The Contribution of Family, School and Community Characteristics to Inequality in Education and Labor Market Outcomes

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Abstract

This paper examines the impact of high school quality on three subsequent outcomes of concern to economists and policymakers: high school graduation, college enrollment, and adult wages. We isolate the causal impact of school/neighborhood combinations from student sorting among schools by exploiting panel data from three national longitudinal surveys. We decompose each of our three outcomes into the within- and between-school contributions of both observed and unobserved student and family characteristics, as well as the contributions of observed and unobserved school and neighborhood variables that vary only across schools. Instead of attempting to disentangle school averages of individual-level unobservable inputs from school-level unobservable inputs, we estimate upper and lower bounds on the contribution of school quality to student outcomes. On the one hand, the vast majority of the variation in students' outcomes can be attributed to some combination of student inputs, parent inputs, and quality of schooling prior to high school. On the other hand, the small fraction of the variance attributable to differences in school quality translates into substantial impacts on high school graduation and college enrollment, since large numbers of students seem to be near the decision margin. Our lower bound estimates of the average increase in the probability of graduation from moving a student from a school at the 10th percentile of the quality distribution to a school at the 90th percentile range from .06 to .13, with the corresponding lower bound estimates for college enrollment ranging from .14 to .23. The upper bound estimates are a few points higher. We also find a substantial effect of schools on adult wage rates. Finally, we find that the impact of attending a high quality school on college enrollment increased between 1972 and 1988, but remained stable between 1988 and 2000.

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1 Introduction

Parents agonize over which school and which community will be best for their children. To alleviate their concerns, a number of state and federal policies have aimed to close, reform, and provide alternatives to "failing" schools. These include expansion of school choice within and across school districts, charter school programs, and the grading and punishing of schools prescribed by the No Child Left Behind Act of 2001. At the neighborhood level, federal, state, and local programs to replace large public housing projects with Section 8 vouchers that can be used anywhere attempt to ensure more equal access to high-quality schools and supportive communities, and are motivated in part by the belief that concentrations of poverty harm children.[1] But how much difference do schools and communities make?

Although there is a large literature examining the impact of school, family, community, and peer inputs on test scores and delinquency measures,[2] less is known about their effects on later outcomes of arguably greater concern: high school completion, college attendance, and permanent wage rates.[3] How segregated are schools in terms of the student background characteristics that predict these outcomes? How much of the impact parents have on their child's outcomes is independent of the school? How much occurs indirectly via their choice of the child's community, school, and peer environment? How much do the differences between schools and communities matter for educational attainment and wages? For what types of students do they matter the most? Has the distribution of inputs and outcomes become more or less equitable over time?

The answers to these questions have important policy implications. On the one hand, suppose parental characteristics predict child outcomes primarily because they predict the quality of the schools their children attend. In this case, interventions to provide some children with a supportive family environment will not result in major aggregate education or wage gains, since to the extent that these children benefit, they do so by taking spots at more effective schools from other students (unless the better schools have room to grow). Finding ways to improve schools would have a big payoff in this context. On the other hand, suppose that most of the impact of family environment on child outcomes stems from enhancing child behavior, raising child expectations, or directly fostering intellectual development, and that the school a child attends predicts his or her eventual outcomes primarily because it provides information about the child's probable family environment. Then, school-level interventions such as changes in administrative personnel or class sizes are unlikely to improve child outcomes.[4]

[1] See Kling et al. (2007) and Oreopoulus (2003) for evidence and references to the literature.

[2] Hanushek et al. (2003), Hoxby (2000) and Goldhaber and Brewer (1997) are just a few examples. Coleman (1966) is a landmark study in this literature.

[3] Speakman and Welch (2006) survey the literature on school quality and wages. Examples include Card and Krueger (1992), Betts (1995), and Dearden, Ferri, and Meghir (2002).

[4] Of course, finding that school-level characteristics do not explain variation in student outcomes (conditional on

Knowing how the distribution of inputs and outcomes has changed over time would allow us to characterize how the system that matches students and parents to schools has been evolving.

To address these questions, we use three rich panel data sets, each of which gathers samples of students from each of a large number of schools and, importantly, tracks outcomes for several years past high school. The National Longitudinal Study of the High School Class of 1972 (NLS72) follows 12th graders in 1972. The National Educational Longitudinal Study: 1988 (NELS88) starts with eighth graders in 1988. The Educational Longitudinal Study: 2002 (ELS02) tracks students who were in 10th grade in 2002. The outcomes considered are high school graduation (in NELS88 and ELS02), enrollment in a four-year college (in all three datasets), years of completed postsecondary education (NLS72 only), and adult wages (NLS72 only). We standardize the set of variables used across the three datasets so that we can examine trends in the relative importance of observable versus unobservable inputs.

Following a number of previous studies,[5] we exploit the fact that the samples are clustered at the school level to decompose the variance in outcomes into the contributions of observed and unobserved student and family characteristics that vary both within and across schools, and observed and unobserved school and neighborhood variables that vary only across schools. We use variation within schools to estimate the direct effect of observed student and family characteristics (such as race or parental education) on the outcomes of students, controlling for the high school and associated community characteristics. These within-school estimates imply that some of the across school variation in outcomes reflects student sorting that is unrelated to school quality. We then use the remaining across school variation to identify the effects of peer characteristics and other school and community characteristics, such as the student/teacher ratio. We use these estimates to calculate approximate bounds on the average effect on educational attainment and wage rates of switching a child from a school and associated community that is at roughly the 10th percentile of the "quality" distribution to one at the 50th or 90th percentile, holding student-specific characteristics fixed.

Although we employ a rich set of family, student, and school and community characteristics in our models, we do not claim to identify the causal effects of particular variables. Instead, we focus on providing an overall assessment of the extent to which students with common observed or unobserved characteristics cluster in the same high schools, and the degree to which disparities in average educational outcomes simply reflect such clustering, as opposed to the causal effects of high school and associated community factors. To characterize such student sorting, we use the

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the direct effect of student-level characteristics) would not imply that schools are unimportant, or that some potential school interventions might not still be successful. It would, however, suggest that the current disparities in school characteristics are not driving the outcome gaps we observe, so that attempts to mitigate these disparities are unlikely to bear fruit. Instead, school-level interventions would need to focus on changing features of schools that are currently common to all schools.

[5] Jencks and Brown (1975), Altonji (1988), and Bryk and Raudenbush (1988) are early examples.

relationship between individual student characteristics and outcomes to aggregate the characteristics into a single index, and we show how the average value of this index varies across schools.

While caution is warranted for reasons detailed in the paper, our main results can be summarized as follows. First, sorting of students with different backgrounds across schools can explain much of the disparity in outcomes between schools that we observe, even before accounting for peer effects and the impact of family background on school quality. In line with this observation, we find that even our upper bound estimate of the variance in school/neighborhood quality accounts for only a small fraction of the variation in educational attainment and wages. However, the size of this fraction is misleading, since it is large enough for a move from a low quality school to a high quality school to have a substantial impact on these outcomes. For example, for students who make it to 10th grade, the lower bound estimates of the effect on the probability of graduating high school of switching from a school at the 10th percentile in quality to one at the 90th percentile range between .064 and .083 depending on the specification and dataset. The effects on the probability of college enrollment range between .142 and .227. The upper bound estimates are significantly larger. Many students seem to be near the decision margin. Indeed, because some subgroups have a disproportionate fraction of students at the decision margin, the sensitivity of high school graduation and college attendance to school quality differs across subgroups. For example, our lower bound estimates indicate that the same 10th to 90th percentile shift in school quality would increase the probability of high school graduation among students at the 10th quantile of our background index by between .135 and .224, but only by between .012 and .041 for students at the 90th quantile.

The paper continues in Section 2, where we provide a simple model of educational attainment and wages. We use the model to help interpret the econometric evidence we present below, taking into account data limitations. Section 3 describes how we estimate the coefficients on student level variables and school/community variables that are required for the variance decompositions. Section 4 contains our methods for variance decomposition. Section 5 discusses the data sets. In Section 6 we present evidence regarding the extent of student sorting across schools on the basis of the student and parent characteristics that best predict our outcomes. Section 7 contains our educational attainment and wage decompositions, while Section 8 presents our estimates of the impact of shifts in school quality on student outcomes. Section 9 considers differential effects of school quality for various subgroups. We close with a discussion of our results and a research agenda.

2 A Model of Educational Attainment and Wage Rates

2.1 The Determinants of Adult Outcomes

In this section we present the underlying econometric model of adult outcomes that provides the basis for the variance decompositions that we present below. Our formulation draws loosely on theoretical discussions in the child development literature, the educational production function literature, and the neighborhood effects literature.[6] Let Y_{si} denote the outcome of student i from high school s. In our application the outcomess are high school graduation, attendance at a four-year college, a measure of years of postsecondary education, and the permanent wage rate. Y_{si} is determined according to

$$Y_{si} = X^*_{si}B' + Z^*_{si}G' + u_{Ysi'} \tag{1}$$

The vector X^*_{si} is a comprehensive set of child and family characteristics that have a causal impact on student i's educational attainment and wages. Examples include race, innate ability, personality traits, values, physical attractiveness, and parental education, income, and employment. The variable $u_{Ysi'}$ captures other influences on student i's outcome that are determined after secondary school. The vector Z^*_{si} is an exhaustive set of school and neighborhood influences experienced by student i, where s denotes the neighborhood and associated school that the parents of student i choose for the high school years. Z^*_{si} is partly determined by the family's choice of a neighborhood and school s, which is characterized by a set of features Z^*_s that shapes the environment the child experiences outside the home, including neighborhood quality, school resources, and peers inside and outside of school. However, Z^*_{si}, also varies within a school attendance area and within a school itself. Examples include the trustworthiness of immediate neighbors and distinct course tracks at a school. Some of the within-school variation is related to parent and child characteristics. Some reflects random influences, such as random variation in the quality of teaching the child receives and random variation in peer influences. The coefficients B' and G' depend implicitly upon the specific outcome under consideration as well as the time period in the case of wages.

Suppose we had access to data at a single point in time on each of the myriad components of X^*_{si} and Z^*_{si} and were able to estimate equation 1. How would we interpret B'? One must first realize that some components of X^*_{si} associated with student inputs (for example, student aptitude) are determined in part by parental inputs from earlier periods (for example, parent income), as well as school and neighborhood inputs from earlier periods (for example, quality of elementary school facilities). Likewise, parents' income may in part be determined by student aptitude and behavior, if parents work less in order to tutor their child. Such links make it difficult to interpret the coefficient associated with a given component of X^*_{si}, since once we have conditioned on the other components, we have removed many of the avenues through which the component determines Y. Consequently, we do not make any attempt to interpret individual components of the coefficient vector B', and thus do not attempt to tease apart the distinct influences of child characteristics, family characteristics, and early childhood schooling inputs, respectively. We aim instead to separate

[6] A good example is Todd and Wolpin (2003), who provide references to the literature. See also Cunha et al. (2006).

the effects of high schools and associated community influences on outcomes from student, family, and prior school/community factors (although some of our specifications using data from NELS88 examine the impact on outcomes of 8th grade schools rather than high schools). If the inequalities in outcomes are primarily attributable to differences in high school quality (as opposed to the other three classes of inputs), then policies designed to equalize high school quality have the potential to close the outcome gaps we observe.

2.2 Toward an Empirical Model

In practice, we actually observe and make use of only a subset of the elements of X_{si}^* and Z_{si}^*. For example, there are many characteristics of the student (e.g., physical attractiveness and temperament) and parents (e.g., parenting skill and time allocation during early childhood) that we do not measure at all. Furthermore, we only measure child and family variables at a single point in time, rather than at various stages of the child's life. Finally, our measures of external influences are common to all students attending a particular high school. Given the data limitations, the model we actually estimate may be written as

$$(2) \qquad Y_{si} = X_{si}B + Z_sG + m_s + v_s + v_{si} \ .$$

In (2), X_{si} is a set of observable student and family characteristics. It represents a subset of X_{si}^*. The error component $v_s + v_{si}$ reflects student and family influences that are unrelated to X_{si}. The component v_s is the mean at high school s of unobserved student-level characteristics that affect the outcome, while v_{si} reflects student-specific variation around the mean. The term v_{si} also captures variation among students who attend the same school in environmental influences $(Z_{si}^* - Z_s^*)$ that are unrelated to X_{si}. For the postsecondary outcomes v_{si} also contains $u_{Ysi'}$. Importantly, $X_{si}B + v_s + v_{si}$ affects the outcome of student i regardless of the average characteristics of the school/neighborhood the student attends. The coefficients B and G are *defined* so that the student-specific error term $v_s + v_{si}$ is uncorrelated with X_{si} and Z_s. More specifically, B is defined as the coefficient of the projection of Y_{si} on X_{si}, holding Z_s, v_s and m_s constant. Likewise, G is defined by the projection of Y_{si} on Z_s, after using B to remove the impact of differences in X_{si}. The term $Z_sG + m_s$ captures school and neighborhood influences that are common to students who attend school s. Z_s is an observable subset of Z_s^*, which are means at high school s of the relevant school inputs received by student i in equation 1, Z_{si}^*. In practice, Z_s is comprised of two components: school-level averages of the individual observable characteristics X_{si} (e.g. average parent income), and school/neighborhood level inputs that do not have a student-level analog (e.g. student-teacher ratio or city-size indicators). The definitions of B and G above also ensure that the unobserved component m_s is uncorrelated with Z_s. Thus, the component m_s is an index of unobserved school and community characteristics that influence the outcomes of students who attend school s, but are unrelated to Z_s. These include the school mean of relevant unobserved peer characteristics as well as the component of the quality of the school principal and teachers that is unpredictable based on Z_s. Note that m_s also depends on the determinants of v_s to the extent that characteristics of peers matter directly or influence unobserved school and community quality. It is likely that v_s and m_s will be positively correlated. However, if governments attempt to counteract the effect of v_s when allocating resources across school districts, m_s and v_s could be negatively correlated.

2.3 Interpretation of B and G

The coefficient vector B is comprised of two components. The first is made up of the causal effects of X_{si} as well as part of the effects of omitted elements of X^*_{si}, to the extent that these observed and unobserved characteristics co-vary within a school. Given that B reflects in part the direct effects of both observed and unobserved characteristics, a student's value of $X_{si}B$ provides a useful summary of the impact of his/her background and prior schooling on the outcome. Furthermore, removing the average value of $X_{si}B$ at each school (denoted X_sB) when comparing average school outcomes allows us to better isolate differences in the quality of the high schools themselves. Since $X_{si}B$ does not fully capture $X^*_{si}B$, the residual differences in school outcome means $(Y_s - X_sB)$ will still reflect (via v_s) differences in background characteristics and prior school quality of student populations which are impervious to high school-level interventions, in addition to true differences in the school's ability to change student outcomes (via Z_s and m_s). The second component of B is an indirect effect. It corresponds to the influence of X_{si} and the other elements of X^*_{si} on the external environment Z^*_{si}, conditional on the child's school/community. The magnitude of this component is determined by the extent to which differences in the micro environment of the student within a school or school neighborhood $(Z^*_{si} - Z^*_s)$ are predictable based on variables such as race, gender, parental education, student aptitude and achievement, etc., that are part of X_{si}. Consequently, the links will depend on how families in general and students in particular are stratified within communities and high schools. They also depend to some degree on policies such as zoning, housing policy, and tracking that were in place at the time.

To observe more clearly the impact of student sorting into micro environments within schools on the estimates of B and G, suppose that the sub-environments that each student experienced, $Z^*_{si} - Z^*_s$, were observable. Then, define v^{Z*}_{si} as the residual from the projection of Y_{si} on X_{si}, when $Z^*_{si} - Z^*_s$ is held constant in addition to Z_s, m_s, and v_s, so that the empirical model in (2) can be rewritten as:

$$Y_{si} = X_{si}B^{Z^*} + (Z^*_{si} - Z^*_s)G' + Z_sG^{Z^*} + m_s + v_s + v^{Z^*}_{si} \quad . \tag{3}$$

Let the projection of $Z^*_{si} - Z^*_s$ on X_{si} and Z_s be captured by:[7]

$$
\begin{aligned}
Z^*_{si} - Z^*_s &= \delta_0 + X_{si}\delta_1 + Z_{s1}\delta_2 + Z_{s2}\delta_3 + \tilde{Z}^*_{si} \\
&= \delta_0 + X_{si}\delta_1 + Z_{s1}(-\delta_1) + \tilde{Z}^*_{si} \qquad (4)
\end{aligned}
$$

Under this version of the model, when Y_{si} is regressed on only X_{si} and Z_s, with $Z^*_{si} - Z^*_s$ omitted (equation 2 above), the estimated coefficients can be written as:

$$B = B^{Z^*} + \delta_1 G' \qquad (5)$$

$$G_1 = G_1^{Z^*} + \delta_2 G' = G_1 - \delta_1 G' \qquad (6)$$

$$G_2 = G_2^{Z^*} + \delta_3 G' = G_2 \qquad (7)$$

$$v_{si} = v_{si}^{Z^*} + \tilde{Z}^*_{si} \qquad (8)$$

One can make a case for assigning to the student heterogenous environmental influences that are driven by variation within a school in student/family characteristics ($\delta_1 G'$), since similar within-school sorting would be likely to arise if the student were moved to another randomly chosen school/community. However, the presence of $\delta_1 G'$ in B implies that $X_s\hat{B}$ is biased upward as an estimator of the importance of differences *between* schools in the index of average student characteristics $X_s B^{Z^*}$.

Analogously, G has two components. The first, represented by G^{Z^*}, reflects the direct influence of the elements of Z_s on Y, along with part of the effect of other elements of Z^*_s that we do not control for. The second component, $-\delta_1 G'$, reflects the part of the between-school variation in Y that has been incorrectly attributed to B due to the correlation between a student's observable characteristics and the characteristics of the external sub-environment he experiences. Thus, $Z_s\hat{G}$ is biased downward as an estimator of the importance of school and neighborhood observable characteristics ($Z_s G^{Z^*}$).

As with $X_{si}B$, our aim is not to interpret individual elements of G, but to capture the collective impact of a number of school/community characteristics, so as to avoid attributing this variation to differences in student background, and to give an overall sense of how much of the differences in school performance are predictable based on school characteristics. Of course, gaps in performances across schools may be difficult to close even if they are predictable, and some of these characteristics may be beyond the school's control (for example, crime in the neighborhood).

Finally, note that v_{si} will include not only $v_{si}^{Z^*}$ but also the component of $Z^*_{si} - Z^*_s$ that cannot be predicted based on observable student or school level characteristics ($\tilde{Z}^*_{si}$).

[7]Since $Z^*_{si} - Z^*_s$ only captures within-school variation in students' external environments, both Z_{s1} and Z_{s2} are unconditionally independent of $Z^*_{si} - Z^*_s$. However, when both X_{si} and Z_1 are included in the projection, δ_1 will take on values such that $(X_{si} - X_s)\delta_1$ best fits $Z^*_{si} - Z^*_s$, and δ_2 will take on values so that $Z_{s1}\delta_2$ offsets the school-level overprediction from $X_s\delta_1$. Since X_s and Z_{s1} are identical, the overprediction is fully offset ($\delta_2 = -\delta_1$), leaving no remaining between-school variation in $Z^*_{si} - Z^*_s$ for Z_{s2} to explain ($\delta_3 = 0$). See Altonji-Mansfield-(Taber?) (2011) for details.

In section 10, we attempt to quantify the magnitude of these biases by using administrative data from North Carolina that includes students' classroom assignments. The estimates we obtain suggest that the bias introduced by student sorting into micro-environments are non-trivial but too small to substantially change the qualitative patterns we report. A more complete model of student sorting and its implications for variance decomposition is contained in Altonji, Mansfield and Taber (2011).

3 Estimation of Model Parameters

In this section we discuss estimation of the coefficients B and G. The estimation strategy depends on the outcome, so we consider the outcomes in turn.

3.1 Years of Postsecondary Academic Education

Parameter estimation is most straightforward in the case of years of postsecondary academic education. We estimate B using ordinary least squares regression with high school fixed effects, which controls for all observed and unobserved school and neighborhood influences.

Recall that Z_s is comprised of two components: $Z_s = [Z_s^1; Z_s^2]$. Z_s^2 consists of school and neighborhood characteristics for which direct measures are available, such as student/teacher ratio, city size, and school type. Z_s^1 consists of school wide averages for each variable in X_{si}, such as parental education or income, which we do not observe directly but must estimate from sample members at each school. Consequently, the makeup of Z_s^1 differs across specifications that use different X vectors. G_1 and G_2 are the corresponding subsets of the coefficients in G.

We replace Z_s^1 with $\bar{Z}_s^1$, where $\bar{Z}_s^1$ is the average of X_{si} computed over all available students from the school.[8] We estimate G by applying least squares regression to

$$Y_{si} - X_{si}\hat{B} = [\overline{Z}_s^1 G_1 + Z_s^2 G_2] \equiv \overline{Z}_s G + e_{si}$$

using the appropriate panel weights from the surveys.

Measurement error in $\bar{Z}_s^1$ as an estimate of Z_s^1 will tend to produce downward bias in the absolute value of the coefficients that make up G_1, although the bias will vary across variables and may be positive in absolute value for some.[9] As we explain in Section 3 of the Appendix, the effect of downward bias in $\hat{G}$ on $\widehat{Var}(\bar{Z}_s\hat{G})$ is partially offset by upward bias in $Var(\bar{Z}_s)$ as an estimator of

[8] A substantial number of persons who appear in the base year of the surveys can be used to construct $\bar{Z}_s^1$ but cannot be used to estimate (3.1) because some variables, such as test scores, are missing, or because the students are not included in the follow-up surveys that provide the measure of Y_{si}. As we discuss in the data section, we impute missing values for most of our explanatory variables prior to estimating B and G, but we do not use the imputed values when constructing the school averages.

[9] We also experimented with the use of two instrumental variables procedures to estimate G, drawing on the discussion in Deaton (1985) and Devereux (2007). Devereux refers to the two estimators as EVIV and UEVE. They yielded extremely noisy estimates of G. We suspect that these estimators are poorly suited to problems that involve large numbers of endogenous variables and instrumental variables, such as ours.

$Var(Z_s)$. The understatement of $Var(Z_sG)$ will be balanced by overstatement of $Var(v_s + m_s)$, so that our upper bound estimates of the impact of school quality will not be affected (see Section 4).

3.2 Permanent Wage Rates

Abstracting from the effects of labor market experience and a time trend, let the log wage W_{sit} of individual i, from school s, at time t be governed by

$$W_{sit} = W_{si} + e_{sit} + \xi_{sit}.$$

In the above equation W_{si} is i's "permanent" log wage (given that he/she attended high school s) as of the time by which most students have completed education and spent at least a couple of years in the labor market, which we take to be 1979 in the case of NLS72. Consequently, W_{si} includes the 1979 value of e_{sit}, a random walk component that reflects the influences of school, family, and neighborhood up to the time that the individual leaves school but evolves as a result of luck in the job search process or within a company, and changes in motivation or productivity due to health and other factors. Given this normalization, e_{sit} is 0 in 1979.[10] ξ_{sit} includes measurement error and relatively short term factors that have little influence on the lifetime earnings of an individual. The permanent wage is given by (2) with Y_{si} defined to be W_{si}. After substituting for W_{si}, the wage equation is

$$W_{sit} = X_{si}B + Z_sG + m_s + v_s + v_{si} + e_{sit} + \xi_{sit}.$$

We estimate B by OLS with school fixed effects included.[11]

Let $\tilde{W}_{sit} \equiv W_{sit} - X_{si}\hat{B}$. We estimate G by applying OLS to

$$\tilde{W}_{sit} = \bar{Z}_sG + m_s + v_s + v_{si} + e_{sit} + \xi_{sit} \qquad (9)$$

The presence of ξ_{sit} complicates the variance decompositions, as we discuss below.

3.3 High School Graduation and College Enrollment

The methods outlined in Sections 3.1 need to be adapted for binary measures such as high school graduation and college attendance. Consequently, for high school graduation we reinterpret Y_{si} to be the latent variable that determines the indicator for whether a student graduates, $HSGRAD_{si}$.

[10] We include e_{sit} as well as ξ_{it} because the earnings dynamics literature typically finds evidence of a highly persistent wage component. Several studies cannot reject the hypothesis that e_{sit} is a random walk. Recent examples include Baker and Solon (2003), Haider (2001), and Meghir and Pistaferri (2004).

[11] In reality, we also include a vector T_{it} consisting of a dummy indicator for the year 1979 (relative to 1986), years of work experience of i at time t, and experience squared. Let Ψ be the corresponding vector of wage coefficients. We adjust wages for differences in labor market experience and for whether the data are from 1979 or 1986 by subtracting $T_{it}\hat{\Psi}$ from the wage prior to performing the variance decompositions. The estimate of $\hat{\Psi}$ depends on whether tests, postsecondary education, or both are in X_{si}. We report results with and without these variables. In our main specification, we exclude postsecondary education from X_{si}.

That is,

$$HSGRAD_{si} = 1(Y_{si} > 0).$$

Or, after substituting for Y_{si},

$$(10) \qquad HSGRAD_{si} = 1(X_{si}B + Z_sG + m_s + v_s + v_{si} > 0)$$

We replace Z_s with $\bar{Z}_s$ and estimate the equation

$$(11) \qquad HSGRAD_{si} = 1(X_{si}B + \bar{Z}_sG + (Z_s - \bar{Z}_s)G + m_s + v_s + v_{si} > 0)$$

using maximum likelihood probit. Measurement error in $\bar{Z}_s$ as a measure of Z_s will lead to downward bias in G, as was the case with estimation of G using (3.1).[12] The underestimate of $Var(Z_sG)$ will be offset by an overstatement of $Var(v_s + m_s)$. The procedure for enrollment in a four-year college is analogous to that of high school graduation.

4 Decomposing the Variance in Educational Attainment and Wages

In this section we discuss an analysis of variance based on equation (2) that can be used to measure the importance of factors that are common to students from the same school.[13] Intuitively, the overall importance of differences in schools and associated communities is determined by comparing how much more alike the outcomes of those who attended the same school are than the outcomes of individuals with the same characteristics who attended different schools.[14] We also consider estimation of the effect of a shift in school and community quality from the tenth to the ninetieth percentile of its distribution. As with parameter estimation, the details of our procedure depend upon the outcome. We begin with years of postsecondary education.

4.1 Years of Postsecondary Education

One may decompose $Var(Y_{si})$ into its within and between school components

$$Var(Y_{si}) = Var(Y_{si} - Y_s) + Var(Y_s)$$

where $(Y_{si} - Y_s)$ is the part of Y_{si} that varies across students in school s and Y_s is the average outcome for students from s. We focus much of our attention on the ratio $\widehat{Var}(Y_s)/\ \widehat{Var}(Y_{si})$, which is the fraction of the total variance that is across schools ("hats" denote estimates). This ratio is also

[12] To a first approximation, the downward bias in G will not affect B even though we are not using the school fixed effects estimator here. By analogy to linear regression, B is largely identified by variation in X_{si} that is orthogonal to the components of $\bar{Z}_s$ that correspond to the sample means of X_{si} for each high school. The component $(Z_s - \bar{Z}_s)G$ contributes to the fraction of the between-school variance that is due to unobserved factors. We are assuming that the composite error term is approximately normally distributed.

[13] Jencks and Brown (1975) propose and implement a similar decomposition.

[14] We include private schools because they are very much a part of the education landscape. However, the connection between characteristics of the school and characteristics of the neighborhood may be weaker for private school students.

known as the "intraclass correlation", where the class is the school. We estimate $Var(Y_{si} - Y_s)$ by using the sample variances of $Var(Y_{si} - \overline{Y}_s)$ with an appropriate correction for degrees of freedom lost in using the sample mean $\overline{Y}_s$ in place of Y_s. Then $Var(Y_s)$ can be estimated as

$$\widehat{Var}(Y_s) = \widehat{Var}(Y_{si}) - \widehat{Var}(Y_{si} - Y_s).$$

Then, from (2),

$$(Y_{si} - Y_s) = (X_{si} - X_s)B + v_{si}$$

and

$$Y_s = X_s B + Z_s G + m_s + v_s \ .$$

Thus, one may express the outcome variance as[15]

$$\begin{aligned} Var(Y_{si}) &= Var((X_{si} - X_s)B + v_{si}) + Var(X_s B + Z_s G + m_s + v_s) \\ &= Var((X_{si} - X_s)B) + Var(v_{si}) + Var(X_s B) + 2Cov(X_s B, Z_s G) + Var(Z_s G) + Var(m_s + v_s) \end{aligned}$$

Given an estimate of B, $Var((X_{si} - X_s)B)$ can be estimated using its corresponding sample variance, $Var((X_{si} - \overline{X}_s)B)$. $Var(v_{si})$ can then be estimated as $\widehat{Var}(Y_{si} - Y_s) - \widehat{Var}((X_{si} - X_s)B)$, and $Var(X_s B)$ can be calculated as $\widehat{Var}(X_{si}B) - \widehat{Var}((X_{si} - X_s)B)$. One can also estimate the component $Var(Z_s G)$ of the school/community contribution and the common term $2Cov(X_s B, Z_s G)$ using the estimates of B and G and the data $\bar{X}_s$ and $\bar{Z}_s$. $Var(m_s + v_s)$ can be calculated as

$$\widehat{Var}(m_s + v_s) = \widehat{Var}(Y_s) - \widehat{Var}(X_s B) - \widehat{Var}(Z_s G) - 2\widehat{Cov}(X_s B, Z_s G)$$

However, $Var(v_s)$ is not identified separately from $Var(m_s)$ and $Cov(m_s, v_s)$ without further assumptions.

Note that $Var(Y_s)$ includes $Var(X_s B) + Var(v_s)$ even though these components do not represent the influence of student body composition or other aspects of a particular high school and community. Rather, they simply reflect the fact that average outcomes will vary across high schools if average characteristics of the students in the high schools vary. Consequently, they should not be counted as neighborhood/school influences. It is unclear whether one should attribute the two covariance terms to the contribution of individual characteristics or to high school and community level factors. Given this ambiguity and the fact that we cannot distinguish the contribution of m_s from that of v_s, we define an "upper bound" estimate of the fraction of the variance attributable to high school and community factors as $Var(Z_s G) + Var(m_s + v_s) + 2Cov(X_s B, Z_s G)$. Our "lower bound" estimate is just $Var(Z_s G)$.[16]

[15] The equation below imposes $Cov(X_{si}B, v_{si}) = 0$, which is implied by our definition of B and v_{si}. The equation also assumes $Cov(Z_s, m_s + v_s) = 0$, which is implied by our definition of G and $m_s + v_s$. We do not need to separately consider $Cov(X_s B, m_s + v_s)$ because the elements of X_s are included in Z_s, and so $Cov(X_s B, m_s + v_s)$ is also 0.

[16] Quotation marks are used for "Upper Bound" and "Lower Bound" because they may not represent true inviolable

4.2 Permanent Wage Rates

We focus on decomposing the permanent wage component W_{si}. We take advantage of the existence of panel data on wages in NLS72 and work with a balanced sample of individuals who report wages in both 1979 and 1986 (the fourth and fifth follow-ups, respectively). We estimate the variance in the permanent component of the wage, $Var(W_{si})$, using the covariance between wage observations from the same individual in different years

$$\begin{aligned} Cov(W_{sit}, W_{sit'}) &= Cov(W_{si} + e_{sit} + \xi_{sit}, W_{si} + e_{sit'} + \xi_{sit'}) \\ &= Var(W_{si}), \end{aligned}$$

where $Cov(\xi_{sit}, \xi_{sit'})$ is assumed to be 0 given that the observations are seven years apart and $Cov(e_{sit}, e_{sit'}) = 0$ from normalizing e_{sit} to be 0 in 1979. We use the sample estimate of $Cov(W_{sit}, W_{sit'})$ as our estimate of $Var(W_{si})$. We estimate this covariance by subtracting out the global mean for W_{sit}, calculating the wage product $(W_{sit})(W_{sit'})$ for each individual, and taking a weighted average across all the individuals in the sample using the weights discussed in Section 2 of the Appendix, adjusting for degrees of freedom. Similarly, we estimate the between-school component of the permanent wage, $Var(W_s)$, by estimating the covariance between wage observations for different years (1979 and 1986) from different individuals from the same school. Specifically, we use the moment condition

$$\begin{aligned} Cov(W_{sit}, W_{sjt'}) &= Cov(W_{si} + e_{sit} + \xi_{sit}, W_{sj} + e_{sjt'} + \xi_{sjt'}),\ i \neq j, t \neq t' \\ &= Var(W_s), \end{aligned}$$

where $Cov(e_{sit}, e_{sjt'})$ is defined to be 0, and $Cov(\xi_{sit}, \xi_{sjt'})$ is assumed to be 0. We estimate this covariance by first calculating $((W_{sit}W_{sjt'}) + (W_{sit'}W_{sjt}))/2$ for each pair of individuals i and j at school s and then computing the weighted mean for each school s. We then average across schools, weighting each school by the sum of the weights of the individuals who contributed to the school-specific estimate.

We estimate the corresponding within school component using

$$\widehat{Var}(W_{si} - W_s) = \widehat{Var}(W_{si}) - \widehat{Var}(W_s).$$

Given $\widehat{Var}(W_{si})$, $\widehat{Var}(W_{si} - W_s)$, $\widehat{Var}(W_s)$, $\hat{G}$, and $\hat{B}$, estimation of the contributions of $X_{si}B$, Z_sG, v_{si}, m_s and v_s to $Var(W_{si})$ proceeds as in Section 4.1.

bounds. First, $Var(X_sB)$ may be overstated due to correlation between X_{si} and $Z^*_{si} - Z^*_s$, thus causing an underestimate of $Var(Z_sG) + Var(v_s + m_s) + 2Cov(X_sB, Z_sG)$. Second, $Var(Z_sG)$ may be overstated if G partly reflects unobserved average student characteristics among X^*_{si} that are unpredictable based on X_{si} and correlated with Z_s, although this will be offset in our upper bound estimate by an increase in $Var(m_s + v_s)$. Third, measurement error in our proxies for some elements of Z_s may lead to downward bias in $Var(Z_sG)$, although this will also be offset in our upper bound estimate by an increase in $Var(m_s + v_s)$.

4.3 High School Graduation and College Enrollment

For both of our binary outcomes, high school graduation and enrollment in a four-year college, we decompose the latent variable that determines the outcome. Given that there is no natural scale to the variance of the latent variable, we normalize $Var(v_{si})$ to one, and define the total variance of the latent variable to be

$$Var(Y_{si}) = \widehat{Var}(X_s B) + \widehat{Var}(Z_s G) + \widehat{Cov}(X_s B, Z_s G) + \widehat{Var}(m_s + v_s) + 1$$

Given that the raw variance component estimates are subject to the choice of normalization, we instead report fractions of the variance contributed by the various components.

4.4 Measuring the Effects of Shifts in School/Community Quality

The variance decompositions provide a good indication of the importance of school/community factors relative to student-specific factors. However, the effect of a shift in school/community quality from the left tail of the distribution to the right tail of the distribution might be socially significant even if most of the outcome variability is student-specific. This is particularly true in the case of binary outcomes such as high school graduation and college enrollment. Below we report upper and lower bound estimates of the effect of a shift in $Z_s\hat{G} + m_s$ from 1.28 standard deviations below the mean to 1.28 standard deviations above the mean. This would correspond to a shift from the 10th percentile to the 90th percentile if $Z_s\hat{G} + m_s$ has a normal distribution. The lower bound estimates set $Var(m_s)$ to 0 and $Var(v_s)$ to $\widehat{Var}(m_s+v_s)$ and the upper bound estimates set $Var(m_s)$ to $\widehat{Var}(m_s + v_s)$ and $Var(v_s)$ to 0.[17] That is, the upper bound attributes all of the variance of the unobserved factors that vary at the school level to school/community factors rather than to differences in the average unobserved characteristics of the students and their families. The lower bound does the opposite. We also report lower and upper bound estimates of the impact of a shift from a school at the 10th percentile to one at the 50th percentile of the distribution of $Z_s\hat{G} + m_s$.

For the binary outcomes, the impact of a 10th-90th percentile shift in $Z_s\hat{G} + m_s$ will depend on the values of a student's observable characteristics, $X_{si}B$. Thus, we report average impacts for certain subpopulations of interest as well as for the full sample distribution of $X_{si}B$.

5 Data

Our analysis uses data from three distinct sources: NLS72, NELS88, and ELS02. These data sources possess a number of common properties that make them well suited for our analysis. First, each samples an entire cohort of American students. The cohorts are students who were 12th graders in 1972

[17] For the binary variables, we estimate the effect of the shift in $Z_s\hat{G} + m_s$ as a weighted average over individuals i of $\Phi([X_{si}\hat{B} + \bar{Z}\hat{G} + 1.28(Var(\bar{Z}_s\hat{G}) + Var(m_s))^{.5}]/(1 + Var(v_s))^{.5}) - \Phi([X_{si}\hat{B} + \bar{Z}\hat{G} - 1.28(Var(\bar{Z}_s\hat{G}) + Var(m_s))^{.5}]/(1 + Var(v_s))^{.5})$.

in the case of NLS72, 8th graders in 1988 for NELS88, and 10th graders in 2002 for ELS02. Second, each source provides a representative sample of American high schools or 8th grades and samples of students are selected within each school. Both public and private schools are represented. Enough students are sampled from each school to permit construction of estimates of the school means of a large array of student-specific variables and to provide sufficient within-school variation to support a between-/within-school variance decomposition. Third, each survey administered questionnaires to school administrators in addition to all sampled individuals at each school. This provides us with a rich set of both individual-level and school-level variables to examine, allowing a meaningful decomposition of observable versus unobservable variation at both levels of observation. Fourth, each survey collects follow-up information from each student past high school graduation, facilitating analysis of the impact of high school environment on two or more of the outcomes economists and policymakers care most about: the dropout decision, college enrollment and completion decisions, and wage profiles.

While these common properties are very helpful, each survey displays idiosyncratic features and questions that complicate efforts to compare results across time. We develop comparable measures for all of the variables in our baseline specification, restricting attention only to variables that are available and measured consistently across all three datasets. In addition, in the baseline specification we only use student-level characteristics that are unlikely to be affected by the high school the child attends. However, we also provide decompositions which include in X_{si} scores from standardized tests taken by students in high school as proxies for ability, in specifications labeled 'w/tests'. These scores may be influenced directly by high school inputs, so including them could cause an underestimate of the contribution of school-level inputs. On the other hand, excluding them could instead cause an overestimate of the contribution of school-level inputs, since we run the risk of understating the extent of ability differences among students who attend different schools.

Restricting our analysis to measures that are common across datasets, however, prevents us from exploiting the full power of these rich datasets to explain the distribution of an important set of outcomes. Thus, since NELS88 and ELS02 feature considerably greater overlap in survey questions, we also constructed a larger set of common variables for these two datasets, which we labeled our "full" specification. We include in the full specification measures of student behavior and parental expectations that, like test scores, are not clearly exogenous, but may allow us to more accurately characterize differences in the backgrounds of students attending different schools. Table 1 lists the final choices of individual-level and school-level explanatory measures used in each dataset. Appendix Tables 1, 3, 5, and 7 display summary statistics of each of the individual-level measures, including the within-school and between-school fractions of each variable's variance.[18] Since intraclass correlations

[18] Appendix Tables 2,4,6, and 8 display summary statistics of our school-level measures.

for binary variables are hard to interpret, we report the intraclass correlation for the latent variable that determines the binary variable.[19] The intraclass correlations provide an indication of the extent to which children with characteristics that are associated with greater educational attainment and higher wages are separated from disadvantaged children. Columns 5 and 6 of the tables report estimates of the school mean of the characteristic for a school whose mean places it at the 10th percentile and a school whose mean places it at the 90th percentile, respectively, under the assumption that school- and individual-specific components are approximately normally distributed.[20]

The outcome variables are defined as follows. $COLL$, the measure of college attendance, is an indicator for whether the student is enrolled in a four year college in the second year beyond the high school graduation year of his/her cohort. It is available in each dataset.[21] $HSGRAD$ is an indicator for whether a student has a high school diploma (not including a GED) as of two years after the high school graduation year of his/her cohort. Notice, though, that since ELS02 first surveys students in 10th grade, it misses a substantial fraction of the early dropouts. Indeed, in NELS88, about one third of the 16 percent who eventually drop out do so before the first follow up survey in the middle of 10th grade. Given that NLS72 first surveys students in 12th grade, we cannot properly examine dropout behavior in this dataset. However, because NLS72 re-surveys students in 1979 and 1986, when respondents are around 25 and 32 years old, respectively, it permits us to analyze completed years of postsecondary education and wages during adulthood. We use years of academic education as of 1979, because attrition and subsampling reduced the 1986 sample by a considerable amount relative to the 1979 follow-up survey, and most respondents have completed their education as of 1979. For the wage analysis, we include only respondents who report wages in both 1979 and 1986.

In each specification, we restrict our sample to those individuals whose school administrator filled

[19] Specifically, we assume that each variable j is determined by the model

$$X_{jsi} = 1(\mu_j + \varepsilon_{js} + \varepsilon_{jsi} > 0)$$

We normalize $Var(\varepsilon_{jsi})$ to 1 and estimate the intraclass correlation $\frac{Var(\varepsilon_{js})}{Var(\varepsilon_{js})+1}$, which is the fraction of the variance in the latent variable that determines X_{jsi} that is common to students from the same school. We estimate μ_j and $Var(\varepsilon_{js})$ by maximum likelihood under the assumption that the error terms are normally distributed. For a few of our variables, particularly race/ethnicity and immigrant status, the normality assumption for ε_{js} is probably invalid. Tipping models of racial/ethnic geographic sorting imply a bimodal distribution. See Card, Mas and Rothstein (2008).

[20] Using the notation of the previous footnote, for binary variables, the school mean at the 10th quantile is estimated as

$$\Phi(\Phi^{-1}(\hat{\mu}_j) * (1 + \widehat{Var}(\varepsilon_{js})^{.5}) - 1.28 * \widehat{Var}(\varepsilon_{js})^{.5}),$$

where Φ is the standard normal CDF. The estimate at the 90th quantile is

$$\Phi(\Phi^{-1}(\hat{\mu}_j) * (1 + \widehat{Var}(\varepsilon_{js})^{.5}) + 1.28 * \widehat{Var}(\varepsilon_{js})^{.5})$$

For continuous variables, the corresponding estimates are simply $\hat{\mu}_j - 1.28 * \widehat{Var}(\varepsilon_{js})^{.5}$ and $\hat{\mu}_j + 1.28 * \widehat{Var}(\varepsilon_{js})^{.5}$. If we had the population of students at each of our schools rather than samples, we would simply identify the 10th and 90th percentile values of the school means of each characteristic with appropriate weighting for school size and the probability that a school is included in the survey. We use our statistical procedure because we have only a few students per school.

[21] However, in NLS72 enrollment status is reported in January-March of the second full school year after graduation, while in NELS88 and ELS02 it is reported in October.

out a school survey, and who have non-missing information on the outcome variable and the following key characteristics: race, gender, SES, test scores, region, and urban/rural status. We then impute values for the other explanatory variables to preserve the sample size, since no one other variable is critical to our analysis.[22] Finally, each specification makes use of a set of panel weights. The appropriate weights depend on the analysis. Our rationale for using weights and the details of how we construct them are provided in Appendix 2.

6 Using $X_{si}\hat{B}$ to Assess Clustering of Students with Favorable Characteristics

To set the stage for the variance decompositions of educational attainment and wage rates, we first investigate the extent to which some high schools have better average outcomes simply because they have advantaged students who would obtain more schooling and higher wages regardless of which high school they attend. We examine this in two ways. First, to compare school-level differences to the overall variation in observable student background, in Column 2 of Table 2 we report the intraclass correlation for the regression index $X_{si}\hat{B}$ for each outcome and data set combination. The index $X_{si}\hat{B}$ is a weighted sum of all of the student and family level characteristics that are included in our models of educational attainment and wage rates. The weight for each variable is the regression coefficient (or probit coefficient) that reflects the variable's impact on the predicted outcome, holding both observed and unobserved school characteristics constant.[23] The coefficients depend on the outcome, so we construct separate indices for each outcome. The indices also depend upon whether we use the baseline specification, the specification with test scores, or the full specification in selecting the components of X_{si}. Second, to provide a better sense of the degree to which differences in the characteristics of school populations matter for our outcomes, we report for each outcome what the average would be for schools with the 10th percentile value and schools with the 90th percentile value of the school mean $X_s\hat{B}$, under the assumption that $X_s\hat{B}$ is normally distributed. Our calculation holds the within-school variance of $X_{si}\hat{B}$ and the distribution of $Z_sG + m_s + v_s + v_{si}$ constant. In

[22]This results in sample sizes for the four year college enrollment analyses of: 12,102 for NLS72, 10,995 for NELS88 using the grade 8 school, 10,706 for NELS88 using the grade 10 school, and 12,439 for ELS02. The sample sizes for the high school graduation analyses are 11,339 for NELS88 (using grade 8 school), 11,043 for NELS88 (using grade 10 school) and 12,366 for ELS02, respectively. The analysis of years of postsecondary education uses 12,070 observations from NLS72, and the wage analysis uses 4,932 individuals with 9,864 wage observations. We also create a missing indicator for mother's education, and include mother's education combined with the missing indicator when performing imputation, along with school averages of all the key characteristics above.

[23]The results for individual variables in Appendix Tables 2, 4, 6, and 8 show a moderate amount of clustering at the school level by family income and parental education and a much more substantial clustering by race/ethnicity and assimilation measures. The degree of clustering in other student level characteristics that are likely to influence educational attainment and wages is more modest. We tend to observe an increase in the grouping of students with similar backgrounds at the same high schools between 1972 and 1988, but no further increase between 1988 and 2002. While the across-school distribution of such salient student characteristics is interesting in its own right, it is difficult to gauge the extent to which differences in school means of student characteristics explain across-school differences in mean outcomes without using information on which characteristics best predict the outcomes. This is why we focus on clustering in the index $X_{si}B$ rather than the individual variables.

particular, we are holding the distribution of peer effects that are captured as part of Z_sG constant even though we are shifting $X_s\hat{B}$, and the components of X_s are a subset of the components of Z_s. For the binary outcome variables, high school graduation and four-year college enrollment, we estimate the mean of the outcome for a school with the 10th percentile value of $X_s\hat{B}$ as

$$\Phi([\Phi^{-1}(\bar{Y}) - 1.28\widehat{Var}(X_s\hat{B})^{.5}]/[\widehat{Var}((X_{si} - X_s)\hat{B}) + \widehat{Var}(\bar{Z}_s\hat{G}) + Var(m_s + v_s) + Var(u_i)]^{.5}).$$

We obtain the value for a school at the 90th percentile value of $X_s\hat{B}$ by replacing -1.28 with 1.28 in the above formula. For years of academic education and the log wage, the 10th and 90th percentile values are $\bar{Y}\ \pm 1.28\widehat{Var}(X_s\hat{B}\ )^{.5}$.

For high school graduation (Panel A), the intraclass correlation of $X_{si}\hat{B}$ using the baseline specification is .28 for NELS88 (10th grade school) and .24 for ELS02. When test scores are added, the corresponding values are .25 for both NELS88 and ELS02. In the case of college attendance, the baseline values are .19 for NLS72, .28 for NELS88, and .29 for ELS02. Adding tests lowers these values slightly. The NLS72 results for years of postsecondary education are similar to the results for four-year college enrollment. In the case of log wages the value for both specifications is .25.

Columns 3 and 4 report the average outcomes for schools at the 10th and 90th quantiles of $X_s\hat{B}$, while Column 5 reports the difference. For NELS88 the graduation rate for a school at the 10th quantile of the $X_s\hat{B}$ distribution is 88 percent using the baseline specification. The value for a school at the 90th quantile is 95 percent. When we cluster on 8th grades and include students who drop out before 10th grade, the values are 79 percent and 93 percent, respectively. The range is slightly wider when we add test scores to the set of student level variables. The results for the full specification are essentially the same as the results for the specification with tests.

The results for ELS02 are remarkably similar to the results for NELS88 based on the 10th grade schools, indicating that there has been little change in the degree of segregation across high schools in student characteristics that matter for high school graduation. The 10th-90th differences in graduation rates are large relative to the mean dropout rates of 9 percent for 1990 sophomores and 10 percent for 2002 sophomores.

The results for four-year college enrollment in Panel B show that differences in $X_s\hat{B}$ alone can account for a difference across 10th and 90th quantile schools in college attendance rates of around 25 percentage points in the baseline case and more than 30 percentage points when test scores are added. However, differences across schools in $X_s\hat{B}$ are less important in NLS72 than for the more recent cohorts of students, in part because fewer people from any school were enrolling. The 10-90 difference is 16 percentage points for the baseline specification and 21 percentage points when test scores are added. These differentials are large relative to the mean enrollment rates of 27 percent, 34 percent, and 37 percent for the three cohorts, respectively.

In NLS72, the average predicted values of the log wage among students whose schools are at the 10th and 90th percentiles of the $X_s\hat{B}$ distribution are 1.02 and 1.22 respectively. This corresponds to a wage differential of about 22 percent.

In summary, when we use the relationship between student characteristics and outcomes to aggregate the student characteristics into a single index, we find that differences in the average characteristics of student populations can lead to substantial differences across schools in average educational attainment and wages that are independent of the influence of the school itself, including peer influences.

7 Variance Decompositions of Educational Attainment and Wages

We now decompose the variance of educational attainment and wages into observed and unobserved characteristics of the student and observed and unobserved characteristics of the school and community. We organize the discussion by outcome. For the binary outcomes, high school graduation and college attendance two years after the graduation year, the decompositions refer to the corresponding latent variable.

7.1 High School Graduation

Table 3 displays the decomposition associated with the latent variable determining high school graduation. Each entry in the table reports the fraction of the total variance of the latent variable for $HSGRAD$ that is accounted for by the variance component indicated in the row label. The first three rows examine the contribution to the total variance of differences among students attending the same school. The next five rows examine variation across schools. The final two rows display the lower and upper bounds on the fraction of variance attributable to school/community quality. Each column reports results for a specific cohort/specification combination. The first two columns labeled "NELS gr 8" are based on NELS88 using eighth grade as the definition of school/neighborhood and the full 8th grade sample.

We begin with the baseline specification in column 1. Overall, the between school variance $Var(Y_{si} - Y_s)$ constitutes 82.7 percent of the total variance in the latent variable for $HSGRAD$. Of this, the observed student and family characteristics term $(X_{si} - X_s)B$ contributes 13.6 percent and the unobserved student and family characteristics term v_{si} contributes 69.1 percent. Furthermore, $Var(X_sB)$ accounts for 5.3 percent of the 17.3 percent of the variance that is between schools ($Var(Y_s)$). Consequently, since $Var(X_sB)$, $Var(v_{si})$ and $Var(X_{si} - E(X_sB))$ account for all but 12.0 percent of the variance in the latent variable for $HSGRAD$, 12.0 percent is our "Upper Bound" estimate of the contribution of observed and unobserved school characteristics. Observable school-level variables ($Var(Z_sG)$) account for 5.1 percent of this 12.0 percent, the covariance between observable student and school variables ($2Cov(X_sB, Z_sG)$) contributes 3.7 percent, and variation across schools in unobservable student and school factors ($Var(v_s + m_s)$) contributes the other 3.2 percent. Thus, our lower bound estimate ($Var(Z_sG)$) is just 5.1 percent. When test scores are included, the upper and lower bounds are just 7.5 percent and 3.1 percent respectively.[24] Almost all of the variation in the factors that affect high school graduation stems from those factors that are specific to the student (including family factors) rather than influences that are common to students who attended the same eighth grade.

Columns 5 and 6 of Table 3 report results for NELS88 using the 10th grade school to define the common school/community environment and using 10th grade tests rather than 8th grade measures ("NELS gr10"). These results are directly comparable to the ELS02 results. The contribution of the school-level variables in each specification is reasonably close to the results for NELS grade 8 in the first two columns. The upper bound estimate for the contribution of school/neighborhood factors is 10.7 percent of the total variance using the baseline controls and 8.8 percent in the model with test scores. The corresponding lower bounds are 4.5 percent and 2.9 percent. We obtain very similar results when we use 8th grade tests, which suggests that the concern that including high school tests in X_{si} would lead one to underestimate the role of schools is unfounded (Column 4). The last two columns report results for ELS02. They are similar to the 10th grade decomposition results for NELS88, but suggest a somewhat smaller role for the school/community variables Z_s and m_s. For both NELS and ELS, using the full set of student variables leads to a small increase in the lower bound and a small reduction in the upper bound relative to the model with test scores (Appendix Table 9).

7.2 Enrollment at a Four Year College

In Table 4 we present variance decompositions of the latent variable that determines enrollment in a four-year college. The ELS02 results are displayed in Columns 7 and 8. The first row shows that about 79 percent of the variance in the latent variable determining college enrollment is within a school, with variation in $X_{si}B$ within a school explaining 15.2 percent. Including test scores in X_{si} increases the contribution of $(X_{si} - X_s)B$ to 29.8 percent, with an offsetting decrease in the contribution of v_{si}. In the baseline model, X_sB accounts for 6 percent of the between school variance, leaving 15.4 percent as the upper bound for the school/community factors Z_sG and m_s.

Columns 5 and 6 of Table 4 present variance decompositions for NELS88 10th grade. The results are very similar to the ELS02 results. The results that group at the 8th grade school in NELS88 are close to those from NELS88 10th grade and those from ELS02.[25]

[24] Adding test scores to X boosts the importance of $Var(X_sB)$ from 5.3 percent to 9.6 percent. Adding test scores also increases $Var((X_{si} - X_s)B)$ and reduces $Var(v_{si})$.

[25] As with high school graduation, NELS88 "Full" and "w/Tests" specification results which use the 10th grade as

In the NLS72 data only about 14 percent of the variance in the latent variable for college attendance is across schools (Table 4, columns 1 and 2). In the baseline specification the school components Z_s and m_s account for at most 10.6 percent of the variance. The lower bound is only 4.7 percent.

7.3 Years of Postsecondary Academic Education

For NLS72 we decompose the number of years of academic postsecondary education obtained by 1979, which is seven years after the normal year for high school graduation for the sampled cohort (Table 5). The mean value of this outcome is 1.61 years and the standard deviation is 1.71 years. The variance within high schools is 90.4 percent of the total, leaving 9.6 percent for between school factors. However, $Var(X_sB)$ accounts for 3.3 of the 9.6 percentage points in the baseline case and 5.2 percentage points when test scores are included. In the baseline specification $Var(Z_sG)$, $2Cov(X_sB, Z_sG)$, and $Var(v_s + m_s)$ combine to contribute 6.4 percent of the variance. When test scores are added (Column 2) this upper bound shrinks to 4.4 percent. The lower bound estimates are 2.6 and 1.5 percent for the baseline and w/tests specifications.

7.4 Variance Decompositions of Permanent Wages

Table 6 reports decompositions of log wages for NLS72. As noted earlier, we use individuals who worked in both 1979 and 1986 and we decompose $Var(W_{si})$, the permanent wage.[26] We focus on the case in which postsecondary education is excluded from X_{si}, on the grounds that it is partially determined by the school (Columns 2 and 3). The school component W_s accounts for 16.2 percent of the variation and has a standard deviation of 0.123, with $Var(X_sB)$ contributing 4.4 percent of the 16.2 percent in the baseline model. $Var(Z_sG)$ contributes 4.2 percent, $2Cov(X_sB, Z_sG)$ contributes 3.2 percent, and $Var(v_s + m_s)$ contributes 4.5 percent, leading to an 11.9 percent upper bound and a 4.2 percent lower bound for the contribution of observed and unobserved school and neighborhood effects.

Adding postsecondary education to X_{si} boosts the contribution of $Var((X_{si} - X_s)B)$ and $Var(X_sB)$ slightly.

7.5 Summary of the Evidence from Variance Decompositions

In summary, the results indicate that differences in the background characteristics of individual students are sufficient to account for almost all of the variance in educational attainment and wages,

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the grouping school, but 8th grade measures of the potentially endogenous variables (test scores, parent expectations, and student behaviors) are very similar to the NELS88 10th grade measures. This suggests that the models with test scores and the full set of variables are not significantly underestimating the contribution of schools to outcomes by assigning the part of the school's impact that works through changing test scores and behavior to $Var(X_sB)$.

[26]In the pooled sample the overall variance of W_{sit} is 0.215 and the standard deviation is 0.464. The permanent component W_{si} accounts for 43.2 percent of the total variance, and has a standard deviation of 0.305. The values change slightly when test scores, postsecondary education or both are included in X_{si}, because including these variables alters the coefficients used to adjust wages for labor market experience and the year. See note 11.

even when test scores, behavior, and expectations measures are excluded. The results are consistent with the unweighted results for NLS72 in Altonji (1988) and are qualitatively consistent with those of Jencks and Brown (1975) for Project Talent. They find only a small role for schools in the distribution of postsecondary educational attainment.

8 The Impact of Shifts in School Quality

As we noted above, even though the contribution of school-specific factors to the variance of an outcome may be relatively small, exposure to a strong school can make a substantial difference. In Table 7 we examine this issue. Again, we organize the discussion by outcome.

8.1 High School Graduation

In Panel A, the row labeled "Upper Bound: 10th to 90th" reports the effect on the graduation probability of a shift in the school/neighborhood environment, $Z_sG + m_s$, from the 10th percentile to the 90th percentile of its distribution, assuming $Z_sG + m_s$ is normally distributed. We refer to these estimates as upper bounds because we set $Var(m_s)$ to $\widehat{Var}(m_s + v_s)$ under the assumption that $Var(v_s) = 0$. The corresponding lower bound estimates attribute $\widehat{Var}(m_s + v_s)$ entirely to $Var(v_s)$ instead. The upper bound estimates for NELS88 gr10 and ELS02 are very similar—about a 10 percentage point increase in the expected graduation rate by virtue of moving from the 10th quantile school to the 90th quantile school. The values are not very sensitive to whether we use the baseline specification or the specification with test scores. The upper bound estimates of the effect of a 10th-50th shift are 6.8 percentage points for NELS88 and 6.5 percentage points for ELS02.[27] The lower bound estimates are just under 5 percentage points for a 10-50 shift, and around 8 percentage points for a 10-90 shift.

When the school is defined as the 8th grade, our upper bound estimate of the effect of a 10th to 90th percentile shift in $Z_sG + m_s$ on the graduation rate is 16.5 percentage points using the baseline model and 14.2 percentage points when test scores are added. The larger numbers are primarily due to the fact that students who drop out prior to 10th grade are included in the sample. Thus, moving from a bad school to a good school still substantially boosts the graduation rate. This is true despite the fact that observed and unobserved school-level factors contribute only a small fraction of the variance in the index that determines high school graduation.

[27] Note that the effect of a 10th to 50th shift in school quality is more than half the effect of a 10th to 90th shift even though the size of the 10th to 90th shift is double the size of the 10th to 50th shift. This is because the normal distribution function is nonlinear and the mean of high school graduation is greater than .5. The effect of a 10th to 50th shift is less than half of the effect of a 10th to 90th shift in the case of college enrollment, which has a mean less than .5.

8.2 Enrollment at a Four-Year College

Panel B displays the estimated impact of a 10th-90th percentile shift in $Z_sG + m_s$ on the probability of enrolling in a four-year college. For NELS88 8th grade (Columns 3 and 4) the upper and lower bounds are large—27.8 and 22.0 percentage point increases (respectively) in the enrollment rate in the baseline case and 23.8 and 18.1 percentage point increases when tests are included. The upper bound values for a 10th to 50th percentile shift are 13.6 percentage points and 12.3 percentage points under the two specifications.

For ELS02 10th grade (Columns 7 and 8) the upper bound estimate is that a shift in $Z_sG + m_s$ from the 10th percentile to the 90th percentile increases the probability of college attendance by 28.2 percentage points in the baseline case and 21.8 percentage points when tests scores are added (Table 7, Panel B, columns 5 and 6). The effect of a 10th to 50th percentile shift is about 13 percentage points. The lower bound estimates are smaller, but still substantial: 21.9 percentage points for the 10th-90th difference and 10.4 percentage points for the 10th-50th difference in the baseline model.

Results for NELS88 10th grade (Columns 5 and 6) are remarkably similar to those for ELS02, while estimates for NLS72 are somewhat smaller: upper and lower bound estimates of 23.2 percentage points and 18.8 percentage points in the baseline case. As with our analysis of background characteristics, these results suggest that the school/community factors that matter for college attendance grew in importance in the 1970's and 80's, but have remained constant since.[28]

8.3 Years of Postsecondary Academic Education

Estimates of the impact of shifting school quality on years of completed postsecondary education are displayed in Table 7, Panel C, Columns 1 and 2. The upper and lower bound estimates of a 10th to 90th percentile shift are .789 and .700 years of college education for the baseline model and .605 and .532 when test scores are included. These are substantial relative to the mean value of 1.61 years.

8.4 Permanent Wages

Columns 3 and 4 of Table 7, Panel C display the corresponding estimates for permanent wages under our preferred specification, in which postsecondary education is excluded from X_{si}. For the baseline specification the upper bound estimate of the effect on the log wage of a 10th-90th quantile shift in $Z_sG + m_s$ is 0.228, which corresponds to a 25.6 percent increase in the wage. The lower bound estimate is 0.153, a 17.1 percent wage increase. The estimates with test scores are similar. Adding postsecondary education to X_{si} reduces the estimates only slightly. Even the lower bound estimate

[28] We also investigated whether the comparison across time is affected by the fact that the NLS72 sample is restricted to students who made it to 12th grade. It does not appear to be. The college attendance results for NELS88 and ELS02 do not change much when we restrict these samples to students who reached 12th grade. This suggests that little change took place between 1988 and 2002 for college enrollment.

is a substantial effect, despite the small variance fraction associated with school and community factors. It is equivalent in value to about 2 years of education.[29]

9 Results for Subgroups

In this section we explore differences across subgroups in the sensitivity of the outcomes to school attendance. We also explore the role of schools in group differences in high school graduation rates and college enrollment.

9.1 Heterogeneous Effects of 10th-90th Percentile Shifts in School Quality

To what extent do the 10-90 differentials reported in Table 7 conceal heterogeneity in the impact of moving schools across students with varying student backgrounds? Because of nonlinearity in the probit function that links Y_{si} to the binary outcome indicators $HSGRAD_{si}$ and $COLL_{si}$, the sensitivity to school quality is higher for groups with values of $X_{si}\hat{B}$ that place them closer to a probability of .5. High school graduation is therefore more sensitive to school quality for disadvantaged groups and less sensitive for advantaged groups. The opposite tends to be true for college enrollment.

Table 8 reports the lower and upper bounds for the effect of a 10th to 90th percentile shift in school quality on graduation rates for two extreme cases: students whose value of the background index $X_{si}\hat{B}$ places them at the 10th quantile of the $X_{si}\hat{B}$ distribution, and students at the 90th quantile of the $X_{si}\hat{B}$ distribution. For the NELS88 grade 8 sample and the baseline specification, the lower bound estimates are a 22.4 percentage point increase for students at the 10th quantile and a 4.1 percentage point increase for students at the 90th quantile, while the upper bound estimates are 28.9 and 5.2 percentage points, respectively. When tests are included, the lower bounds for the students at the 10th and 90th quantiles fall to 20.8 percentage points and 1.1 percentage points, respectively. For NELS88 grade 10, the numbers are smaller: lower bounds of 14.7 percentage points and 2.7 percentage points, and upper bounds of 19.3 percentage points and 3.5 percentage points in the baseline specification. This reflects the fact that the average dropout rate is lower for those who make it to 10th grade. ELS02 results are very similar to NELS88 grade 10. The results show that advantaged students graduate high school regardless of the school they attend, while disadvantaged students are strongly affected by school quality.

Table 8 also reports the average impact of a 10th-90th shift for three subpopulations of interest: black students, white students with single mothers who did not attend college, and white students

[29] There is evidence in the earnings dynamics literature that the influence of permanent differences in skill on wages grows for a number of years after an individual enters the labor market. In our wage model, this can be captured by multiplying W_s by a scalar, say q_t, where q_{1985} might be greater than q_{1979} and both might be less than the average value of q_t over a career. Normalize W_{si} so that the average value of q_t is 1. One may show that to a first approximation, this generalization would have no effect on our decomposition of the variance of W_{si}. Our estimate of the standard deviation of W_s and the 10th and 90th percentile values are equal to $(q_{79} * q_{85})^{.5}$ times the corresponding values for W_s.

with both parents, at least one of whom completed college. For the baseline specification in the NELS88 grade 8 sample, the lower and upper bound estimates are 12.8 and 16.4 percentage points for black students. The estimates for white students with single mothers who did not attend college are 20.7 and 26.6 percentage points, while the estimates for white students with both parents, at least one of whom completed college, are 5.6 and 7.0. As with the main results, estimates are about two-thirds as large for NELS88 grade 10 and ELS02, and are very similar to one another. Thus, the impact of a shift in school quality on high school graduation is considerably smaller for advantaged students and larger for disadvantaged students, although the predicted increase in the graduation probability is substantial for nearly all populations.

Table 9 reports a corresponding set of results for $COLL$. The college enrollment rates of whites with single mothers who did not attend college and students at the 10th percentile of the $X_{si}\hat{B}$ distribution are less sensitive to school quality. Their lower bound estimates are between 12 and 20 percentage points and between 7 and 15 percentage points, respectively, depending on the sample and specification. By contrast, the lower bound estimates for whites with both parents, at least one of whom completed college, are between 19 and 26 percentage points, and the lower bound estimates for students at the 90th quantile of the $X_{si}\hat{B}$ distribution are between 17 and 26 percentage points. The values for blacks are similar to the results for the full sample.

Overall, it appears that at each stratum of student background, a considerable fraction of students are close enough to the decision margin for a major shift in school quality to be a deciding factor.

9.2 Characterizing the School Environment Experienced by Various Subgroups

In this section we explore the role of schools in determining the average high school graduation rates and college enrollment rates of population subgroups. The first row of Table 10, Panel A reports the average graduation rate for blacks. We focus first on the NELS grade 10 results (Columns 5 and 6). The average graduation rate is 90.4 percent. To quantify how this rate is affected by the distribution of school quality that blacks are exposed to, the second row reports what the graduation rate would be if blacks were assigned to schools at random. It is 90.7 percent, which indicates that the schools blacks actually attend are only slightly worse than a representative sample of schools, at least in the dimensions that affect the high school graduation rates of those who make it to 10th grade. The results for ELS, in Columns 7 and 8 of the table, indicate that the black graduation rate is about .01 lower because of the schools they attend, while the NELS results for students clustered at the eighth grade indicate that an inferior school environment reduces the black graduation rate by .045 (Columns 1 and 2).

The comparison of actual graduation rate and the expected graduation rate in a random school for whites with single mothers without a college education indicates that the distribution of schools attended by this group is similar to the unconditional distribution. In the case of whites with both parents present, at least one of whom has a college degree, the actual graduation rate exceeds the expected graduation rate by about .01 or .02. This indicates that this group attends schools that are a bit better than average, perhaps because of peer effects. However, very little of the large difference in graduation rates between the two groups of whites is due to differences in school/community quality.

Panel B of the table reports a corresponding set of results for four-year college enrollment. The results suggest that the school quality advantage enjoyed by whites from an intact family with a college-educated parent increases the enrollment rate by between .05 and .10, depending upon the specification and control set. In the case of both blacks and whites with single mothers without any college education, the results suggest that the distribution of schools these students attend is fairly typical, relative to the overall population of students.

10 Estimating the Magnitude of Bias from Tracking within Schools

Section 3 demonstrated that sorting of students into micro environments within their high schools or associated communities can bias downward both lower and upper bound estimates of the impact of schools and communities. In this section, we exploit administrative data from North Carolina to investigate the magnitude of this bias. The data we use generally mirrors those of the three data sources used thus far.[30] However, these data offer two notable advantages. First, rather than merely sampling individuals from each school, the North Carolina data offer a full census of each high school's population, including those that drop out early in high school, thus removing the need to approximate school averages of individual characteristics. Second, the data link students to classrooms in up to ten subjects, providing a direct way to measure an important component of an individual's sub-environment. More specifically, for each individual-level variable in X_{si}, we calculate the mean of the variable among the classmates in student i's classes, and subtract the average classroom mean taken over all students from i's school.[31] We denote the vector of such individual-specific deviations of classroom averages by $X_{sc(i)}$.

Suppose that each student's micro environment within the school and community could be fully predicted based on their classroom peer environment: $(Z^*_{si} - Z^*_s)G' = X_{sc(i)}\Gamma$. Then the augmented model in equation (3) can be written as:

$$Y_{si} = X_{si}B^{Z^*} + X_{sc(i)}\Gamma + Z_sG^{Z^*} + m_s + v_s + v_{si}^{Z^*} \quad (12)$$

[30] See Appendix Table 2 for a list of the relevant individual- and school- level variables for this dataset.

[31] Note that if class sizes do not vary systematically with individual-level variables, then the mean classroom average at each school of characteristic k is simply the school average of the characteristic, Z_{sk1}, and its impact is reflected in G_{k1}.

Let the projection of $X_{sc(i)}$ on X_{si} and Z_s be captured by:

$$X_{sc(i)} = \pi_0 + X_{si}\pi_1 + Z_{s1}\pi_2 + Z_{s2}\pi_3 + \tilde{Z}^*_{si} \tag{13}$$

Then the coefficients estimated by (2) can be rewritten as:

$$B = B^{Z^*} + \pi_1\Gamma \tag{14}$$

$$G_1 = G_1^{Z^*} + \pi_2\Gamma = G_1^{Z^*} - \pi_1\Gamma \tag{15}$$

$$G_2 = G_2^{Z^*} + \pi_3\Gamma = G_2^{Z^*} \tag{16}$$

$$v_{si} = v_{si}^{Z^*} + \tilde{Z}^*_{si} \tag{17}$$

At first blush, when $X_{sc(i)}$ is observed, it seems natural to estimate equation (12) directly via probit regression. However, Altonji, Mansfield, and Taber (2011) show that the kinds of tracking systems used in high schools cause inconsistent estimates of B^{Z^*}, Γ, and G^{Z^*}. Essentially, such an estimator estimates B using only within-classroom variation in X_{si}, and the selection involved in tracking can introduce a significant correlation between X_{si} and v_{si}, even when B is *defined* so that X_{si} and v_{si} are uncorrelated before conditioning on classroom environment.

To sidestep this problem, we follow AMT(2011) and assume that the impact of classroom averages of individual characteristics is proportional to the impact of the individual characteristics themselves:

$$\Gamma = \phi B \tag{18}$$

Under this assumption, the coefficient vectors B, G_1, and G_2, and the variance of v_{si}, can be estimated as:

$$\hat{B}^{Z^*} = (I + \pi_1\phi)^{-1}\hat{B} \tag{19}$$

$$\hat{G}_1^{Z^*} = \hat{G}_1 + -\pi_1\phi\hat{B} \tag{20}$$

$$\hat{G}_1^{Z^*} = G_2 + \pi_3\phi\hat{B} = G_2 \tag{21}$$

$$\widehat{Var}(v_{si}^{Z^*}) = \widehat{Var}(v_{si}) - \widehat{Var}(\tilde{Z}^*_{si}) \tag{22}$$

Since theory does not guide the selection of a value for ϕ, we estimate the model (12), imposing restriction (18), for $\phi = \frac{1}{4}$, $\frac{1}{2}$, and 1.

Table 11 displays the results of this exercise. Its format parallels that of Table 3. As a basis for comparison, the first column contains the results from the decomposition using NELS88 data with the full specification, using the 10th grade school as the grouping school, but with student behavior measures collected in 8th grade. This specification mirrors most closely those estimated with the North Carolina data.

Column 2 contains the results from decomposing the North Carolina data using the methods employed in the rest of the paper (ignoring the information on classroom environment). Comparing

Columns 1 and 2, we see that the the two datasets provide quite similar results. The most notable difference is that a greater fraction of variance is attributed to the unobservable school-level component $m_s + v_s$ in North Carolina, leading to a somewhat higher upper bound estimate of the contribution of schools and communities.

Column 3 displays the results of naively estimating equation 12 directly. We see that the estimate of the fraction of within-school variance attributable to observable characteristics, $\widehat{Var}((X_{si} - X_s)B)$, shrinks to a fraction of its size in the first two columns. As AMT(2011) document, this is exactly what we should expect from a simple model of track selection.

Columns 4-6 display the results of estimating using restriction (18), for $\phi = \frac{1}{4}$, $\frac{1}{2}$, and 1, respectively. Comparing the final two rows of Columns 4 and 5 to Column 2, we see that, for moderate values of ϕ, adjusting for the impact of classroom peer environment causes rather small increases (less than a percentage point) in both the lower and upper bound estimates of the fraction of variance attributable to schools and their associated communities. Column 6 displays the results of setting $\phi = 1$, which restricts a student's classmates' average background to matter as much as his own background. Even under this extreme assumption, estimates of the fraction of variance attributable to schools and communities increases by less than 2 percent.

Finally, since the elements of Γ are unlikely to be exactly proportional to those of B, we also examine sensitivity to the proportionality component of assumption (18) by estimating the model using an alternative restriction, in which the impact of classroom averages of individual characteristics is proportional to the impact of school averages of these characteristics: $\Gamma = \phi G_1$. We display results for this restriction in Columns 7 and 8. The results are quite similar to those in Column 2, which ignores the sorting of students into sub-environments within schools.

Table 12 performs the same analysis for our estimates of the expected impact of shifting a randomly chosen student from the 10th quantile of school/community quality to the 90th percentile. Again, we find that adjusting for the bias introduced by within-school tracking via restriction (18) increases the estimated impact of such 10th-90th quantile shifts on the graduation rate by between 0.2 and 1.9 percentage points, depending on the choice of bound and the choice of ϕ. While adjustments on the order of a 1 percentage point change in the high school graduation rate are not trivial, Table 12 does suggest that the downward bias in the results obtained from NLS72, NELS88, and ELS02 from ignoring sorting into classroom peer environments is not likely to be large enough to substantially change the qualitative conclusions that we draw from these data sources. Note, though, that one may not definitively conclude that omitting sorting into sub-environments within schools and communities does not introduce substantial bias. After all, a student's peers outside of school or the safety of the block they live on may be more important factors contributing to a student's external environment, and may not be very well predicted by the characteristics of the student's peers in the classroom. Nonetheless, given that the classroom environment does constitute a large fraction of a student's time, these preliminary results provide considerable comfort.

11 Conclusion

While caution is warranted, we offer the following answers to the questions posed in the introduction. How much do peers and the resources of parents differ across schools? The index $X_{si}B$, which weights student and family characteristics by how much they matter for education and for wages, provides a useful summary of the background of students. The fraction of the variance in $X_{si}B$ that is between schools ranges from .15 to .29 for the various education outcomes in our specification with test scores and is typically larger in the basic model and slightly smaller in the full specification. The difference between the 10th and 90th percentile values of the school mean of $X_{si}B$ is large enough to lead to a difference in the high school graduation rate of students who attend 10th grade of about 10 percentage points, holding the distribution of all other influences fixed. The figures are larger when we do not condition on attending 10th grade. The corresponding differences in the college enrollment rate and in future wages are even larger—around 28 percentage points and 22 percentage points, respectively. These results indicate that there is enough clustering of students at the high school level to account directly for substantial differences in average outcomes across high schools even if there were no peer effects and the student and parent composition of schools had no influence on school and community resources.

For a particular child, how much of the effect of parents on his/her outcomes is direct, and how much is through community/schools? Most of the effect is either direct or operates by influencing the environment of the student *within* a school and community. While we do not directly address the extent to which parents steer students to particular schools and communities, the amount of within-school and between-school variation in outcomes that can be explained by the direct influence of observable background variables swamps the part of the between-school variation which might be determined by school/community environment. This implies that only a small part of parent's influence could possibly be through choice of eighth grade or high school and the associated community.

How much do schools and communities matter for educational attainment and wages? On one hand, our estimates of the percentage of the variance in education and in wages that is due to observed and unobserved school characteristics is only modest. The upper bound estimates lie between 6.4 and 12 percent for high school graduation, 8.2 and 15.4 percent for college attendance, 4.4 and 6.4 percent for years of postsecondary education, and 10.3 and 11.7 percent for wages, with the specific value depending on the data set and explanatory variables used. It is important to emphasize that these estimates account for unobserved as well as observed factors, and include peer effects.

Furthermore, the upper bound estimates are probably overstated and the lower bound estimates are often considerably smaller. On the other hand, the average effect on each of the outcomes of switching students from a school/community at the 10th percentile of the quality distribution (in terms of factors that influence education and wages) to a school/community at the 90th percentile is substantial even though student-specific factors are much more important. For example, in the case of both the NELS88 and ELS02 10th grade samples, even the lower bound estimates indicate that such a shift boosts the high school graduation percentage by about 8 points and the college attendance percentage by about 20 points. A sizable fraction of students seem to be sufficiently close to the decision margin for high school graduation and for college attendance for the difference between a weak school/community and a strong one to be decisive. A particularly large fraction of less advantaged students seem to be on the decision margin for dropping out, while a particularly large fraction of more advantaged students seem to be on the decision margin for college enrollment.[32] The pattern echoes the evidence from Solon et al. (2000), who find that common neighborhood influences (including schools) explain only about 10 percent of the variance in educational attainment, but also point out that the effect of a one standard deviation shift in the common component is economically significant.[33]

How has the importance of student, school and neighborhood factors changed since the early 1970s? We tend to observe an increase in the grouping of students with similar backgrounds at the same high schools between 1972 and 1990, but no further increase between 1990 and 2002. The importance of high school/community level factors in college attendance increased between 1972 and 1990. However, the college attendance results and high school graduation results for NELS88 and ELS02 are very similar once we condition on 10th grade enrollment, suggesting that there has not been much change since 1990.

To what extent do differences in the school quality distributions experienced by particular subgroups account for group differences in high school graduation and college enrollment rates? In several cases, school quality advantages or disadvantages play a relatively small role in explaining outcome across groups. However, the average high school graduation rate for blacks would increase by about 4.5 percentage points if each was assigned to a random eighth grade rather than the one he

[32]There is not much quasi-experimental evidence concerning the effects of high school quality on later outcomes, at least not for the U.S. Deming et al (2009) use variation in high school assignment associated with school choice lottery outcomes to show that female lottery winners from low-performing schools are more likely to finish high school and substantially more likely to attend a four-year college, while male lottery winners are more likely to finish high school but less likely to attend college. They do not find effects for students whose home schools were of average quality or better. Cullen et. al. (2006), using a similar identification strategy with lotteries in Chicago Public Schools, find no effect of attending one's choice of high school on one's probability of graduation, although they do find some evidence of lower arrest and incarceration rates.

[33] Kling et al.'s (2007) experimental analysis and Oreopolous' (2003) quasi-experimental analysis of the effects of living in a poor neighborhood generally find small effects on adolescents. However, the nature of the "treatments" they consider is very different.

or she attended. At the opposite extreme, the college enrollment rate for whites from intact families and at least one college educated parent would be reduced by about 7 percentage points if they were assigned to a random high school rather than to high schools from the conditional distribution for this group.

As is often the case with empirical research, our assessment of the role of family background, schools, and community factors in educational attainment and wages is less precise than one would like. Part of the difficulty reflects differences across the data sets that we use and the fact that we do not have complete personal histories of school/community characteristics and family characteristics. Another part is due to the fact that important student level and school/community level factors are not measured directly and non-random sorting is evident. This restricts our ability to distinguish school/community effects from unobserved variation in student level variables across schools. Finally, parental characteristics and other student level characteristics influence the environment within a school. Observed and unobserved student-level variables get credit for these environmental influences in our analysis. This will lead to an understatement of the importance of average school and community level factors, although other biases go in the opposite direction.

In closing we wish to highlight two areas for future research. The first is the examination of the effects of parental characteristics and student characteristics determined prior to a given level of schooling on the environment the student experiences within a school. With existing data, one could make progress on this issue. NELS88 and ELS02 contain some information about peers. ADHLTH provides rich information on social networks for samples of students from a substantial number of schools.[34] A large literature on the importance of schools, specific teachers and peers is emerging based on administrative data sets from Texas, North Carolina, Chicago, and other jurisdictions. These data sets are weak on family background characteristics but do permit one to track students through specific classrooms and teachers.[35] This information could be used to study heterogeneity within a school and associated neighborhood. The second research area is the study of the cumulative effects of school influences, from kindergarten (or even pre-school) forward. This will involve modeling neighborhood and school choices in a dynamic context. Using data from the Early Childhood Longitudinal Study, Kindergarten Class of 1998-99, the Early Childhood Longitudinal Study, Birth Cohort (ECLS-B), and NELS:88, one would have full coverage from infancy through age 26. It might be possible to stitch together the information from the three data sets to get a comprehensive picture of how much difference the schools one attends make.[36]

[34]See, for example, Duncan et. al. (2001) for an analysis of ADHLTH with references to other studies.

[35]See, for example, Clotfelter et al (2006), Hanushek et al (2005), Aaronson, Barrow and Sander (2007), Kramartz et al (2008) and Mansfield (2010).

[36]In work in progress, Richard Mansfield is using administrative data from North Carolina to examine the effects of elementary school and teacher quality on high school performance.

Appendix 1. The Effects of Measurement Error in $\bar{Z}_s$ on Estimates of $Var(Z_sG)$ and $Var(m_s + v_s)$

Ultimately, we are interested in the variances of the regression indices. Sampling error in $\bar{Z}_s$ as an estimate of Z_s affects the variance of the indices both through $\hat{G}$ and through $Var(\bar{Z}_s)$. If Z_s^1 contained only one variable and there were no variables in Z_s^2, then the probability limit of the OLS estimator of $\hat{G}$ would be $[Var(Z_s)/Var(\bar{Z}_s)]G$. Note that

$$Var([Var(Z_s)/Var(\overline{Z})]GZ_s) = (Var(Z_s)/Var(\overline{Z}_s))^2G^2Var(Z_s),$$

while

$$Var([Var(Z_s)/Var(\bar{Z}_s)]G\bar{Z}_s) = (Var(Z_s)/Var(\bar{Z}_s))G^2Var(\bar{Z}_s).$$

Thus, the effect of downward bias in G on the estimator of $Var(Z_sG)$ is partially offset by the fact that $Var(\bar{Z}_s)$ is upward biased as an estimator of $Var(Z_s)$. The contribution of $v_s + m_s$ will be overstated by an equal amount: $Var(\bar{Z}_s - Z_sG)$. With multiple variables in Z_s^1 and correlation between Z_s^1 and Z_s^2, the effects of measurement in $\bar{Z}_s^1$ are more complicated, and we cannot make a precise statement. If we were to use an unbiased estimate of $Var(Z_s)$, we would obtain a smaller estimate of $Var(Z_sG)$ and a correspondingly larger estimate of $Var(v_s + m_s)$.

Appendix 2. Construction and Use of Weights

In the NLS72 analyses of four-year college enrollment and postsecondary years of education, we use a set of panel weights (w22) designed to make nationally representative a sample of respondents who completed the base-year and fourth-follow up (1979) questionnaires. For the NLS72 wage analysis, we chose a set of panel weights (comvrwt) designed for all 1986 survey respondents for whom information exists on 5 of 6 key characteristics: high school grades, high school program, educational attainment as of 1986, gender, race, and socioeconomic status. Since there are very few 1986 respondents who did not also respond in 1979, this weight matches the wage sample fairly well. For the NELS88 sample, we use a set of weights (f3pnlwt) designed to make nationally representative the sample of respondents who completed the first four rounds of questionnaires (through 1994, when our outcomes are measured). For the ELS02 sample, we use a set of weights (f2bywt) designed to make nationally representative a sample of respondents who completed the second follow up questionnaire (2006) and for whom information was available on certain key baseline characteristics (gathered either in the base year questionnaire or the first follow-up). This seemed most appropriate given that our outcomes are measured in the 2006 questionnaire and we require non-missing observations on key characteristics for inclusion in the sample.

We use panel weights in the estimation for a number of reasons. The first is to reduce the influence of choice-based sampling, which is an issue in NELS88 and in the wage analysis based on NLS72. The second is to correct for non-random attrition from follow-up surveys. The third is a pragmatic adjustment to account for the possibility that the link between the observables and outcomes involves interaction terms or nonlinearities that we do not include. The weighted estimates may provide a better indication of average effects in such a setting. Finally, various populations and school types were oversampled in the three datasets, so that applying weights makes our sample more representative of the universe of American 8th graders, 10th graders, and 12th graders, respectively. Note, though, that we do not adjust weights for item non-response associated with the key variables required for inclusion in our sample. Thus, even after weighting, our estimates do not represent estimates of population parameters for the populations of American high school students of which the surveys were designed to be representative.

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Table 1: Variables Used in Baseline and Full (in Italics) Specifications

Student Characteristics
Female, Black, Hispanic, Asian, *Immigrant*
Student Ability
*Math Standardized Score**, *Reading Standardized Score**
Student Behavior
Hrs./Wk. Spent on Homework, *Parents Often Check Homework*, *Hrs./Wk. Spent on Leisure Reading*, *Hrs./Wk. Spent Watching TV*, *Often Arrives at Class Without a Pencil*, *Physical Fight This Year*
Family Background
Standardized SES, Number of Siblings, Both Bio. Parents Present, Mother and Male Guardian Present, Father and Female Guardian Present, Mother Only Present, Father Only Present, Father's Years of Education, Mother's Years of Education, Moth. Yrs. Ed. Missing, English Spoken at Home, Log(Family Income), *Immigrant Mother*, *Immigrant Father*, *Employed Mother*, *Employed Father*, *Parents are Married*
Parental Expectations
Mother's Desired Yrs. of Ed., *Father's Desired Yrs. of Ed.*
School Characteristics
School is Catholic, School is Private Non-Catholic, Student-Teacher Ratio, Pct. Teacher Turnover Since Last Year, Pct. on College Prep. Track, Pct. of Teachers w/ Master's Degrees or More, Average Pct. Daily Attendance, School Pct. Minority, School Teacher Pct. Minority, Total School Enrollment *Log(Min. Teacher Salary)*, *School Pct. Free/Reduced Price Lunch*, *School Pct. LEP*, *School Pct. Special Ed.*, *School Pct. Remedial Reading*, *School Pct. Remedial Math*
Neighborhood Characteristics
School in Urban Area, School in Suburban Area, School in Rural Area, School in Northeast U.S. Region, School in South U.S. Region, School in Midwest U.S. Region, School in West U.S. Region

*Standardized test scores are also included in the w/tests specifications, along with all of the baseline variables.

Table 2: Summary Statistics for Regression Indices (XB) of Predicted Outcomes Based on Student-Level Demographic Variables, by Outcome and Data Source

Panel A: High School Graduation

Source	Specification	Sample Mean ($\overline{Y}$)	Between Var./ Total Var.	10th Quantile School: E[Y]	90th Quantile School: E[Y]	90th-10th Difference
		(1)	(2)	(3)	(4)	(5)
NELS gr 8	Baseline	0.86	0.28	0.79	0.93	0.13
	w/Tests	0.86	0.27	0.77	0.94	0.18
	Full	0.86	0.25	0.77	0.94	0.18
NELS gr 10	Baseline	0.91	0.28	0.88	0.95	0.08
	w/Tests	0.91	0.25	0.86	0.96	0.10
	Full	0.91	0.22	0.86	0.96	0.10
ELS	Baseline	0.90	0.24	0.86	0.94	0.08
	w/Tests	0.90	0.25	0.85	0.95	0.11
	Full	0.90	0.23	0.85	0.95	0.11

Panel B: Enrollment in a Four-Year College

Source	Specification	Sample Mean ($\overline{Y}$)	Between Var./ Total Var.	10th Quantile School: E[Y]	90th Quantile School: E[Y]	90th-10th Difference
		(1)	(2)	(3)	(4)	(5)
NLS	Baseline	0.27	0.19	0.19	0.35	0.16
	w/Tests	0.27	0.15	0.17	0.38	0.21
NELS gr 8	Baseline	0.31	0.30	0.18	0.44	0.25
	w/Tests	0.31	0.29	0.16	0.47	0.31
	Full	0.31	0.29	0.15	0.48	0.33
NELS gr 10	Baseline	0.34	0.28	0.21	0.46	0.25
	w/Tests	0.34	0.26	0.18	0.50	0.32
	Full	0.34	0.25	0.18	0.50	0.32
ELS	Baseline	0.37	0.29	0.24	0.50	0.25
	w/Tests	0.37	0.27	0.21	0.54	0.34
	Full	0.37	0.27	0.20	0.55	0.34

Panel C: Years of Postsecondary Education

Source	Specification	Sample Mean ($\overline{Y}$)	Between Var./ Total Var.	10th Quantile School: E[Y]	90th Quantile School: E[Y]	90th-10th Difference
		(1)	(2)	(3)	(4)	(5)
NLS	Baseline	1.68	0.20	1.29	2.08	0.79
	w/Tests	1.68	0.16	1.18	2.18	1.00

Panel D: Permanent Wages

Source	Specification	Sample Mean ($\overline{Y}$)	Between Var./ Total Var.	10th Quantile School: E[Y]	90th Quantile School: E[Y]	90th-10th Difference
		(1)	(2)	(3)	(4)	(5)
NLS	Baseline	2.98	0.25	2.90	3.06	0.16
	w/Tests	2.98	0.25	2.89	3.07	0.18

NELS gr8 refers to a decomposition that uses the 8th grade school as the class variable.
NELS gr10 refers to a decomposition that uses the 10th grade school as the class variable, which naturally restricts the sample to those who reached 10th grade.
Between Var./Total Var. is the fraction of the variance in $X_{si}\hat{B}$ that is between schools. This value is also known as the intraclass correlation of $X_{si}\hat{B}$.
10th (90th) Quantile School: E[Y] refers to expected high school graduation rate at a school with the 10th percentile value (90th percentile value) of the school mean $X_s\hat{B}$. Our calculation holds the within school variance of $X_{si}\hat{B}$ and the distribution of $Z_sG + m_s + v_s + v_i$ constant. Col. 5 is Col. 4 - Col. 3.

Table 3: Variance Decomposition of Latent Variable Determining High School Graduation

	NELS gr8		NELS gr10 w/ gr8 char.		NELS gr10		ELS	
Variance Component	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within School:								
Total	0.827	0.829	0.857	0.853	0.857	0.848	0.872	0.874
$Var(Y_{si} - Y_s)$	(0.019)	(0.017)	(0.022)	(0.020)	(0.022)	(0.021)	(0.017)	(0.016)
Observable Student-Level:	0.136	0.255	0.094	0.177	0.094	0.189	0.108	0.186
$Var((X_{si} - X_s)B)$	(0.009)	(0.013)	(0.009)	(0.012)	(0.009)	(0.014)	(0.010)	(0.013)
Unobservable Student-Level:	0.691	0.574	0.763	0.676	0.763	0.659	0.764	0.687
$Var(V_{si})$	(0.018)	(0.018)	(0.021)	(0.019)	(0.021)	(0.022)	(0.018)	(0.019)
Between School:								
Total	0.173	0.171	0.143	0.147	0.143	0.152	0.128	0.126
$Var(Y_s)$	(0.019)	(0.017)	(0.022)	(0.020)	(0.022)	(0.021)	(0.017)	(0.016)
Observable Student-Level:	0.053	0.096	0.036	0.067	0.036	0.065	0.033	0.062
$Var(X_sB)$	(0.006)	(0.009)	(0.006)	(0.008)	(0.006)	(0.008)	(0.005)	(0.007)
Observable School-Level:	0.051	0.031	0.045	0.039	0.045	0.029	0.035	0.025
$Var(Z_sG)$	(0.011)	(0.008)	(0.013)	(0.012)	(0.013)	(0.010)	(0.009)	(0.007)
Observable Student-Level/	0.037	0.019	0.028	0.023	0.028	0.027	0.035	0.015
School-Level Covariance:	(0.011)	(0.013)	(0.013)	(0.016)	(0.013)	(0.014)	(0.007)	(0.010)
$2 * Cov(X_sB, Z_sG)$								
Unobservable School-Level/	0.032	0.026	0.033	0.019	0.033	0.031	0.024	0.025
$Var(V_s + M_s)$	(0.013)	(0.010)	(0.016)	(0.013)	(0.016)	(0.015)	(0.012)	(0.011)
Upper Bound								
$Var(Z_sG) + Var(V_s + M_s)$	0.120	0.075	0.107	0.080	0.107	0.088	0.095	0.064
$+2 * Cov(X_sB, Z_sG)$	(0.020)	(0.019)	(0.023)	(0.022)	(0.023)	(0.023)	(0.018)	(0.017)
Lower Bound	0.051	0.031	0.045	0.039	0.045	0.029	0.035	0.025
$Var(Z_sG)$	(0.011)	(0.008)	(0.013)	(0.012)	(0.013)	(0.010)	(0.009)	(0.007)

The table entries are fractions of the total variance, $Var(Y_{si})$.

NELS gr8 refers to a decomposition that uses the 8th grade school as the class variable, and uses 8th grade test scores in the w/tests specification.

NELS gr10 w/ gr8 char. refers to a decomposition that uses the 10th grade school as the class variable, but uses 8th grade measures of student behavior and parental expectations, and 8th grade test scores in the full specification.

NELS gr10 refers to a decomposition that uses the 10th grade school as the class variable, which naturally restricts the sample to those who reached 10th grade. It also uses 10th grade measures of student behavior and parental expectations, and 10th grade test scores in the full specification.

Upper Bound/Lower Bound refer to approximate upper and lower bounds on the direct contribution of schools to the variance in the outcome, independent of differences in student composition.

Table 4: Variance Decomposition of the Latent Variable for Enrollment at a Four Year College as of Two Years after the Graduation of a Respondant's High School Class

	NLS		NELS gr8		NELS gr10		ELS	
Variance Component	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within School:								
Total	0.859	0.859	0.776	0.776	0.791	0.786	0.784	0.791
$Var(Y_{si} - Y_s)$	(0.012)	(0.011)	(0.016)	(0.015)	(0.020)	(0.021)	(0.012)	(0.012)
Observable Student-Level:	0.150	0.346	0.170	0.278	0.161	0.306	0.152	0.298
$Var((X_{si} - X_s)B)$	(0.022)	(0.016)	(0.009)	(0.012)	(0.010)	(0.014)	(0.010)	(0.012)
Unobservable Student-Level:	0.709	0.512	0.606	0.497	0.630	0.480	0.632	0.493
$Var(V_{si})$	(0.022)	(0.015)	(0.015)	(0.013)	(0.018)	(0.015)	(0.012)	(0.013)
Between School:								
Total	0.141	0.141	0.224	0.224	0.209	0.214	0.216	0.209
$Var(Y_s)$	(0.012)	(0.011)	(0.016)	(0.015)	(0.020)	(0.021)	(0.012)	(0.012)
Observable Student-Level:	0.035	0.060	0.073	0.112	0.064	0.107	0.062	0.110
$Var(X_s B)$	(0.004)	(0.005)	(0.007)	(0.010)	(0.006)	(0.008)	(0.006)	(0.008)
Observable School-Level:	0.047	0.028	0.053	0.039	0.053	0.041	0.047	0.028
$Var(Z_s G)$	(0.006)	(0.004)	(0.007)	(0.005)	(0.008)	(0.006)	(0.006)	(0.004)
Observable Student-Level/	0.036	0.030	0.067	0.046	0.057	0.032	0.077	0.050
School-Level Covariance:	(0.006)	(0.008)	(0.011)	(0.013)	(0.013)	(0.015)	(0.007)	(0.010)
$2 * Cov(X_s B, Z_s G)$								
Unobservable School-Level/	0.024	0.025	0.031	0.028	0.035	0.034	0.030	0.020
$Var(V_s + M_s)$	(0.006)	(0.005)	(0.008)	(0.006)	(0.011)	(0.008)	(0.006)	(0.005)
Upper Bound								
$Var(Z_s G) + Var(V_s + M_s)$	0.106	0.082	0.151	0.112	0.145	0.107	0.154	0.099
$+2 * Cov(X_s B, Z_s G)$	(0.012)	(0.011)	(0.016)	(0.015)	(0.020)	(0.020)	(0.013)	(0.013)
Lower Bound	0.047	0.028	0.053	0.039	0.053	0.041	0.047	0.028
$Var(Z_s G)$	(0.006)	(0.004)	(0.007)	(0.005)	(0.008)	(0.006)	(0.006)	(0.004)

The table entries are fractions of the total variance, $Var(Y_{si})$.

NELS gr8 refers to a decomposition that uses the 8th grade school as the class variable, and uses 8th grade test scores in the w/tests specification.

NELS gr10 refers to a decomposition that uses the 10th grade school as the class variable, which naturally restricts the sample to those who reached 10th grade. It also uses 10th grade measures of student behavior and parental expectations, and 10th grade test scores in the full specification.

Upper Bound/Lower Bound refer to approximate upper and lower bounds on the direct contribution of schools to the variance in the outcome, independent of differences in student composition.

Table 5: Variance Decomposition of Years of Post-Secondary Education, using NLS Data

	Fraction of $Var(Y_{si})$	
Variance Component	Baseline	w/Tests
	(1)	(2)
Within School:		
Total:	0.904	0.904
$Var(Y_{si} - Y_s)$	(0.008)	(0.008)
Observable Student-Level:	0.128	0.267
$Var((X_{si} - X_s)B)$	(0.007)	(0.007)
Unobservable Student-Level:	0.776	0.636
$Var(V_{si})$	(0.010)	(0.008)
Between School:		
Total:	0.096	0.096
$Var(Y_s)$	(0.008)	(0.008)
Observable Student-Level:	0.033	0.052
$Var(X_s B)$	(0.003)	(0.004)
Observable School-Level:	0.026	0.015
$Var(Z_s G)$	(0.004)	(0.002)
Observable Student-Level/	0.031	0.025
School-Level Covariance:	(0.005)	(0.006)
$2 * Cov(X_s B, Z_s G)$		
Unobservable School-Level/	0.007	0.004
$Var(V_s + M_s)$	(0.003)	(0.003)
Upper Bound		
$Var Z_s G) + Var(V_s + M_s)$	0.064	0.044
$+2 * Cov(X_s B, Z_s G)$	(0.008)	(0.008)
Lower Bound	0.026	0.015
$Var(Z_s G)$	(0.004)	(0.002)

The total variance of years of post-secondary education is 2.923 Upper Bound/Lower Bound refer to approximate upper and lower bounds on the direct contribution of schools to the variance in the outcome, independent of differences in student composition.

Table 6: Variance Decomposition of Wages, Using NLS Data from 1979 and 1986, Controlling and Not Controlling for Completed Years of Post-Secondary Education

	Fraction of Total Wage Variance	Fraction of Permanent Wage Variance		Fraction of Permanent Wage Variance	
		No Post-sec Ed.		w/ Post-sec Ed.	
Variance Component		Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)
Transitory	0.573	–	–	–	–
$Var(W_{sit} - W_{si})$	(0.013)				
Permanent	0.427	–	–	–	–
$Var(W_{si})$	(0.013)				
Within School:					
Total:	–	0.838	0.835	0.829	0.829
$Var(W_{si} - W_s)$		(0.458)	(0.460)	(0.462)	(0.462)
Observable Student-Level:	–	0.128	0.167	0.209	0.221
$Var((X_{si} - X_s)B)$		(0.046)	(0.055)	(0.063)	(0.066)
Unobservable Student-Level:	–	0.710	0.668	0.621	0.608
$Var(V_{si})$		(0.476)	(0.482)	(0.485)	(0.486)
Between School:					
Total:	–	0.162	0.165	0.171	0.171
$Var(W_s)$		(0.458)	(0.460)	(0.462)	(0.462)
Observable Student-Level:	–	0.044	0.055	0.064	0.068
$Var(X_sB)$		(0.024)	(0.028)	(0.029)	(0.031)
Observable School-Level:	–	0.042	0.042	0.036	0.039
$Var(Z_sG)$		(0.029)	(0.028)	(0.026)	(0.027)
Observable School-Level/	–	0.032	0.029	0.034	0.030
School-Level Covariance:		(0.027)	(0.030)	(0.031)	(0.032)
$2 * Cov(X_sB, Z_sG)$					
Unobservable School-Level/	–	0.045	0.040	0.037	0.034
$Var(V_s + M_s)$		(0.424)	(0.423)	(0.426)	(0.424)
Upper Bound					
$VarZ_sG) + Var(V_s + M_s)$	–	0.119	0.110	0.107	0.103
$+2 * Cov(X_sB, Z_sG)$		(0.451)	(0.451)	(0.453)	(0.451)
Lower Bound	–	0.042	0.042	0.036	0.039
$Var(Z_sG)$		(0.029)	(0.028)	(0.026)	(0.027)

Total pooled variance ($Var(W_{sit})$) = 0.215.

No Post-sec Ed. refers to specifications in which we do not control for years of completed post-secondary education when estimating the student-level coefficient vector B.

w/ Post-sec Ed. refers to specifications in which we control for years of completed post-secondary education when estimating the student-level coefficient vector B.

Upper Bound/Lower Bound refer to approximate upper and lower bounds on the direct contribution of schools to the variance in the outcome, independent of differences in student composition.

Table 7: Effect on Outcomes of Transferring from a School at the 10th Percentile of the Distribution of School Quality to a School at the 50th or 90th Percentile: Approximate Upper and Lower Bound Estimates

Panel A: High School Graduation

Upper/Lower Bound	NELS gr8		NELS gr10 w/ gr8 char.		NELS gr10		ELS	
	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upper Bound: 10th-90th	0.165	0.142	0.107	0.094	0.107	0.092	0.107	0.098
$Var(V_s) = 0$	(0.016)	(0.014)	(0.012)	(0.011)	(0.012)	(0.010)	(0.010)	(0.009)
Lower Bound: 10th-90th	0.129	0.104	0.082	0.078	0.082	0.064	0.083	0.070
$Var(M_s) = 0$	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)	(0.009)	(0.008)	(0.008)
Upper Bound: 10th-50th	0.101	0.083	0.068	0.058	0.068	0.057	0.065	0.059
$Var(V_s) = 0$	(0.013)	(0.010)	(0.011)	(0.009)	(0.011)	(0.009)	(0.008)	(0.007)
Lower Bound: 10th-50th	0.075	0.059	0.049	0.046	0.049	0.037	0.048	0.039
$Var(M_s) = 0$	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.005)

Panel B: Enrollment in a Four Year College (Baseline and w/Tests Specifications)

Upper/Lower Bound	NLS		NELS gr8		NELS gr10		ELS	
	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upper Bound: 10th-90th	0.232	0.196	0.278	0.238	0.295	0.264	0.282	0.218
$Var(V_s) = 0$	(0.015)	(0.011)	(0.019)	(0.015)	(0.019)	(0.016)	(0.015)	(0.012)
Lower Bound: 10th-90th	0.188	0.142	0.220	0.181	0.227	0.193	0.219	0.166
$Var(M_s) = 0$	(0.015)	(0.012)	(0.018)	(0.014)	(0.018)	(0.014)	(0.014)	(0.011)
Upper Bound: 10th-50th	0.103	0.089	0.126	0.109	0.136	0.123	0.131	0.104
$Var(V_s) = 0$	(0.006)	(0.005)	(0.008)	(0.006)	(0.008)	(0.007)	(0.006)	(0.005)
Lower Bound: 10th-50th	0.085	0.067	0.102	0.085	0.107	0.092	0.104	0.080
$Var(M_s) = 0$	(0.007)	(0.005)	(0.008)	(0.006)	(0.008)	(0.007)	(0.006)	(0.005)

(Cont'd) Table 7: Effect on Outcomes of Transferring from a School at the 10th Percentile of the Distribution of School Quality to a School at the 50th or 90th Percentile: Approximate Upper and Lower Bound Estimates

Panel C: Years of Postsecondary Education and Permanent Wages (NLS72 data)						
Upper/Lower Bound	Yrs. Postsec. Ed.		Perm. Wages No Post-sec Ed.		Perm. Wages w/ Post-sec Ed.	
	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)
Upper Bound: 10th-90th	0.789	0.605	0.228	0.221	0.211	0.210
$Var(V_s) = 0$	(0.049)	(0.044)	(0.064)	(0.065)	(0.066)	(0.066)
Lower Bound: 10th-90th	0.700	0.532	0.158	0.159	0.148	0.153
$Var(M_s) = 0$	(0.048)	(0.039)	(0.016)	(0.016)	(0.015)	(0.015)
Upper Bound: 10th-50th	0.395	0.303	0.114	0.111	0.105	0.105
$Var(V_s) = 0$	(0.025)	(0.022)	(0.032)	(0.032)	(0.033)	(0.033)
Lower Bound: 10th-50th	0.350	0.266	0.079	0.079	0.074	0.077
$Var(M_s) = 0$	(0.024)	(0.019)	(0.008)	(0.008)	(0.008)	(0.008)

NELS gr8 refers to a decomposition that uses the 8th grade school as the class variable, and uses 8th grade measures of student behavior and parental expectations, and 8th grade test scores in the full specification.
NELS gr10 w/ gr8 char. refers to a decomposition that uses the 10th grade school as the class variable, but uses 8th grade measures of student behavior and parental expectations, and 8th grade test scores in the full specification.
NELS gr10 refers to a decomposition that uses the 10th grade school as the class variable, which naturally restricts the sample to those who reached 10th grade. It also uses 10th grade measures of student behavior and parental expectations, and 10th grade test scores in the full specification.
Full specification includes student ability, student behavior, and parent expectation measures in addition to an enhanced set of student, parent, and school characteristics.
No Post-sec Ed. refers to specifications in which we do not include years of completed post-secondary education as an element of X_{si}.
w/ Post-sec Ed. refers to specifications in which we include years of completed post-secondary education as an element of X_{si}.

Table 8: The Impact of 10th-90th Percentile Shifts in School Quality on High School Graduation Rates for Selected Subpopulations

	NELS gr8		NELS gr10 w/ gr8 char.		NELS gr10		ELS	
Subpopulation	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black								
Upper Bound	0.164	0.155	0.121	0.112	0.121	0.110	0.124	0.123
	(0.019)	(0.019)	(0.021)	(0.020)	(0.021)	(0.021)	(0.016)	(0.017)
Lower Bound	0.128	0.114	0.092	0.092	0.092	0.077	0.096	0.087
	(0.013)	(0.013)	(0.014)	(0.015)	(0.014)	(0.013)	(0.011)	(0.011)
White w/ Single Mother Who Did Not Attend College								
Upper Bound	0.266	0.235	0.175	0.161	0.175	0.157	0.154	0.138
	(0.027)	(0.024)	(0.026)	(0.027)	(0.026)	(0.024)	(0.019)	(0.018)
Lower Bound	0.207	0.172	0.133	0.132	0.133	0.109	0.119	0.098
	(0.022)	(0.021)	(0.020)	(0.021)	(0.020)	(0.017)	(0.015)	(0.013)
White w/ Both Parents, At Least One Completed College								
Upper Bound	0.070	0.047	0.046	0.033	0.046	0.032	0.046	0.035
	(0.010)	(0.007)	(0.008)	(0.006)	(0.008)	(0.006)	(0.007)	(0.005)
Lower Bound	0.056	0.035	0.036	0.028	0.036	0.023	0.036	0.025
	(0.008)	(0.005)	(0.007)	(0.005)	(0.007)	(0.005)	(0.005)	(0.004)
XB: 10th Quantile								
Upper Bound	0.289	0.285	0.193	0.194	0.193	0.203	0.178	0.192
	(0.026)	(0.026)	(0.021)	(0.022)	(0.021)	(0.022)	(0.016)	(0.019)
Lower Bound	0.224	0.208	0.147	0.159	0.147	0.141	0.137	0.135
	(0.023)	(0.023)	(0.018)	(0.021)	(0.018)	(0.019)	(0.013)	(0.015)
XB: 90th Quantile								
Upper Bound	0.052	0.014	0.035	0.013	0.035	0.012	0.032	0.016
	(0.008)	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)	(0.006)	(0.003)
Lower Bound	0.041	0.011	0.027	0.011	0.027	0.009	0.025	0.012
	(0.006)	(0.002)	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.002)

NELS gr8 refers to a decomposition that uses the 8th grade school as the class variable, and uses 8th grade measures of student behavior and parental expectations, and 8th grade test scores in the full specification.

NELS gr10 w/ gr8 char. refers to a decomposition that uses the 10th grade school as the class variable, but uses 8th grade measures of student behavior and parental expectations, and 8th grade test scores in the full specification.

NELS gr10 refers to a decomposition that uses the 10th grade school as the class variable, which naturally restricts the sample to those who reached 10th grade. It also uses 10th grade measures of student behavior and parental expectations, and 10th grade test scores in the full specification.

Upper Bound/Lower Bound refer to approximate upper and lower bounds on the increase in the probability of graduation associated with a move from the 10th percentile school to the 90th percentile school, independent of differences in student composition.

XB: 10th (90th) Quantile reports results for students whose values of $X_{si}B$ equal the estimated 10th (90th) quantile value of the $X_{si}B$ distribution. See Section 6.

Table 9: The Impact of 10th-90th Percentile Shifts in School Quality on Four-Year College Enrollment Rates for Selected Subpopulations

	NELS gr8		NELS gr10 w/ gr8 char.		NELS gr10		ELS	
Subpopulation	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black								
Upper Bound	0.271	0.234	0.290	0.266	0.290	0.250	0.263	0.203
	(0.018)	(0.015)	(0.022)	(0.019)	(0.022)	(0.019)	(0.016)	(0.012)
Lower Bound	0.214	0.178	0.222	0.197	0.222	0.183	0.204	0.154
	(0.017)	(0.013)	(0.019)	(0.016)	(0.019)	(0.016)	(0.014)	(0.011)
White w/ Single Mother Who Did Not Attend College								
Upper Bound	0.198	0.160	0.221	0.191	0.221	0.190	0.258	0.209
	(0.017)	(0.015)	(0.019)	(0.017)	(0.019)	(0.020)	(0.016)	(0.014)
Lower Bound	0.157	0.123	0.171	0.142	0.171	0.140	0.200	0.159
	(0.015)	(0.012)	(0.016)	(0.014)	(0.016)	(0.015)	(0.014)	(0.012)
White w/ Both Parents, At Least One Completed College								
Upper Bound	0.343	0.291	0.342	0.308	0.342	0.308	0.315	0.244
	(0.016)	(0.012)	(0.022)	(0.018)	(0.022)	(0.018)	(0.017)	(0.014)
Lower Bound	0.270	0.221	0.262	0.228	0.262	0.225	0.244	0.186
	(0.018)	(0.014)	(0.020)	(0.016)	(0.020)	(0.016)	(0.015)	(0.013)
XB: 10th Quantile								
Upper Bound	0.148	0.089	0.179	0.120	0.179	0.094	0.197	0.096
	(0.014)	(0.010)	(0.016)	(0.012)	(0.016)	(0.012)	(0.015)	(0.010)
Lower Bound	0.118	0.070	0.139	0.091	0.139	0.071	0.154	0.074
	(0.012)	(0.008)	(0.014)	(0.009)	(0.014)	(0.009)	(0.013)	(0.008)
XB: 90th Quantile								
Upper Bound	0.348	0.291	0.340	0.294	0.340	0.294	0.307	0.224
	(0.016)	(0.015)	(0.023)	(0.022)	(0.023)	(0.020)	(0.018)	(0.016)
Lower Bound	0.274	0.221	0.260	0.217	0.260	0.215	0.238	0.171
	(0.018)	(0.015)	(0.020)	(0.018)	(0.020)	(0.016)	(0.016)	(0.013)

Notes: See Table 8

Table 10: The Average School Environment Experienced by Members of Selected Subpopulations, as Measured by Average Outcomes and Average Peer Quality

Panel A: High School Graduation

	NELS gr8		NELS gr10 w/ gr8 char.		NELS gr10		ELS	
Subpopulation	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black								
Actual Grad. Rate	0.810	0.810	0.904	0.904	0.904	0.904	0.864	0.864
	(0.011)	(0.011)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Expected Grad. Rate in Random School	0.865	0.853	0.907	0.902	0.907	0.907	0.885	0.875
	(0.012)	(0.013)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)
White w/ Single Mother Who Did Not Attend College								
Actual Grad. Rate	0.734	0.734	0.842	0.842	0.842	0.842	0.863	0.863
	(0.022)	(0.022)	(0.020)	(0.020)	(0.020)	(0.020)	(0.022)	(0.022)
Expected Grad. Rate in Random School	0.735	0.721	0.851	0.841	0.851	0.851	0.853	0.857
	(0.015)	(0.017)	(0.014)	(0.016)	(0.014)	(0.014)	(0.012)	(0.012)
White w/ Both Parents, At Least One Completed College								
Actual Grad. Rate	0.977	0.977	0.985	0.985	0.985	0.985	0.981	0.981
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Expected Grad. Rate in Random School	0.958	0.967	0.973	0.978	0.973	0.979	0.969	0.974
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)

Panel B: Four-Year College Enrollment

	NLS		NELS gr8		NELS gr10		ELS	
Subpopulation	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests	Baseline	w/Tests
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Black								
Actual Enroll. Rate	0.229	0.229	0.284	0.284	0.329	0.329	0.281	0.281
	(0.010)	(0.010)	(0.013)	(0.013)	(0.015)	(0.015)	(0.011)	(0.011)
Expected Enroll. Rate in Random School	0.235	0.217	0.296	0.275	0.327	0.307	0.291	0.270
	(0.017)	(0.016)	(0.019)	(0.019)	(0.022)	(0.022)	(0.013)	(0.013)
White w/ Single Mother Who Did Not Attend College								
Actual Enroll. Rate	0.199	0.199	0.149	0.149	0.178	0.178	0.241	0.241
	(0.019)	(0.019)	(0.018)	(0.018)	(0.021)	(0.021)	(0.027)	(0.027)
Expected Enroll. Rate in Random School	0.159	0.172	0.153	0.135	0.180	0.167	0.245	0.246
	(0.012)	(0.013)	(0.012)	(0.013)	(0.014)	(0.017)	(0.015)	(0.015)
White w/ Both Parents, At Least One Completed College								
Actual Enroll. Rate	0.602	0.602	0.647	0.647	0.652	0.652	0.697	0.697
	(0.013)	(0.013)	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)
Expected Enroll. Rate in Random School	0.508	0.532	0.564	0.598	0.583	0.614	0.612	0.645
	(0.012)	(0.013)	(0.012)	(0.012)	(0.014)	(0.012)	(0.011)	(0.012)

See Table 3 for definitions of the different NELS samples/specifications.

Table 11: Variance Decomposition of Latent Variable Determining High School Graduation

	NELS gr10 w/ gr8 char.	NC						
				$\Gamma = \phi B$			$\Gamma = \phi G$	
Variance Component	Full	No Cl.	Cl. Avg.	$\phi = \frac{1}{4}$	$\phi = \frac{1}{2}$	$\phi = 1$	$\phi = \frac{1}{2}$	$\phi = 1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within School:								
Total	0.852	0.855	0.858	0.855	0.855	0.855	0.855	0.855
$Var(Y_{si} - Y_s)$	(0.019)	(0.017)	(0.022)	(0.020)	(0.022)	(0.021)	(0.017)	(0.016)
Observable Student-Level:	0.193	0.193	0.026	0.160	0.136	0.103	0.182	0.171
$Var((X_{si} - X_s)B)$	(0.009)	(0.013)	(0.009)	(0.012)	(0.009)	(0.014)	(0.010)	(0.013)
Observable Classroom-Level:	*	*	0.171	0.003	0.009	0.025	0.022	0.096
$Var((\overline{X}_{sc(i)} - \overline{X}_{sc})C)$	(0.009)	(0.013)	(0.009)	(0.012)	(0.009)	(0.014)	(0.010)	(0.013)
Cov(Stu.-/Class.-Level):	*	*	0.067	0.031	0.051	0.074	0.008	0.008
$2 * Cov((\overline{X}_{sc(i)} - \overline{X}_{sc})C,$ $(X_{si} - X_s)B)$	(0.009)	(0.013)	(0.009)	(0.012)	(0.009)	(0.014)	(0.010)	(0.013)
Unobservable Student-Level:	0.659	0.662	0.593	0.661	0.659	0.653	0.643	0.580
$Var(V_{si})$	(0.018)	(0.018)	(0.021)	(0.019)	(0.021)	(0.022)	(0.018)	(0.019)
Between School:								
Total	0.148	0.145	0.142	0.145	0.145	0.145	0.145	0.145
$Var(Y_s)$	(0.019)	(0.017)	(0.022)	(0.020)	(0.022)	(0.021)	(0.017)	(0.016)
Observable Student-Level:	0.066	0.032	0.003	0.027	0.022	0.017	0.031	0.029
$Var(X_s B)$	(0.006)	(0.009)	(0.006)	(0.008)	(0.006)	(0.008)	(0.005)	(0.007)
Observable School-Level:	0.044	0.036	0.066	0.039	0.041	0.046	0.038	0.040
$Var(Z_s G)$	(0.011)	(0.008)	(0.013)	(0.012)	(0.013)	(0.010)	(0.009)	(0.007)
Observable Student-Level/	0.021	0.024	0.021	0.027	0.029	0.031	0.024	0.024
School-Level Covariance: $2 * Cov(X_s B, Z_s G)$	(0.011)	(0.013)	(0.013)	(0.016)	(0.013)	(0.014)	(0.007)	(0.010)
Unobservable School-Level/	0.017	0.052	0.052	0.052	0.052	0.052	0.052	0.052
$Var(V_s + M_s)$	(0.013)	(0.010)	(0.016)	(0.013)	(0.016)	(0.015)	(0.012)	(0.011)
Upper Bound								
$Var(Z_s G) + Var(V_s + M_s)$	0.082	0.113	0.139	0.119	0.123	0.128	0.114	0.116
$+2 * Cov(X_s B, Z_s G)$	(0.020)	(0.019)	(0.023)	(0.022)	(0.023)	(0.023)	(0.018)	(0.017)
Lower Bound	0.044	0.036	0.066	0.039	0.041	0.046	0.038	0.040
$Var(Z_s G)$	(0.011)	(0.008)	(0.013)	(0.012)	(0.013)	(0.010)	(0.009)	(0.007)

The table entries are fractions of the total variance, $Var(Y_{si})$.

NELS gr10 w/ gr8 char. refers to a decomposition that uses the 10th grade school as the class variable, but uses 8th grade measures of student behavior and parental expectations, and 8th grade test scores in the full specification.

Upper Bound/Lower Bound refer to approximate upper and lower bounds on the direct contribution of schools to the variance in the outcome, independent of differences in student composition.

Table 12: Effect on Outcomes of Transferring from a School at the 10th Percentile of the Distribution of School Quality to a School at the 50th or 90th Percentile: Approximate Upper and Lower Bound Estimates

	NELS gr10 w/ gr8 char.	NC						
				$\Gamma = \phi B$			$\Gamma = \phi G$	
Variance Component	Full	No Cl.	Cl. Avg.	$\phi = \frac{1}{4}$	$\phi = \frac{1}{2}$	$\phi = 1$	$\phi = \frac{1}{2}$	$\phi = 1$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Upper Bound: 10th-90th $Var(V_s) = 0$	0.165	0.243	0.281	0.246	0.249	0.255	0.242	0.240
Lower Bound: 10th-90th $Var(M_s) = 0$	0.129	0.154	0.208	0.160	0.164	0.173	0.156	0.157
Upper Bound: 10th-50th $Var(V_s) = 0$	0.101	0.139	0.165	0.141	0.143	0.147	0.139	0.137
Lower Bound: 10th-50th $Var(M_s) = 0$	0.075	0.084	0.117	0.087	0.090	0.095	0.085	0.086

Appendix Table 1: Summary Statistics for Individual-Level Variables from the National Longitudinal Survey of the Class of 1972 (NLS72), Using All Non-Missing Base Year Observations

Variable Name	Sample Mean	Standard Deviation	Between/ Total Var.	Between-School Std Dev.	10th Quantile School	90th Quantile School
Student Characteristics						
Female	0.50	0.50	0.09	.	0.35	0.66
Black	0.08	0.28	0.73	.	0.00	0.29
Hispanic	0.03	0.18	0.61	.	0.00	0.09
Asian	0.01	0.10	0.50	.	0.00	0.02
Student Ability						
Math Std. Score	0.02	1.00	0.13	0.36	-0.44	0.48
Reading Std. Score	0.02	1.00	0.11	0.34	-0.41	0.45
Family Background						
Standardized SES	0.00	0.99	0.33	0.57	-0.73	0.73
Number of Siblings	2.77	2.33	0.05	0.52	2.10	3.44
Both Bio. Parents Present	0.77	0.42	0.07	.	0.66	0.87
Mother and Male Guardian Present	0.02	0.15	0.07	.	0.01	0.04
Father and Female Guardian Present	0.01	0.08	0.00	.	0.01	0.01
Mother Only Present	0.12	0.32	0.05	.	0.06	0.18
Father Only Present	0.03	0.18	0.00	.	0.03	0.03
Father's Years of Education	12.62	2.47	0.17	1.03	11.31	13.93
Mother's Years of Education	12.33	2.05	0.12	0.72	11.41	13.25
Moth. Yrs. Ed. Missing	0.01	0.07	0.07	.	0.00	0.01
Log(Family Income)	10.90	0.71	0.21	0.33	10.48	11.32
English Spoken at Home	0.92	0.27	0.12	.	0.85	0.97
Enrolled at a 4-Year College (COLL)	0.27	0.44	0.17	.	0.11	0.46
Outcome Measures						
Years of Post-Secondary Education	1.68	1.74	0.11	0.56	0.96	2.40
Log(1979 Wage)	2.74	0.48	0.04	0.10	2.61	2.87
Log(1986 Wage)	2.98	0.49	0.09	0.15	2.79	3.16

Between school variances group using the grade 12 school.
Between/Total Var. is the fraction of the variance in $X_{si}\hat{B}$ that is between schools. This value is also known as the intraclass correlation of $X_{si}\hat{B}$.
10th (90th) Quantile School refers to the estimated average value of the variable at a school whose average value for this variable puts it at the 10th (90th) percentile among all high schools.

Appendix Table 2: Summary Statistics for School-Level Variables from 12th Grade Schools in the National Longitudinal Survey of the Class of 1972 (NLS72)

Variable Name	Sample Mean	Standard Deviation
School Characteristics		
School is Catholic	0.06	0.24
School is Private Non-Catholic	0.00	0.07
Student-Teacher Ratio	20.30	4.42
Pct. Teacher Turnover Since Last Year	0.09	0.09
Pct. on College Prep. Track	0.42	0.25
Pct. of Teachers w/ Master's Degrees or More	0.41	0.21
Average Pct. Daily Attendance	0.91	0.05
School Pct. Minority	0.21	0.27
School Teacher Pct. Minority	0.10	0.16
Total School Enrollment	1407.05	925.96
Neighborhood Characteristics		
School in Urban Area	0.31	0.46
School in Suburban Area	0.50	0.50
School in Rural Area	0.19	0.39
School in Northeast U.S. Region	0.22	0.41
School in South U.S. Region	0.33	0.47
School in Midwest U.S. Region	0.27	0.44
School in West U.S. Region	0.18	0.38

Note that, in addition to the variables listed above, school averages of all individual-level variables are also included in Z.

Appendix Table 3: Summary Statistics for Individual-Level Variables from the 1988 National Educational Longitudinal Survey (NELS88), Decomposing Using the 10th Grade School, and Restricting the Sample to Students Reaching the 10th Grade

Variable Name	Sample Mean	Standard Deviation	Between/ Total Var.	Between-School Std Dev.	10th Quantile School	90th Quantile School
Student Characteristics						
Female	0.51	0.50	0.03	.	0.41	0.60
Black	0.10	0.30	0.70	.	0.00	0.35
Hispanic	0.09	0.29	0.61	.	0.00	0.30
Asian	0.03	0.18	0.37	.	0.00	0.09
Immigrant	0.04	0.20	0.33	.	0.00	0.11
Student Ability						
Math Std. Score	0.15	1.00	0.20	0.45	-0.43	0.73
Reading Std. Score	0.13	0.99	0.14	0.38	-0.35	0.61
Student Behavior						
Hrs./Wk. Spent on HW	7.93	6.94	0.08	1.92	5.47	10.39
Parents Often Check HW	0.25	0.44	0.03	.	0.19	0.32
Hrs./Wk. Spent on Leisure Reading	2.35	2.64	0.03	0.49	1.72	2.98
Hrs./Wk. Spent Watching TV	18.78	10.58	0.10	3.28	14.58	22.97
Often Shows Up to Class Without a Pencil	0.10	0.30	0.03	.	0.06	0.14
Physical Fight This Year	0.17	0.37	0.04	.	0.10	0.24
Family Background						
Standardized SES	0.09	0.97	0.31	0.54	-0.60	0.78
Number of Siblings	2.20	1.52	0.09	0.45	1.62	2.77
Both Bio. Parents Present	0.69	0.46	0.08	.	0.56	0.82
Mother and Male Guardian Present	0.10	0.30	0.04	.	0.06	0.15
Father and Female Guardian Present	0.02	0.15	0.03	.	0.01	0.03
Mother Only Present	0.14	0.34	0.05	.	0.08	0.21
Father Only Present	0.02	0.15	0.05	.	0.01	0.04
Father's Years of Education	13.54	2.73	0.26	1.38	11.77	15.31
Mother's Years of Education	13.05	2.21	0.20	1.00	11.77	14.32
Moth. Yrs. Ed. Missing	0.02	0.14	0.19	.	0.00	0.05
Log(Family Income)	10.94	0.85	0.27	0.44	10.38	11.51
English Spoken at Home	0.92	0.28	0.49	.	0.75	1.00
Immigrant Mother	0.10	0.30	0.49	.	0.00	0.29
Immigrant Father	0.09	0.29	0.52	.	0.00	0.28
Employed Mother	0.53	0.50	0.05	.	0.42	0.64
Employed Father	0.90	0.29	0.08	.	0.84	0.96
Parents are Married	0.81	0.39	0.09	.	0.70	0.91
Parent Expectations						
Mother's Desired Yrs. of Ed.	15.94	1.93	0.09	0.57	15.21	16.66
Father's Desired Yrs. of Ed.	15.94	1.94	0.09	0.57	15.21	16.67
Outcome Measures						
Enrolled at a 4-Year College (COLL)	0.34	0.47	0.21	.	0.13	0.58
Graduated HS (HSGRAD)	0.91	0.28	0.13	.	0.83	0.97

Between school variances group using the grade 10 school
Between/Total Var. is the fraction of the variance in $X_{si}\hat{B}$ that is between schools. This value is also known as the intraclass correlation of $X_{si}\hat{B}$.
10th (90th) Quantile School refers to the estimated average value of the variable at a school whose average value for this variable puts it at the 10th (90th) percentile among all high schools.

Appendix Table 4: Summary Statistics for School-Level Variables from 10th Grade Schools in the 1988 National Educational Longitudinal Survey (NELS88)

Variable Name	Sample Mean	Standard Deviation
School Characteristics		
School is Catholic	0.07	0.25
School is Private Non-Catholic	0.08	0.28
Student-Teacher Ratio	16.06	4.50
Pct. Teacher Turnover Since Last Year	0.03	0.03
Pct. on College Prep. Track	0.54	0.29
Pct. of Teachers w/ Master's Degrees or More	0.54	0.21
Average Pct. Daily Attendance	0.93	0.05
School Pct. Minority	0.25	0.30
School Teacher Pct. Minority	0.09	0.15
Total School Enrollment	1207.51	743.03
Log(Min. Teacher Salary)	9.87	0.20
School Pct. Free/Reduced Price Lunch	0.20	0.22
School Pct. LEP	0.07	0.12
School Pct. Special Ed.	0.08	0.07
School Pct. Remedial Reading	0.09	0.11
School Pct. Remedial Math	0.09	0.11
Neighborhood Characteristics		
School in Urban Area	0.35	0.48
School in Suburban Area	0.46	0.50
School in Rural Area	0.19	0.39
School in Northeast U.S. Region	0.21	0.41
School in South U.S. Region	0.35	0.48
School in Midwest U.S. Region	0.25	0.43
School in West U.S. Region	0.19	0.39

Note that, in addition to the variables listed above, school averages of all individual-level variables are also included in Z.

Appendix Table 5: Summary Statistics for Individual-Level Variables from the 1988 National Educational Longitudinal Survey (NELS88), Using All Non-Missing Base Year Observations

Variable Name	Sample Mean	Standard Deviation	Between/ Total Var.	Between-School Std Dev.	10th Quantile School	90th Quantile School
Student Characteristics						
Female	0.50	0.50	0.01	.	0.44	0.56
Black	0.11	0.31	0.70	.	0.00	0.39
Hispanic	0.10	0.30	0.60	.	0.00	0.31
Asian	0.03	0.18	0.35	.	0.00	0.09
Immigrant	0.04	0.20	0.34	.	0.00	0.12
Student Ability						
Math Std. Score	0.07	1.01	0.20	0.45	-0.51	0.64
Reading Std. Score	0.05	1.00	0.14	0.38	-0.43	0.54
Student Behavior						
Hrs./Wk. Spent on HW	5.90	5.08	0.07	1.33	4.20	7.60
Parents Often Check HW	0.45	0.50	0.03	.	0.36	0.53
Hrs./Wk. Spent on Leisure Reading	2.23	2.67	0.02	0.40	1.71	2.74
Hrs./Wk. Spent Watching TV	21.74	10.82	0.08	3.06	17.83	25.66
Often Shows Up to Class Without a Pencil	0.22	0.41	0.05	.	0.14	0.31
Physical Fight This Year	0.21	0.41	0.05	.	0.13	0.29
Family Background						
Standardized SES	0.02	1.00	0.30	0.55	-0.69	0.72
Number of Siblings	2.26	1.57	0.07	0.41	1.74	2.78
Both Bio. Parents Present	0.67	0.47	0.09	.	0.53	0.81
Mother and Male Guardian Present	0.11	0.31	0.04	.	0.06	0.15
Father and Female Guardian Present	0.02	0.15	0.04	.	0.01	0.04
Mother Only Present	0.15	0.36	0.07	.	0.08	0.23
Father Only Present	0.02	0.15	0.07	.	0.01	0.04
Father's Years of Education	13.40	2.75	0.25	1.39	11.63	15.17
Mother's Years of Education	12.92	2.23	0.19	0.98	11.66	14.18
Moth. Yrs. Ed. Missing	0.02	0.14	0.13	.	0.00	0.05
Log(Family Income)	10.88	0.90	0.26	0.46	10.30	11.46
English Spoken at Home	0.91	0.29	0.47	.	0.74	1.00
Immigrant Mother	0.10	0.30	0.48	.	0.00	0.29
Immigrant Father	0.09	0.29	0.51	.	0.00	0.27
Employed Mother	0.53	0.50	0.05	.	0.41	0.64
Employed Father	0.90	0.30	0.09	.	0.83	0.96
Parents are Married	0.79	0.40	0.11	.	0.66	0.91
Parent Expectations						
Mother's Desired Yrs. of Ed.	16.18	2.05	0.06	0.51	15.52	16.84
Father's Desired Yrs. of Ed.	16.14	2.09	0.07	0.53	15.46	16.82
Outcome Measures						
Enrolled at a 4-Year College (COLL)	0.31	0.46	0.22	.	0.11	0.55
Graduated HS (HSGRAD)	0.86	0.35	0.17	.	0.73	0.96

Between school variances group using the grade 8 school.
Between/Total Var. is the fraction of the variance in $X_{si}\hat{B}$ that is between schools. This value is also known as the intraclass correlation of $X_{si}\hat{B}$.
10th (90th) Quantile School refers to the estimated average value of the variable at a school whose average value for this variable puts it at the 10th (90th) percentile among all high schools.

Appendix Table 6: Summary Statistics for School-Level Variables from 8th Grade Schools in the 1988 National Educational Longitudinal Survey (NELS88)

Variable Name	Sample Mean	Standard Deviation
School Characteristics		
School is Catholic	0.09	0.29
School is Private Non-Catholic	0.11	0.31
Student-Teacher Ratio	17.65	5.31
Pct. of Teachers w/ Master's Degrees or More	0.48	0.25
Average Pct. Daily Attendance	0.94	0.04
School Pct. Minority	0.25	0.31
School Teacher Pct. Minority	0.12	0.20
Total School Enrollment	669.33	390.35
Log(Min. Teacher Salary)	9.76	0.18
School Pct. Free/Reduced Price Lunch	0.24	0.24
School Pct. LEP	0.07	0.09
School Pct. Special Ed.	0.06	0.06
School Pct. Remedial Reading	0.10	0.14
School Pct. Remedial Math	0.08	0.11
Neighborhood Characteristics		
School in Northeast U.S. Region	0.21	0.41
School in South U.S. Region	0.35	0.48
School in Midwest U.S. Region	0.25	0.44
School in West U.S. Region	0.19	0.39

Note that, in addition to the variables listed above, school averages of all individual-level variables are also included in Z.

Appendix Table 7: Summary Statistics for Individual-Level Variables from the 2002 Educational Longitudinal Survey (ELS2002), Using All Non-Missing Base Year Observations

Variable Name	Sample Mean	Standard Deviation	Between/ Total Var.	Between-School Std Dev.	10th Quantile School	90th Quantile School
Student Characteristics						
Female	0.51	0.50	0.04	.	0.41	0.62
Black	0.14	0.35	0.53	.	0.00	0.42
Hispanic	0.15	0.36	0.44	.	0.01	0.41
Asian	0.04	0.19	0.38	.	0.00	0.11
Immigrant	0.08	0.27	0.29	.	0.01	0.19
Student Ability						
Math Std. Score	0.05	1.00	0.21	0.46	-0.54	0.63
Reading Std. Score	0.05	1.00	0.20	0.45	-0.52	0.62
Student Behavior						
Hrs./Wk. Spent on HW	10.60	8.90	0.07	2.41	7.52	13.68
Parents Often Check HW	0.35	0.48	0.02	.	0.29	0.42
Hrs./Wk. Spent on Leisure Reading	2.80	4.13	0.02	0.58	2.05	3.55
Hrs./Wk. Spent Watching TV	23.06	12.17	0.05	2.64	19.68	26.44
Often Arrives at Class Without a Pencil	0.17	0.37	0.03	.	0.11	0.23
Physical Fight This Year	0.13	0.34	0.06	.	0.07	0.20
Family Background						
Standardized SES	0.03	1.01	0.26	0.51	-0.62	0.68
Number of Siblings	2.31	1.52	0.06	0.37	1.84	2.78
Both Bio. Parents Present	0.59	0.49	0.09	.	0.43	0.74
Mother and Male Guardian Present	0.13	0.34	0.03	.	0.08	0.18
Father and Female Guardian Present	0.03	0.17	0.00	.	0.03	0.03
Mother Only Present	0.19	0.39	0.07	.	0.10	0.28
Father Only Present	0.03	0.17	0.01	.	0.02	0.04
Father's Years of Education	13.75	2.62	0.21	1.21	12.20	15.30
Mother's Years of Education	13.52	2.28	0.18	0.97	12.28	14.76
Moth. Yrs. Ed. Missing	0.03	0.18	0.07	.	0.01	0.06
Log(Family Income)	10.92	0.96	0.24	0.47	10.31	11.52
English Spoken at Home	0.90	0.30	0.49	.	0.71	1.00
Immigrant Mother	0.17	0.38	0.47	.	0.01	0.46
Immigrant Father	0.17	0.38	0.48	.	0.01	0.46
Employed Mother	0.59	0.49	0.05	.	0.48	0.70
Employed Father	0.88	0.33	0.11	.	0.78	0.95
Parents are Married	0.74	0.44	0.08	.	0.61	0.85
Parent Expectations						
Mother's Desired Yrs. of Ed.	16.64	2.38	0.03	0.44	16.07	17.21
Father's Desired Yrs. of Ed.	16.60	2.48	0.05	0.54	15.91	17.29
Outcome Measures						
Enrolled at a 4-Year College (COLL)	0.37	0.48	0.23	.	0.14	0.63
Graduated HS (HSGRAD)	0.90	0.30	0.12	.	0.82	0.97

Between school variances group using the grade 10 school.
Between/Total Var. is the fraction of the variance in $X_{si}\hat{B}$ that is between schools. This value is also known as the intraclass correlation of $X_{si}\hat{B}$.
10th (90th) Quantile School refers to the estimated average value of the variable at a school whose average value for this variable puts it at the 10th (90th) percentile among all high schools.

Appendix Table 8: Summary Statistics for School-Level Variables from 10th Grade Schools in the 2002 Educational Longitudinal Survey (ELS2002)

Variable Name	Sample Mean	Standard Deviation
School Characteristics		
School is Catholic	0.13	0.33
School is Private Non-Catholic	0.10	0.31
Student-Teacher Ratio	16.41	4.35
Pct. Teacher Turnover Since Last Year	0.06	0.07
Pct. on College Prep. Track	0.60	0.34
Pct. of Teachers w/ Master's Degrees or More	0.46	0.22
Average Pct. Daily Attendance	0.95	0.05
School Pct. Minority	0.34	0.31
School Teacher Pct. Minority	0.12	0.19
Total School Enrollment	1234.74	835.61
Log(Min. Teacher Salary)	10.22	0.21
School Pct. Free/Reduced Price Lunch	0.24	0.25
School Pct. LEP	0.04	0.08
School Pct. Special Ed.	0.09	0.09
School Pct. Remedial Reading	0.05	0.08
School Pct. Remedial Math	0.06	0.10
Neighborhood Characteristics		
School in Urban Area	0.33	0.47
School in Suburban Area	0.48	0.50
School in Rural Area	0.19	0.39
School in Northeast U.S. Region	0.18	0.38
School in South U.S. Region	0.38	0.48
School in Midwest U.S. Region	0.25	0.43
School in West U.S. Region	0.20	0.40

Note that, in addition to the variables listed above, school averages of all individual-level variables are also included in Z.

Appendix Table 9: Variance Decomposition of the Latent Variables Determining High School Graduation and Enrollment at a Four-Year College: Full Specifications

	High School Graduation				Enrollment at a Four-Year College			
	NELS gr8	NELS gr10 w/ gr8 char.	NELS gr10	ELS	NELS gr8	NELS gr10 w/ gr8 char.	NELS gr10	ELS
Variance Component	Full	Full	Full	Full	Full	Full	Full	Full
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Within School:								
Total	0.834	0.852	0.842	0.877	0.771	0.781	0.783	0.790
$Var(Y_{si} - Y_s)$	(0.017)	(0.020)	(0.022)	(0.016)	(0.015)	(0.019)	(0.022)	(0.012)
Observable Student-Level:	0.279	0.193	0.221	0.206	0.303	0.293	0.329	0.314
$Var((X_{si} - X_s)B)$	(0.013)	(0.012)	(0.015)	(0.013)	(0.012)	(0.012)	(0.015)	(0.013)
Unobservable Student-Level:	0.555	0.659	0.621	0.672	0.469	0.487	0.454	0.476
$Var(V_{si})$	(0.017)	(0.019)	(0.022)	(0.019)	(0.013)	(0.015)	(0.015)	(0.013)
Between School:								
Total	0.166	0.148	0.158	0.123	0.229	0.219	0.217	0.210
$Var(Y_s)$	(0.017)	(0.020)	(0.022)	(0.016)	(0.015)	(0.019)	(0.022)	(0.012)
Observable Student-Level:	0.095	0.066	0.064	0.061	0.122	0.110	0.112	0.113
$Var(X_sB)$	(0.009)	(0.008)	(0.009)	(0.007)	(0.010)	(0.009)	(0.008)	(0.008)
Observable School-Level:	0.035	0.044	0.040	0.033	0.044	0.046	0.047	0.031
$Var(Z_sG)$	(0.008)	(0.012)	(0.011)	(0.007)	(0.005)	(0.006)	(0.007)	(0.004)
Observable Student-Level/	0.015	0.021	0.025	0.014	0.041	0.031	0.033	0.049
School-Level Covariance:	(0.013)	(0.016)	(0.015)	(0.010)	(0.013)	(0.014)	(0.015)	(0.010)
$2 * Cov(X_sB, Z_sG)$								
Unobservable School-Level/	0.020	0.017	0.029	0.014	0.022	0.032	0.026	0.016
$Var(V_s + M_s)$	(0.010)	(0.013)	(0.015)	(0.010)	(0.005)	(0.008)	(0.007)	(0.005)
Upper Bound								
$Var(Z_sG) + Var(V_s + M_s)$	0.070	0.082	0.094	0.061	0.107	0.109	0.106	0.097
$+2 * Cov(X_sB, Z_sG)$	(0.018)	(0.022)	(0.025)	(0.018)	(0.015)	(0.018)	(0.020)	(0.013)
Lower Bound	0.035	0.044	0.040	0.033	0.044	0.046	0.047	0.031
$Var(Z_sG)$	(0.008)	(0.012)	(0.011)	(0.007)	(0.005)	(0.006)	(0.007)	(0.004)

The table entries are fractions of the total variance, $Var(Y_{si})$.
NELS gr8 refers to a decomposition that uses the 8th grade school as the class variable, and uses 8th grade test scores in the w/tests specification.
NELS gr10 w/ gr8 char. refers to a decomposition that uses the 10th grade school as the class variable, but uses 8th grade measures of student behavior and parental expectations, and 8th grade test scores in the full specification.
NELS gr10 refers to a decomposition that uses the 10th grade school as the class variable, which naturally restricts the sample to those who reached 10th grade. It also uses 10th grade measures of student behavior and parental expectations, and 10th grade test scores in the full specification.
Upper Bound/Lower Bound refer to approximate upper and lower bounds on the direct contribution of schools to the variance in the outcome, independent of differences in student composition.