responses. Burstein et al. (1995) assess the validity of NELS instructional strategy items using an enhanced version of the teacher survey instruments, teacher interviews, and collection of class assignments and homework, with a small sample of teachers in the original NELS sample. Their results suggest such survey items and response scales need to be treated cautiously.

confirmed this in auxiliary regressions of teacher behavior on teacher characteristics.[16]

Several results are worth highlighting. Students with teachers who have little or no control over their teaching technique have significantly lower test scores. Variables associated with NCTM type standards, such as teaching in smaller groups and emphasizing problem solving, appear to lower student math scores. This does not necessarily imply that these teaching techniques are invalid but may simply indicate that these methods do not improve achievement on traditional standardized tests. Murnane and Phillips (1981) found a similar statistically significant negative coefficient on percentage of time devoted to subgroup instruction for sixth grade vocabulary. In fact, all of our results, at the secondary level, are strikingly consistent with their results at the primary level. On net, it appears that these types of variables should be included in educational production functions but since our focus here is primarily on biases in traditional education production functions, we do not discuss these variables and do not include them in subsequent models shown. Our conclusions below are unaffected by this simplification.

School, Teacher, and Class One-Way Random and Fixed Effects Models

Table 3 shows the results of one-way random effects models with included school (column (1)), teacher (column (2)), and class (column (3)) random effects, as shown in equation (6). These models were also estimated omitting observed variables as in equation (7). The results are very similar to those of the base model shown in Table 1. However, a Lagrange multiplier test confirms that the random effects specification of the model is superior to a standard OLS specification. Following (8), we also estimate 1-way fixed effects models which allow us to test for unobservable school, teacher, and class effects.[17] Hausman tests suggest that random effects specifications are

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[16] We ran a series of simple regression models in which each teacher behavior variable was regressed against observable teacher characteristics variables. There were few consistent results across models. Further, the fit of these models was extremely poor: the R-squared was typically less than 5%.

[17] There have been several previous studies which have estimated teacher fixed effects and found them to be similarly important (see Hanushek, 1986, p. 1159).

appropriate for these data relative to fixed effects models.[18]

[Table 3 about here]

Column (1) of Table 4 shows the results of a school level fixed effects model, column (2) shows the results of a teacher level fixed model, and column (3) shows the results of a class level fixed effects model. In these fixed effects models we cannot include observed variables at the same level as the fixed effect (e.g. teacher observed variables with a teacher specific effect), nor can we include higher level observed variables than the level of the fixed effect (e.g. school level observed variables with a class level effect). A comparison of the estimated teacher and class coefficients in our base model that includes observed school, teacher, and class variables (column (6) of Table 1) with our model that replaces the observed school variables with a school specific effect (column (1) of Table 4) shows few changes in the estimates of teacher and class variables when a school level fixed effect is included in the model.[19]

[Table 4 about here]

The explained portion of the variation of student achievement when we move from a model with our complete set of observed characteristics to our model with class effects, rises from .77 to .93. Adding a teacher fixed effect to the standard model also explains a significantly higher portion of the variance in test scores than a model with teacher observable characteristics, a result consistent with the findings of other studies which have estimated teacher fixed effects models.[20] To determine whether these models better fit the data, we perform F-tests of the hypotheses that the coefficients of the fixed effects are jointly equal to zero. In all cases we are able to reject these hypotheses at the 1 percent significance level. Thus, unobservable school, teacher, and class effects do play a

[18] The student data used by Montmarquette and Mahseredjian (1989) suggests that a two way (school and class) random effects, rather than a fixed effects, education production function model is appropriate.

[19] However, when teacher behavior variables are included in the school fixed effects model, many of the teacher behavior variables which were significant in the OLS specification of the model shown in Table 1 become statistically insignificant. This may suggest that teacher behavior is strongly associated with unobserved aspects of school organization, and we control for this with the inclusion of the school level effect.

[20] See Hanushek, 1986, p. 1159 for citations and discussion of these studies.

significant role in determining student outcomes but these effects do not appear to be jointly correlated with included explanatory variables.

Auxiliary Models Using Estimated Fixed Effects

To obtain consistent estimates of individual teacher observable variables we regress our estimates of teacher fixed effects on the set of observed teacher characteristics.[21] As we found earlier, the auxiliary regression results suggest that teacher certification, experience, and degrees in math are all statistically significant in the expected direction. Further, the magnitudes and significance of these coefficients are larger in each case. The results are shown in table 5.

[Table 5 about here]

These results confirm our earlier findings regarding the importance of teacher characteristics. The marked difference in the coefficient estimates suggests that although the set of teacher variables are not jointly correlated with a teacher specific effect, these individual variables may be.

VI. Conclusion

In this paper we assess the importance of educational resources in explaining student achievement on a tenth grade mathematics standardized test. Using data from the *National Longitudinal Study of 1988* which permit us to link students with a particular teacher and math class, we find that traditional (OLS) educational production function models do show some educational resources to be significant in influencing tenth grade mathematics test scores. Although school level variables do not, in general, seem to have much affect on student achievement, some teacher characteristics do. Teachers who are certified in mathematics, and those with Bachelors or Masters degrees in math, are identified with higher test scores. Auxiliary regression models in which an estimated teacher fixed effect is regressed on observable teacher characteristics to obtain consistent estimates of these effects, strengthens our conclusion that these variables influence student

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[21] This methodology may also be applied to school and class effects. We choose to focus here on teacher effects as a confirmation of our earlier positive results with respect to key teacher characteristics.

achievement. Extending the work of Murnane and Phillips (1981) we also find that some aspects of teacher behavior influence student achievement, independent of teacher characteristics.

Our findings regarding teacher traits may be due to the unique nature of the NELS data among national surveys in providing a direct student-teacher-class link. This link enables us to avoid problems with aggregation that may have plagued earlier studies. Also, subtle differences in model specification can result in very different interpretation of whether teachers, for example, affect student outcomes. Student achievement models estimated with variables specifying whether a teacher has a BA or an MA but without the subject of the degrees, show teacher degree to be statistically insignificant; this is also true of teacher certification. When degree subject is added, teachers with mathematics degrees are clearly associated with higher student scores on the NELS mathematics test.

The NELS data permit us to estimate a variety of econometric models including one-way fixed and random effects models. Our results suggest that while observable school, teacher or class variables account for a relatively small fraction of the variation in student test scores, unobservable factors associated with these schooling characteristics are important. However, we find that unobservable school, teacher, and class effects do not appear to be correlated with observable variables included in our models, and thus do not cause biased estimates of the effects of these variables.

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Table 1
Educational Production Functions with Individual, School, Teacher, and Class Variables (absolute value t-statistics)
Standard OLS Models

Category	Dependent Variable: 10th Grade Test Score					
	(1)	(2)	(3)	(4)	(5)	(6)
School Variables						
Urban	-0.329 (1.1)	-0.286 (1.0)	-0.114 (0.4)	-0.346 (1.2)	-0.308 (1.1)	-0.135 (0.5)
Rural	-0.294 (1.3)	-0.326 (1.4)	-0.357 (1.5)	-0.240 (1.0)	-0.257 (1.1)	-0.307 (1.3)
Northeast	0.583 (1.9)	0.578 (1.9)	0.548 (1.7)	0.451 (1.5)	0.450 (1.4)	0.406 (1.3)
North central	-0.011 (0.0)	-0.036 (0.1)	-0.121 (0.5)	0.047 (0.2)	0.035 (0.1)	-0.053 (0.2)
West	0.059 (0.2)	0.215 (0.7)	0.181 (0.6)	0.178 (0.6)	0.303 (1.0)	0.285 (0.9)
School size*	0.167 (0.9)	0.083 (0.4)	0.083 (0.4)	0.116 (0.6)	0.057 (0.3)	0.072 (0.4)
Percent white school	-0.006 (1.3)	-0.007 (1.5)	-0.028 (5.0)	-0.005 (1.2)	-0.006 (1.3)	-0.027 (4.9)
Percent four-year college	0.022 (3.6)	0.019 (3.2)	0.020 (3.3)	0.020 (3.4)	0.019 (3.1)	0.019 (3.1)
Percent teachers with M.A.	-0.001 (0.1)	-0.001 (0.3)	-0.002 (0.3)	-0.002 (0.4)	-0.002 (0.5)	-0.002 (0.5)
Percent single-parent families	-0.004 (0.7)	-0.006 (0.9)	-0.007 (1.1)	-0.000 (0.0)	-0.002 (0.3)	-0.003 (0.5)
Teacher Characteristic Variables						
Female teacher	--	0.580 (2.9)	0.605 (3.0)	--	0.508 (2.5)	0.528 (2.7)
Black teacher	--	-1.178 (2.2)	-0.999 (1.9)	--	-0.774 (1.5)	-0.588 (1.1)
Hispanic teacher	--	0.716 (1.0)	1.176 (1.7)	--	0.795 (1.1)	1.271 (1.8)
Asian teacher	--	0.745 (0.9)	0.967 (1.1)	--	1.156 (1.4)	1.382 (1.6)
Teacher years experience at secondary level	--	0.019 (1.6)	0.016 (1.4)	--	0.014 (1.2)	0.011 (1.0)
Teacher is certified	--	-2.499 (2.5)	-2.265 (2.3)	--	-1.780 (1.8)	-1.600 (1.6)
Teacher certified in math	--	2.271 (2.4)	2.150 (2.2)	--	1.406 (1.4)	1.330 (1.4)
Teacher has B.A.	--	-0.797 (2.6)	-0.736 (2.4)	--	-0.801 (2.6)	-0.748 (2.4)
Teacher has B.A. major in math	--	0.867 (3.7)	0.823 (3.5)	--	0.756 (3.2)	0.717 (3.1)
Teacher has M.A. or more	--	-0.134 (0.5)	-0.055 (0.2)	--	-0.205 (0.8)	-0.130 (0.5)
Teacher has M.A. major in math	--	0.632 (2.2)	0.606 (2.2)	--	0.617 (2.2)	0.590 (2.1)

Teacher Behavior Variables						
Teacher feels very well prepared	--	--	--	0.896 (4.3)	0.711 (3.3)	0.748 (3.5)
Teacher has no control over discipline	--	--	--	-0.553 (1.1)	-0.482 (1.0)	-0.403 (0.8)
Teacher has no control over technique	--	--	--	-3.882 (3.7)	-3.740 (3.5)	-3.532 (3.3)
Teacher has no control over context	--	--	--	0.350 (1.4)	0.384 (1.5)	0.421 (1.7)
Percent teacher time instructing small groups	--	--	--	-0.018 (2.3)	-0.015 (1.9)	-0.015 (1.8)
Percent teacher time instructing individuals	--	--	--	-0.028 (4.5)	-0.026 (4.2)	-0.024 (3.9)
Percent teacher time maintaining order	--	--	--	-0.020 (3.0)	-0.021 (3.0)	-0.021 (3.1)
Percent teacher time doing administrative tasks	--	--	--	0.018 (1.2)	0.018 (1.1)	0.015 (0.9)
Teacher uses oral questions frequently	--	--	--	0.701 (3.1)	0.577 (2.5)	0.601 (2.6)
Teacher emphasizes problem solving	--	--	--	-0.342 (1.6)	-0.371 (1.7)	-0.377 (1.7)
Class Variables						
Student class size	--	--	0.039 (2.7)	--	--	0.031 (2.1)
Percent minority students in class	--	--	-0.038 (6.2)	--	--	-0.039 (6.3)
Individual and Family Background Variables	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	.763	.766	.768	.768	.770	.772

*Coefficient multiplied by 1000.

Table 2
Comparison of Selected Coefficients from Educational Production Functions
(absolute value t-statistics)

	(1)	(2)	(3)	(4)
Teacher years experience at secondary level	0.022 (1.9)	0.023 (2.0)	0.016 (1.4)	0.017 (1.5)
Teacher is certified	-0.072 (0.1)	-0.305 (0.5)	-2.265 (2.3)	-2.412 (2.4)
Teacher certified in math	--	--	2.150 (2.2)	2.024 (2.1)
Teacher has B.A.	-0.183 (0.7)	-0.047 (0.2)	-0.736 (2.4)	-0.578 (1.8)
Teacher has B.A. major in math	--	--	0.823 (3.5)	0.748 (3.1)
Teacher has M.A. or more	0.130 (0.5)	0.162 (0.7)	-0.055 (0.2)	-0.010 (0.0)
Teacher has M.A. major in math	--	--	0.606 (2.2)	0.536 (1.9)
State Dummies	No	Yes	No	Yes
Adjusted R^2	.767	.770	.768	.772

All models contain individual and family background variables, school variables, teacher characteristic variables (except as specified in table), and class variables. Table 1, col. (3), reproduced in Table 2,col. (3).

Table 3
Educational Production Functions with Individual, School, Teacher, and Class Variables
(absolute value t-statistics)
One Way Random Effects Models

Category	Dependent Variable: 10th Grade Test Score		
	(1)	(2)	(3)
School Variables			
Urban	-0.123 (0.4)	-0.148 (0.5)	-0.142 (.55)
Rural	-0.332 (1.2)	-0.407 (1.6)	-0.323 (1.3)
Northeast	0.396 (1.1)	0.428 (1.3)	0.426 (1.3)
North central	-0.238 (0.8)	-0.165 (0.6)	-0.148 (0.0)
West	0.081 (0.2)	0.149 (0.5)	0.012 (0.0)
School size*	0.078 (0.4)	0.087 (0.4)	0.167 (0.8)
Percent 10th graders white	-0.031 (5.1)	-0.030 (5.0)	-0.029 (4.9)
Percent school graduates who attend four-year college	0.019 (2.8)	0.019 (2.9)	0.022 (3.4)
Percent teachers with M.A. at school	-0.002 (0.3)	-0.002 (0.4)	.001 (0.1)
Percent school from single-parent families	-0.006 (0.8)	-0.006 (0.9)	-.005 (0.7)
Teacher Characteristic Variables			
Female teacher	0.546 (2.7)	0.598 (2.8)	0.572 (2.8)
Black teacher	-1.019 (1.5)	-0.982 (1.8)	-1.123 (2.1)
Hispanic teacher	1.086 (1.5)	1.213 (1.7)	0.991 (1.4)
Asian teacher	0.948 (1.1)	0.896 (1.0)	0.017 (0.7)
Teacher years experience at secondary level	0.019 (1.6)	0.012 (1.4)	0.021 (1.7)
Teacher is certified	-2.313 (2.3)	-2.345 (2.3)	-2.783 (2.1)
Teacher certified in math	2.185 (2.2)	2.230 (2.2)	2.445 (2.4)
Teacher has B.A.	-0.726 (2.3)	-0.666 (2.0)	-0.663 (2.0)
Teacher has B.A. major in math	0.847 (3.5)	0.847 (3.4)	0.781 (3.2)
Teacher has M.A. or more	-0.092 (0.4)	0.570 (0.2)	0.160 (0.6)
Teacher has M.A. major in math	0.621 (2.1)	0.567 (1.9)	0.520 (1.8)
Class Variables			
Student class size	0.046 (3.1)	0.046 (3.0)	0.056 (3.7)
Percent minority students in class	-0.043 (6.7)	-0.041 (6.5)	-0.042 (6.5)
School Random Effects	Yes	No	No
Teacher Random Effects	No	Yes	No
Class Random Effects	No	No	Yes
Adjusted R^2	.770	.770	.770

*Coefficient multiplied by 1000.

Table 4
Educational Production Functions with Individual, School, Teacher, and Class Variables (absolute value t-statistics)
One Way Fixed Effects Models (OLS)

Category	Dependent Variable: 10th Grade Test Score		
	(1)	(2)	(3)
Teacher Characteristic Variables			
Female teacher	0.674 (3.5)	--	--
Black teacher	-0.809 (1.6)	--	--
Hispanic teacher	1.360 (1.9)	--	--
Asian teacher	0.886 (1.0)	--	--
Teacher years experience at secondary level	0.016 (1.4)	--	--
Teacher is certified	-2.617 (2.6)	--	--
Teacher certified in math	2.240 (2.3)	--	--
Teacher has B.A.	-0.705 (2.3)	--	--
Teacher has B.A. major in math	0.763 (3.3)	--	--
Teacher has M.A. or more	0.503 (0.2)	--	--
Teacher has M.A. major in math	0.609 (2.2)	--	--
Class Variables			
Student class size	0.040 (2.9)	0.054 (1.7)	--
Percent minority students in class	-0.016 (3.7)	-0.078 (4.6)	--
Individual and Family Background Variables	Yes	Yes	Yes
School Fixed Effects	Yes	No	No
Teacher Fixed Effects	No	Yes	No
Class Fixed Effects	No	No	Yes
Adjusted R^2	.784	.801	.815
R^2	.812	.888	.933

Table 5
Comparison of Selected Coefficients from Educational Production Functions
(absolute value t-statistics)

	(1) OLS	(2) Random Effects	(3) Auxiliary
Teacher years experience at secondary level	0.019 (1.6)	0.012 (1.4)	0.030 (2.3)
Teacher is certified	-2.499 (2.5)	-2.345 (2.3)	-3.552 (3.2)
Teacher certified in math	2.271 (2.4)	2.230 (2.2)	3.254 (3.0)
Teacher has B.A.	-0.797 (2.6)	-0.666 (2.0)	-0.935 (2.7)
Teacher has B.A. major in math	0.867 (3.7)	0.847 (3.4)	1.098 (4.2)
Teacher has M.A. or more	-0.134 (0.5)	0.570 (0.2)	0.090 (0.3)
Teacher has M.A. major in math	0.632 (2.2)	0.567 (1.9)	0.885 (2.8)

The OLS coefficients reported are from Table 1, col. (3). The random effects coefficients reported are from Table 3, col. (2). Col. (3) is estimated by GLS.

Appendix Table 1
Variable Means (Standard Deviations)

Category	Mean (Standard Deviation)	
Individual and Family Background Variables		
10th grade mathematics test score	43.94	(13.6)
8th grade mathematics test score	36.57	(11.7)
Female	0.51	(0.5)
Black	0.09	(0.3)
Hispanic	0.11	(0.3)
Asian	0.05	(0.2)
Parental education	14.07	(2.3)
Family income	37152.48	(31418.82)
Mother only	0.07	(0.3)
Father only	0.14	(0.1)
School Variables		
Urban	0.20	(0.4)
Rural	0.41	(0.5)
Northeast	0.15	(0.4)
North central	0.33	(0.5)
West	0.17	(0.4)
School size	1188.29	(689.1)
Percent 10th graders white	76.44	(29.1)
Percent school graduates who attend four-year college	39.92	(18.6)
Percent teachers with M.A. at school	50.24	(22.5)
Percent school from single-parent families	28.79	(16.2)
Teacher Characteristic Variables		
Female teacher	0.46	(0.5)
Black teacher	0.04	(0.2)
Hispanic teacher	0.02	(0.1)
Asian teacher	0.01	(0.1)
Teacher years experience at secondary level	15.50	(9.0)
Teacher is certified	0.96	(0.2)
Teacher certified in math	0.94	(0.2)
Teacher has B.A.	0.77	(0.4)
Teacher has B.A. major in math	0.52	(0.4)
Teacher has M.A. or more	0.50	(0.5)
Teacher has M.A. major in math	0.17	(0.4)
Teacher Behavior Variables		
Teacher feels very well prepared	0.72	(0.4)
Teacher has no control over discipline	0.04	(0.2)
Teacher has no control over technique	0.01	(0.1)
Teacher has no control over context	0.19	(0.4)
Percent teacher time instructing small groups	11.23	(12.6)
Percent teacher time instructing individuals	18.00	(16.4)
Percent teacher time maintaining order	8.39	(14.9)
Percent teacher time doing administrative tasks	5.52	(6.4)
Teacher uses oral questions frequently	0.75	(0.4)
Teacher emphasizes problem solving	0.24	(0.4)
Class Variables		
Student class size	23.37	(7.0)
Percent minority students in class	20.38	(28.4)
Sample Size	5149	

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