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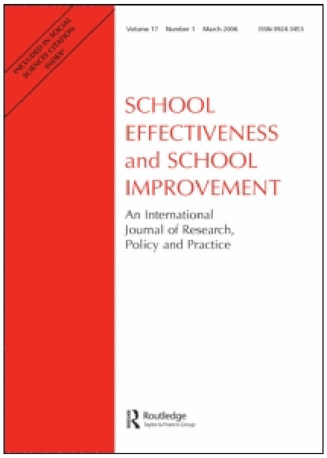

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Differential school effects among low, middle, and high social class composition schools: a multiple group, multilevel latent growth curve analysis

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This study uses large-scale survey data and a multiple group, multilevel latent growth curve model to examine differential school effects between low, middle, and high social class composition public schools. The results show that the effects of school inputs and school practices on learning differ across the 3 subpopulations. Moreover, student learning in low social class schools is far more sensitive to school factors than in middle and high social class schools. Yet, even after controlling for an extensive set of student background characteristics and school inputs, students attending low social class schools continued to learn at significantly slower rates. Widespread differences in the characteristics of schools across the subpopulations, which consistently challenge the educational milieu in low social class schools, likely contribute to differential school effects, as well as to the disparity in learning rates. The findings of this study accentuate the importance of school effectiveness research that goes beyond generic models to examine differential effects.

Keywords: differential school effects; social class composition; multiple group multilevel latent growth curve analysis; generic and specific models

Introduction

A considerable proportion of the quantitative research on school effectiveness has been conducted using large-scale databases (e.g., Bryk, Lee, & Holland, 1993; Lee, Smith, & Croninger, 1997; Willms, 1986). These databases are highly useful for studying schools – in part because they provide large, representative samples of a population of students and schools. Having a representative sample of a broad population is important for producing generalizable results. Yet subgroups or subpopulations of schools may exist that differ substantially from the general population in ways that impact both the school's effectiveness and the relationship between certain school factors and student outcomes. Statistical models of school effects that fail to account for these differential effects can produce misleading results (Aitkin & Zuzovsky, 1994; Lee & Burkam, 2003; Teddlie, Stringfield, & Reynolds, 2000). That is, studies that employ large representative samples may fail to identify important school effects that exist only in certain subpopulations of schools. In addition, the effects that are identified may not apply to certain subpopulations of schools.

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Surprisingly little attention has been given to this issue until some recent studies emphasized the importance transcending so-called "generic" models of school effects – one-size-fits-all approaches that assume effects apply across a population of schools – to examine differential effects in subgroups or subpopulations of students or schools (Muijs, Campbell, Kyriakides, & Robinson, 2005; Thrupp & Lupton, 2006). Indeed, a recent critique of school effectiveness research specifically mentions the failure to differentiate school effects as a major shortcoming of school effectiveness literature (Luyten, Visscher, & Witziers, 2005). When used to inform school improvement efforts, results from generic models may be ineffective – or even harmful – in certain types of schools. Consequently, their usefulness for assisting school improvement efforts is uncertain.

This study employs a large U.S. government database, the National Educational Longitudinal Study of 1988 (NELS:88), to investigate differential school effects in low, middle, and high social class composition public high schools. It examines whether the social class composition of schools, which is defined as the average socioeconomic status of the student body, moderates the association between student and school factors, and student learning. The focus is on differential school effects based on social class composition because the school effectiveness literature has recognized the importance of this variable to educational outcomes. This variable, which can be considered a measure of school-based social class stratification or socioeconomic segregation, is a robust and potent predictor of student achievement, learning, and dropout (Bryk & Driscoll, 1988; Chubb & Moe, 1990; Coleman et al., 1966; Jencks & Mayer, 1990; Murnane, 1981; Rumberger, 1995; Rumberger & Palardy, 2005; Thrupp, 1999; Willms, 1986). This body of research has demonstrated that the social class composition of schools impacts student achievement above and beyond the effects of students' individual social class background and may have the largest association with student achievement and learning of any school factor (Coleman et al., 1966; Rumberger & Palardy, 2005). The importance of this finding to school effectiveness research is heightened by recent evidence suggesting that schools are becoming increasingly segregated along racial and social class lines (Orfield, 2005).

While the effect of social class composition on educational outcomes has received considerable attention in the research literature, little is known about differential effects based on this powerful contextual factor or about why school effects may differ on this dimension. Contingency theory (Scheerens & Bosker, 1997) provides a viable explanation, which posits that the environmental conditions of an organization dictate the importance of various organizational factors to effectiveness. In other words, there is not a single set of best structures, resources, or practices for organizational functioning, but rather the optimal factors depend on aspects of the organization's environment. In the context of school effectiveness research, contingency theory suggests that the importance of various school structures, resources, and practices to effectiveness will depend on environmental conditions at the school. Social class composition is hypothesized to represent a critical condition that impacts the educational milieu – or learning environment – of schools through various mechanisms such as peer effects and resource allocation (e.g., attracting and retaining quality teachers). As a result, factors predictive of school effectiveness depend on the social class composition of the school.

This study broadly examines differential effects based on social class composition, dividing variables into three distinct classes – student-level factors, school inputs, and

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school practices – all of which are described below. Specifically, it addresses the following research questions:

(1) Do the effects of student background variables on learning differ in low, middle, and high social class high schools?
(2) Do the effects of school input variables on learning differ in low, middle, and high social class high schools?
(3) Do the effects of school practice variables on learning differ in low, middle, and high social class high schools?

Review of the research literature

In this section, two related bodies of research literature are reviewed. First, factors associated with school effectiveness, which includes both student and school characteristics, are reviewed. Second, the literature on differential school effectiveness based on social class composition is considered.

School effects research

The research literature has recognized a wide range of factors that account for differences in student outcomes across schools. These factors can be grouped into two classes: *school inputs*, which consist of student characteristics, as well as school resources and structural features, and *school practices and policies*. School inputs are conceptualized as factors that are given to schools and, as such, school site personnel tend to have little influence over their effects. School practices and policies, on the other hand, consist of factors that schools have greater control over, and thus are of particular interest to school practitioners and policy-makers (Fitz-Gibbon & Kochan, 2000; Good & Brophy, 1986; Palardy, 2003; Rumberger & Thomas, 2000). Below is an outline of specific factors within these two broad categories that have been shown to be associated with achievement and learning in schools.

Student characteristics

Both individual student characteristics and mean student body characteristics at schools (i.e., compositional effects) have been shown to be predictive of student achievement and learning. Research has demonstrated that a wide variety of individual student characteristics are related to achievement and learning, including demographic characteristics, such as ethnicity and gender; family characteristics, such as socioeconomic status (SES) and family structure; and academic background, such as prior achievement and retention (e.g., Coleman et al., 1966; Lee & Bryk, 1989; Lee & Smith, 1993, 1995; Lee et al., 1997; McNeal, 1997; Park & Palardy, 2004). Research has also documented that the composition of the student body in a school, such as the mean socioeconomic and ethnic composition of the student body, can influence student achievement and learning apart from the effects of individual student characteristics (Coleman et al., 1966; Lee & Bryk, 1989; Lee & Smith, 1993, 1995; Lee et al., 1997; McNeal, 1997; Rumberger, 1995; Rumberger & Palardy, 2005).

Resources

School resources consist of both fiscal resources and the material and human resources that they can buy, such as textbooks and quality teachers. There is debate in the research

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community about the extent to which school resources contribute to school effectiveness (Hanushek, 1994, 1997; Hedges, Laine, & Greenwald, 1994; Ludwig & Bassi, 1999). And while there generally is agreement that teacher quality matters (McCaffrey, Lockwood, Koretz, & Hamilton, 2003), the aspects of teachers and teaching that matter most, such as credentials and classroom practices, are less clear (Darling-Hammond, Berry, & Thorenson, 2001; Goldhaber & Brewer, 2001; Wayne & Youngs, 2003). Beyond the quality of teachers, there is evidence that teacher density – as measured by the pupil-to-teacher ratio – has a positive association on some student outcomes (McNeal, 1997).

Structural characteristics

Structural characteristics, such as school location (urban, suburban, rural), size, and sector (public, Catholic, or other private), have also been found to predict school performance (Bryk et al., 1993; Coleman & Hoffer, 1987; Lee & Bryk, 1989; Lee & Smith, 1997). However, some research suggests that these structural effects are due to student body composition and school resources, which tend to be correlated with the structural features of schools (Witte, 1992). For example, urban schools tend to have difficulties attracting and retaining quality teachers and tend to have more problems with safety and student misbehavior.

School practices

Although public school personnel typically have little control over input factors, they do have a fair amount of control over school policies and practices. The literature has identified several school practices that are associated with student achievement, including: teacher and parental involvement in decision-making (e.g., Lee & Smith, 1993, 1995; Lee et al., 1997; Morgan & Sorensen, 1999); teachers' expectations and efficacy, as well as their instructional practices (Carbonaro & Gamoran, 2002; Lee et al., 1997); and the social and academic climate of schools (as reflected by measures such as the number of advanced academic courses taken by students and the amount of homework that they do) (Gamoran, 1996; Lee & Smith, 1993, 1999; Lee et al., 1997; Phillips, 1997).

Differential school effects based on social class composition

This review focuses on quantitative studies that examine *school-level* differential effects based on social class composition, rather than on student-level differential effects. Over the past 15 years, surprisingly little research has focused on this topic – and studies that have contained notable limitations. Three studies are reviewed here.

In a study comparing low and high social class composition schools, Teddlie and Stringfield (1993) found that those two types of schools tended to implement somewhat different effectiveness practices. However, the study compared mean differences in the degree to which certain practices were employed and did not test differential school effects. This is not a trivial distinction for school improvement efforts because, while it is interesting to know which practices are most pervasive in certain contexts, it is perhaps more relevant to know whether the practices are differentially effective across contexts.

Mussoline and Shouse (2001) examined the association between school restructuring and 10th-grade mathematics achievement in very low, low, middle, and high socio-economic composition schools. School restructuring, captured by a single composite measure, was found to have a negative association with mathematics achievement in low

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and very low socioeconomic schools, but not in middle or high. Rumberger (1995) found that in low socioeconomic schools, resources (e.g., student-to-teacher ratio) and academic climate (e.g., average time spent on homework) had significant impacts on dropout rates; however, in the overall population that was not the case. A limitation of these two studies is that neither explicitly tests for differential effects across the social class composition groups, but rather models were estimated on each social class composition group separately, and it was noted whether the effects were significant in certain groups and not in others. As a result, they do not address whether the school effects actually differ across the subpopulations.

Methods

Data source

Data from the National Education Longitudinal Study of 1988 (NELS:88) were used for this study (Curtin, Ingles, Wu, & Heurer, 2002). NELS, which was designed and funded by the National Center for Educational Statistics (NCES), employed a stratified two-stage probability sampling procedure to select a nationally representative sample of American eighth graders in the spring of 1988. A school questionnaire was administered to the principal of each school, a teacher questionnaire was administered to about five teachers per school who taught courses to the sampled students, and a parent questionnaire was administered to the parents of the sampled students. Follow-up surveys were collected in the spring of 1990 and 1992, when the students should have been finishing 10th and 12th grades, respectively. This study focuses on public schools because they are financed by public funds, and their resources, policies, and practices are largely public domain.

The sample of 779 public high schools was divided into three groups – low, middle, and high social class composition schools – based on the mean SES of the students attending.[1] Schools were classified based on the location of their mean SES in the approximately normal distribution. Schools one or more standard deviations below the sample mean were classified as low social class composition, schools one or more standard deviations above the sample mean were classified as high social class composition, and the remainder were classified as middle social class composition.[2] This classification scheme resulted in 112 low, 550 middle, and 117 high social class schools. From the middle group, 115 schools were randomly selected, so that group sizes were balanced. The final sample included data from 5,326 students nested in 344 schools.[3]

Variables

This study is based on a conceptual framework that recognizes school effects as part of a multilevel phenomenon including student, classroom, and school components (see Figure 1).[4] Each contributes to the variation in student performance. As outlined in the literature review above, students' backgrounds may impact school outcomes both directly and indirectly by way of their aggregate or compositional effects. Students' backgrounds also impact their educational experiences, such as the amount of homework they do or whether they use a computer outside of school, which, in turn, impacts their educational outcomes. At the classroom and school levels, effects can be categorized into three classes: inputs, process, and outputs. While inputs and processes both impact outcomes directly, processes may also mediate or moderate the effects inputs have on outcomes. At the school level, inputs include the compositional characteristics of the student body, the structural characteristics of the school, and the human and financial

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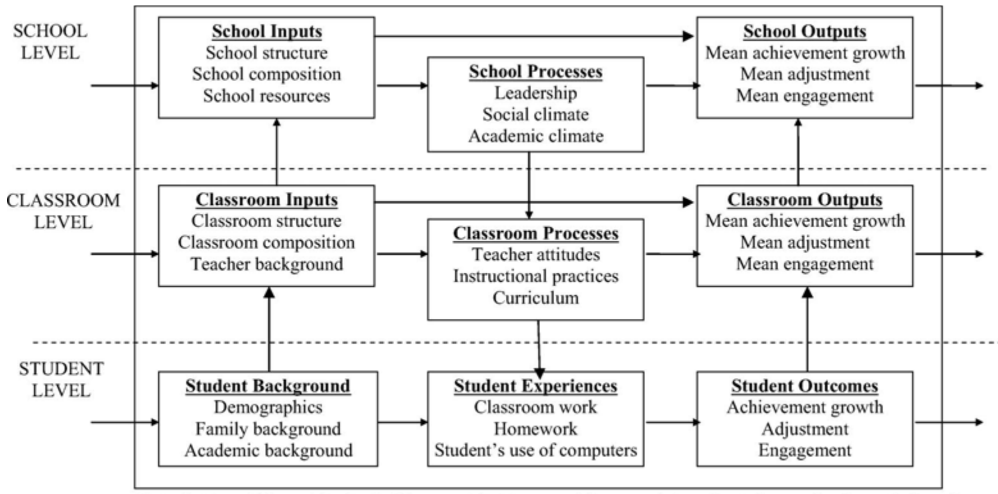

Note that in a differential school effects model, this general framework is estimated on each subpopulation of schools. Also note that the classroom level of analysis has been excluded from this study due to the prohibitive complexity of such a model in a longitudinal analysis, as well as to the limitations of the NELS data (see endnote 4).

Figure 1. General multilevel conceptual framework for studying school effects.

resources available, whereas processes include principal leadership and, among other things, social and academic climate.

The outcome variable utilized in this study is students' achievement growth or learning rate on a composite score of four academic subjects – math, reading, science, and history – over a 4-year period when most students were attending high school.[5] This learning outcome was derived in two steps: first, the mean of the four achievement tests was computed for each student at each of three occasions of NELS-administered tests.[6] Next, the measurement model described below, which is part of a multilevel growth model, was used to estimate the rate of achievement growth (learning) for each student over the 4-year period.

Data from student, parent, teacher, and principal surveys were used to construct a comprehensive set of a priori determined independent variables. These variables were designed to measure specific student and school characteristics and test for differential associations with student learning across the three social class composition groups of schools. An overview of the seven variable types (three student types and four school types) and examples of each are provided below. A description of each variable used in this study is provided in Appendix Table A. Appendix Table B shows the means and standard deviations for each variable categorized by social class composition. Appendix Table C shows the results of factor analyses that were conducted to construct the composite measures used in this study.

The student background variables examined can be classified into three types: demographic, family background, and academic background. Demographic variables consisted of a series of dummy-coded racial indicators including Asian, Black, Hispanic, and Native American. Family background characteristics included SES and nontraditional family structures, which indicated whether students lived with both birth parents. Academic background was measured by several variables including self-reported grades, plans to finish college, retention between the first and eighth grades, school transfer during

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grades 10–12, and school dropout during grades 10–12. Previous research has shown that each of these variables is predictive of student achievement (e.g., Lee et al., 1997; Rumberger & Palardy, 2005). Because the primary interest of this study is school effectiveness, these student background variables were used largely to control for differences in the background characteristics of students across schools. School personnel have limited influence over the ways these background characteristics affect student learning. Consequently, statistically controlling for background characteristics is typically important when modeling school effectiveness (Raudenbush & Willms, 1995; Rumberger & Palardy, 2004).

Four types of school-level characteristics were used in this study: student body composition, school structure, school resources, and school practices. The first three types are considered to be *school inputs* since they are characteristics of the schools or student body that are largely given to schools. Note that schools were grouped by the most potent measure of student body composition – social class composition – which tends to correlate with other aspects of student body composition. Thus, this grouping would likely moderate any compositional effects and reduce the likelihood that variables of this class would be significant. Examples of student body composition variables include variation in SES, proportion of students who have been retained at a prior grade level, and mean parental aspirations for their child. The second type measured the *structural characteristics* of schools, which included measures such as urbanicity (i.e., urban or rural vs. suburban) and school size (which was coded as a series of dummy variables with 601–1,200 students representing the comparison category). The third type measured *school resources*, including mean teacher salary. The fourth type measured *school practices and processes*, which included the proportion of students who reported feeling unsafe while at school, the proportion of students in the academic track, the disciplinary climate (the proportion of students who reported that the school's discipline policies were fair), and the proportion of the teachers rated excellent by the principal.

Statistical models

Because students in the NELS data are nested or clustered within schools, a multilevel model was used. This study employs the recently developed Multilevel Latent Growth Curve (MLGC) (Bollen & Curran, 2006; Duncan, Duncan, Strycker, Li, & Alpert, 1999; Muthen, 1997; Palardy, 2003), which extends the latent growth curve (McArdle & Epstein, 1987; Meredith & Tisak, 1990) to the multilevel context. The MLGC combines the virtues of structural equation modeling (SEM), latent growth curve analysis, and multilevel modeling. Under certain conditions, the MLGC will produce equivalent parameter estimates such as the multilevel regression (HLM) growth model, but it is arguably a more flexible model in that it can readily incorporate indirect effects, complex measurement error structures, and multiple group analysis (Palardy, 2003). The multilevel, longitudinal, and multiple group capabilities of the MLGC make it ideally suited for addressing the research questions of this study. The MLGC has three levels of analysis, including the measurement, student, and school levels.

Using the repeated measurements of achievement test scores, the measurement model estimates students' initial achievement status upon entering high school and their learning rate during high school. Those two sets of parameter estimates are referred to as the intercepts and slopes. At the student level, achievement intercepts and slopes for each student are the outcomes, while at the school level, mean school intercepts and slopes are the outcomes. Student predictors, which were grand mean centered if continuous and left

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uncentered if dummy coded, account for variation at both the student and school levels, while school predictors used in the school-level model account only for variation between schools. The statistical formulations for the multiple group MLGC are represented below in Equations 1–3. The g superscript throughout the equations indicates that the parameter is estimated for each group using group-specific data. As is typically the case with SEMs, the equations are separated into measurement and structural components. Equation 1 displays the measurement model, which estimates within-student growth in achievement over time, where Y^g_{tij} is the achievement test composite score at time t of student i attending high school j of subpopulation g. The intercepts $\left(n^g_{0ij}\right)$ and slopes $\left(n^g_{1ij}\right)$ represent the within-student initial achievement level and learning rate for student i in school j of subpopulation g. These intercepts and slopes are factor scores that are used as outcomes in the structural model.

$$Y^g_{tij} = n^g_{0ij} + n^g_{1ij}a_t + e^g_{tij} \quad \text{Measurement Model} \tag{1}$$

This equation is highly similar to the Level 1 equation in a multilevel regression growth model, one difference being that a_t represents the "time" variable in the multilevel regression growth model context, whereas it represents the fixed loading of a factor in the MLGC.[7] In the case of the NELS data, where three waves of achievement data are available, the measurement model is typically limited to the linear form. The "time" loadings on the slope factor were fixed to 0.0, 0.5, and 1.0, corresponding to achievement values at 8th, 10th, and 12th grades. Thus, a one-unit change in the slope is the entire 4-year period during high school. This specification yields a growth parameter (η^g_{1ij}) interpretation of the expected change in student i's achievement over the 4-year period between the end of the 8th grade and the end of the 12th grade – the period when the vast majority of the students were attending high school.[8] The measurement error term, e^g_{tij}, represents the residual at time t for student i in school j of subpopulation g.

Structural model

The conditional structural models are shown in Equations 2 and 3. The variance in the intercepts and slopes are partitioned into within- (Equation 2a and 2b) and between-school (Equation 3a and 3b) components, which can also be thought of as the student- and school-level models. Equations 2a and 2b are within-school formulae for the intercept and slope outcomes. In Equation 2a, β^g_{00j} represents the mean initial achievement for students attending school j in subpopulation g. β^g_{0qj} represents the estimated association between student background variable, X^g_{qij}, and initial achievement η^g_{0ij}. Similarly, in Equation 2b, β^g_{10j} represents the mean learning rate for students attending school j in subpopulation g, while β^g_{1qj} represents the estimated association between student background variable, X^g_{qij}, and learning, η^g_{1ij}. ζ^g_{0ij} and ζ^g_{1ij} are disturbance terms or residuals for the student-level intercept and slope models. Each has a variance associated with it and the two covary as well.

$$\eta^g_{0ij} = \beta^g_{00j} + \sum_{q=1}^{Q_0} \beta^g_{0qj} X^g_{qij} + \zeta^g_{0ij} \quad \text{Within-school intercept} \tag{2a}$$

$$\eta^g_{1ij} = \beta^g_{10j} + \sum_{q=1}^{Q_1} \beta^g_{1qj} X^g_{qij} + \zeta^g_{1ij} \quad \text{Within} - \text{school slope} \tag{2b}$$

$$\beta^g_{00j} = \gamma^g_{000} + \sum_{s=1}^{S_0} \gamma^g_{00s} W^g_{sj} + u^g_{00j} \quad \text{Between} - \text{school intercept} \tag{3a}$$

$$\beta^g_{10j} = \gamma^g_{100} + \sum_{s=1}^{S_1} \gamma^g_{10s} W^g_{sj} + u^g_{10j} \quad \text{Between} - \text{school slope} \tag{3b}$$

Equations 3a and 3b represent the conditional between-school or school-level models for the intercepts and slopes, where γ^g_{000} is the mean of the school means for initial achievement and γ^g_{100} the mean of the school means for the learning rate. The *W*'s represent school-level independent variables and γ^g_{001}- γ^g_{00s} and γ^g_{101}- γ^g_{10s} are the coefficients that represent estimates of their association with the respective outcome. u^g_{00j} and u^g_{10j} are school-level disturbance terms that vary and covary.

The primary interest in the present study is the slope equations (2b and 3b), which represent student and school learning outcomes, respectively. This study investigates group differences in the association between student- and school-level variables and learning. However, because learning tends to covary with initial achievement, the correct estimation of the parameters in the growth outcome models requires that the intercept models be fully specified as well (Raudenbush & Bryk, 2002). Due to space limitations, only the slope model results are presented. Version 4 of M*plus* software (Muthen & Muthen, 1998–2006) was used to estimate the multiple group MLGC, and SPSS version 14 was used to generate descriptive statistics and test for mean differences across subpopulations on individual variables.

Procedures for model building

The model building procedure involved estimating three models sequentially: (1) an unconditional model, (2) a student model, and (3) a school model. At each step, the model was first estimated on the full sample of students and then in a multiple group specification. In an effort to obtain reasonably parsimonious results, variables were retained at each step if they had a significant association with learning at the 0.10 alpha level in any group. Thus, the same set of predictors was used in each social class composition group model. Variables listed in Appendix Table A, but not in the results tables, were nonsignificant predictors of learning in all the models. In the student-level model, continuous variables were grand mean centered, while dummy-coded variables were not centered. This centering strategy resulted in intercept terms in the within-school slope model, β_{10j}, representing the adjusted mean achievement growth rate for each school (which is the expected learning rate for a student who had zeros on all of the dummy variables and who had average characteristics on the continuous variables). Centering the student variables in this way controls for differences in students' inputs across schools.

The unconditional model, which included no student- or school-level predictors, was used to compute the unconditional intra-class correlation coefficients for the intercepts and slopes. It also served as a baseline model from which the proportion of the variance explained by subsequent conditional models was derived. The student model was primarily for the purpose of controlling for the effects that student background had on learning, because mean student characteristics tended to vary substantially across subpopulations (see Appendix Table B for a comparison of subpopulation means). The school-level models were then estimated to examine differential effects in school-level factors.

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Two sequential school-level models were estimated. First, a school input model was estimated, which included compositional, structural, and resource variable types. Similar to the student model, the purpose of the school input models was to control for aspects of the school that might moderate effectiveness practices. The second step was to estimate the school practice model, which is the primary focus of this study. This final model included the input variables that were retained in the previous step, as well as measures of school practices.[9]

At each step, models were compared across social class groups for differential effects. Individual coefficients were tested for differences across subpopulations. These univariate group differences were tested based on two criteria, one far more rigorous than the other. The first criterion was if a coefficient had a significant association with student learning in some social class composition subpopulation(s) but not in others. This is considered to be a test of *weak evidence* of differential effects because coefficient estimates with similar p values in two groups (e.g., 0.06 vs. 0.04) can be judged as different. The second and far more conservative criterion was that the magnitude of a coefficient varied significantly across subpopulations. This criterion was examined by fixing the coefficients to be equal across groups (known as an "equality constraint" in SEM terminology) and using a likelihood ratio test to determine if the chi square statistic of model fit increased significantly. This is considered to be a test of *strong evidence* of differential effects.

Besides conducting univariate tests for differential effects on individual coefficients, a multivariate or global test of group differences was conducted at each step of model building to test for omnibus differences in the school effects model across social class composition groups. This test involved constraining all structural coefficients to be equal across groups for a given set of variables and using a likelihood ratio test to determine if the chi square statistic increased by a statistically significant amount compared with the unconstrained model chi square statistic. If the chi square statistic increased significantly, the unconstrained model fit the data better than the constrained model and it was concluded that there were global differences across social class subpopulations in the effects in the set of variables being tested. This conclusion indicates that, taken together, the set of variables being tested fit the socioeconomic groups differentially.

Finally, to examine whether collinearity may have impacted the results, the Variance Inflation Factor (VIF) was computed for each of the school-level predictors. Because variables tend to be more highly correlated within social class composition groups, the VIF was computed for each variable within each group separately. VIF values ranged from 1.04 (Teacher Excellence in Middle group) to 1.66 (Salary in Middle group). All values were far below the conventionally suggested level for concern of 10.0.

Results

Subpopulation differences in means

Before estimating the multilevel latent growth curve models, student and school predictors were tested for mean differences across subpopulations (see Appendix Table B). The results show widespread differences in mean student characteristics across groups. Many of these variables have been associated with educational disadvantage, and the results suggest that they consistently work against students at low social class schools. For example, compared with students attending high social class composition high schools, students at low social class high schools entered with significantly lower middle school grades and achievement test scores; were approximately twice as likely to have been retained before entering high school; were three times more likely to have a friend who

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dropped out of school; were 55% less likely to aspire to attain a bachelor's degree; were six times more likely to drop out of high school; were 64% more likely to live in a nontraditional household; were five times more likely to be Black, and seven times more likely to be Hispanic. The discrepancy in school resources across groups is also pervasive. Teachers at low social class schools earned significantly lower salaries, were less likely to have earned an advanced degree, were less likely to have earned a bachelor's degree in the subject area they teach, were less experienced, and were less likely to be fully certified. Low social class schools were nearly twice as likely to be located in urban areas and three times more likely to be located in rural areas than high social class schools. Finally, the use of effective school practices also differed significantly across groups. Compared with students attending high social class schools, students attending low social class schools spent 63% less time on homework, were less likely to take college prep courses, were less likely to be enrolled in the academic track, and were 2.6 times more likely to report feeling unsafe at school. Compared with teachers at high social class schools, teachers at low social class schools were rated by students as being of lower quality, were confronted with significantly greater levels of class disruptions, were less likely to coordinate their curriculum with other teachers in the school, had a lower sense of control over their work environment, and had a lesser locus of control. These mean differences suggest that, based on a broad array of factors, the educational milieu in low social class schools presents a consistent barrier to learning.

Differential effects in the unconditional model

Table 1a shows the unconditional model parameter estimates for the full sample and each social class composition subpopulation, as well as the univariate likelihood ratio tests of subpopulation differences. Several parameters vary significantly across subpopulations, including mean initial achievement ($\chi^2_{df=2} = 283.12$, $p < 0.01$) and mean learning rate ($\chi^2_{df=2} = 84.59$, $p < 0.01$). Students entering low social class composition high schools had considerably lower achievement (40.87), on average, than students entering middle social class composition schools (45.38) or high social class composition schools (49.45).

Table 1a. Unconditional model results.

Parameter	Full Sample	Low	Middle	High	LRT $\left(\chi^2_{df=2}\right)$
Within or student level					
Initial achievement variance	41.97**	33.12**	42.90**	44.72**	29.33**
Achievement growth variance	7.97**	4.55**	7.42**	7.10**	7.07*
Slope-intercept covariance	9.37**	9.52**	9.08**	9.62**	0.24
Between or school level					
Mean achievement growth	7.61**	6.71**	7.52**	9.01**	84.59**
Mean initial achievement	45.35**	40.87**	45.38**	49.45**	283.12**
Initial achievement variance	10.52**	5.11**	7.33**	3.10**	7.47*
Achievement growth variance	2.34**	1.49**	1.56**	1.23**	0.33
Slope-intercept covariance	3.15**	0.13	−0.83	0.15	2.37
Intra-class correlation					
Initial achievement	0.20	0.13	0.15	0.07	–
Achievement growth	0.23	0.25	0.17	0.14	–

*significant at $\alpha = 0.05$, **significant at $\alpha = 0.01$.

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A similar pattern was observed for learning rates. Students attending low social class composition schools learned less over the 4-year high school period (6.71) than students at middle (7.52) and high social class schools (9.01). Further elaboration on the magnitude of these effects and their implications is provided in the discussion section.

Attention is focused on the learning rate outcome rather than initial achievement because that outcome is the primary interest of this study. The intra-class correlation coefficient[10] for learning rate differs across subpopulations, being highest in low social class schools (0.25) and lowest in high social class schools (0.14). This suggests that school factors have a greater relative impact on learning among students attending low social class schools than among students attending the middle and high social class composition schools. Learning rate also varies significantly both within and between schools for each subpopulation. Moreover, within-school variation differs significantly across subpopulations ($\chi^2_{df=2} = 7.07$, $p < 0.05$) and is substantially lower (35.9%) in the low social class composition subpopulation compared with the high (4.55 in low vs. 7.10 in high). However, the amount of between-school variance does not differ significantly across subpopulations ($\chi^2_{df=2} = 0.33$, $p > 0.10$). Taken together, these two findings indicate that the higher intra-class correlation noted in the low social class subpopulation is due to less within-school variation in learning rates and not more between-school variation. This issue is revisited below.

Table 1b displays the results of the multivariate or global test of subpopulation differences for the unconditional model. The results show that the unconstrained model fits the data significantly better than the constrained model ($\chi^2_{df=16} = 396.01$, $p < 0.01$). This indicates that, on the whole, the unconditional school effectiveness model differs across subpopulations.

Differential effects in student characteristics

The next model tests for differential effects in student characteristics (see Table 2a). Only one student variable – Asian – provided strong evidence of a differential effect, indicating Asian student learning relative to the reference category, White students differed significantly across social class groups. In high social class schools, Asian students learned significantly more than White students, but not in middle or low social class schools. This implies that Asian students benefit more from attending high social class schools compared with White students.

Several other variables provided weak evidence of differential effects. Controlling for the other student background variables in the model, family socioeconomic status had a significant positive association with learning in high social class composition schools, but not in the middle or low social class subpopulations.[11] Moreover, the magnitude of the family socioeconomic status coefficient in the high subpopulation is more than double that of the low or middle subpopulations and more than one third larger than the full sample.

Table 1b. Unconditional model global invariance test across social class composition groups.

Model	*df*	χ^2	ΔX^2	Δdf	RMSEA	CFI
1. Unconstrained model (from Table 1a)	20	503.72	–	–	0.117	0.967
2. Constrained null model	36	899.73	396.01**	16	0.116	0.940

*significant at $\alpha = 0.05$, **significant at $\alpha = 0.01$.

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Table 2a. Student model results.

Variable Name	Full Sample	Low	Middle	High	LRT $\left(\chi^2_{df=2}\right)$
Mean initial achievement	45.50**	41.92**	45.15**	48.28**	117.60**
Mean achievement growth	7.61**	7.13**	8.04**	8.74**	11.17**
Student Achievement Growth					
SES	0.49**	0.25	0.30	0.67**	2.68
Asian	1.06**	0.06	0.47	1.51**	5.05†
Black	−1.08**	−1.13**	−0.90†	−0.38	1.19
Hispanic	−0.01	0.40	−0.81†	−0.16	4.52
Native	−0.17	−0.83	−1.86	2.58	3.29
Nontraditional family	−0.24**	−0.44	−0.04	−0.28	0.44
Eighth grade GPA	0.74**	0.53**	0.78**	0.78**	0.23
College aspirations	0.36**	0.42	−0.22	−0.46	3.55
Retained Grades 1-8	−0.91**	−1.06**	−0.26	−0.86*	2.66
Had dropout friends	−0.49**	−0.22	−0.46	−0.63†	0.88
Transferred Grades 10-12	−0.23	−1.01†	−0.91	−0.75	0.11
Dropped out Grades 10-12	−1.16**	−1.70**	−0.94*	−0.87	1.57
Achievement Growth Variance Explained					
Within school	16%	26%	14%	21%	–
Between school	21%	24%	−13%[a]	0%	–
Intra-class correlation					
Achievement growth	0.22	0.23	0.22	0.18	–

[a]Between-school variance increased after controlling for student background; †0.10, *significant at $\alpha = 0.05$, **significant at $\alpha = 0.01$.

Considering the robust association between socioeconomic status and learning that has been established by previous researchers, this finding is intriguing because it suggests that the social class context of the school one attends plays a role in the strength of the association between socioeconomic status and learning.

Black students attending low social class schools, on the other hand, had significantly lower learning rates than Whites, but no differences existed in middle or high social class schools, which implies that a low social class composition environment is more harmful for Black compared with White students. Students who were retained had significantly lower learning rates in low and high social class composition schools, but not in middle. Dropouts had significantly lower learning rates in low and middle schools, but not high. This suggests that, unlike dropouts from low and middle social class composition schools, students who drop out of high social class composition schools tend not to have learning challenges.

As should be expected, controlling for student background characteristics reduced the disparity in mean initial achievement and mean achievement growth across groups. The difference in mean initial achievement between the low and high social class groups was reduced 26% from 8.58 (49.45–40.87) to 6.36 (48.28–41.92), and the difference in mean learning rate was reduced 30% from 2.30 (9.01–6.71) to 1.61 (8.74–7.13). These findings show that a substantial proportion of the performance disparity between the subpopulation of schools is due to differences in the background characteristics of the students attending. Yet, sizable unexplained differences remain.

The explanatory power of the student model differed substantially across subpopulations. When student background characteristics were held constant, the between-school

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variation in learning rates was reduced by 32% in the low social class composition subpopulation, while it *increased* 13% in middle and remained unchanged in high. Recall that the intra-class correlation for the unconditional model was higher in the low social class composition schools compared with middle or high. The results from the student model show that intra-class correlations are very similar after controlling for student background characteristics. Thus, when controlling for the background characteristics of the students attending, the proportion of the variance in learning due to school factors is very similar across subpopulations. This change in the intra-class correlation is the result of student background factors reducing between-school variance in learning in the low social composition subpopulation but not altering it or even increasing it in the other subpopulations.

The results of the multivariate or global test of differential effects are shown in Table 2b. The unconstrained model does not fit the data significantly better than the constrained model. This finding indicates that, taken together, the associations between student characteristics and learning do not differ significantly across social class groups ($\chi^2_{df=24} = 31.53$, $p > 0.05$). This is not surprising, given that only one student background variable provided strong evidence of a differential effect. This finding suggests that, on the whole, the background characteristics students bring to school have a similar impact on learning, regardless of the social class composition of the school.

Differential effects in school characteristics

The school-level model results, summarized in Table 3a, show that several school inputs and practices have differential effects across the social class composition groups.[12] Differential effects were found on six school inputs, for three of which the evidence was strong. The difference in mean learning at urban schools compared with suburban schools varied across the three groups ($\chi^2_{df=2} = 5.19$, $p < 0.10$). Students attending middle social class urban schools learned significantly more than students attending middle social class suburban schools. The difference in learning at extra large schools compared with middle-size schools varied significantly across groups ($\chi^2_{df=2} = 6.77$, $p < 0.05$), with extra large schools performing significantly better than middle-size schools only in the low social class subpopulation. The effect of mean teacher salary on learning varied significantly across subpopulations ($\chi^2_{df=2} = 6.75$, $p < 0.05$), having a significant positive effect in the low group and nonsignificant effects in the middle and high groups. The variation in socioeconomic status within schools was negatively associated with learning in low social class composition schools but a nonsignificant effect in the middle and high subpopulations. Low social class composition rural schools performed significantly better than their suburban counterparts, which was not the case in the other subpopulations. Mean parental aspirations had a significant positive association with learning in the low group and nonsignificant associations in the middle and high groups.

Table 2b. Global test of differential effects for student background.

Model	*df*	χ^2	$\Delta\chi^2$	Δdf	RMSEA	CFI
1. Unconstrained model (from Table 2a)	56	544.88	–	–	0.070	0.972
2. Constrained model (coefficients constrained as equal)	80	576.41	31.53	24	0.059	0.971

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Table 3a. School model results.

Variable Name	Full Sample	Low	Middle	High	LRT $(\chi^2_{df=2})$
Mean initial achievement	45.40**	41.91**	45.35**	48.40**	60.70**
Mean achievement growth	7.52**	6.87**	7.68**	8.92**	18.38**
School Inputs					
SES variation	−0.66†	−2.53**	−0.27	−0.43	2.86
Urban	0.28	−0.51	1.08†	0.07	5.19†
Rural	0.19	1.02**	0.15	0.45	2.47
Small	0.07	−0.58	−0.16	0.19	1.00
Large	0.50**	0.03	−0.13	0.17	0.28
Extra large	0.57**	1.04*	−0.95	−0.23	6.77*
Mean salary	0.04*	0.09*	0.02	−0.06	6.75*
Mean parental aspirations	0.27**	0.38*	0.19	0.10	0.87
School Practices					
Proportion students feel unsafe	−3.46**	−1.35	−5.67*	−3.68	2.09
Proportion fair discipline	0.00	2.95**	−2.15†	−1.31	12.57**
Proportion academic track	−0.25	−2.04*	−0.72	0.26	3.39
Proportion excellent teachers	−0.52	−1.63*	−1.40†	0.44	4.88†
Between-School Achievement Growth Variance Explained					
School model	8%	54%	23%	17%	–
Total (Student and School models)	29%	78%	10%	17%	–
Intra-class correlation					
Achievement growth	0.20	0.09	0.18	0.15	–

†0.10, *significant at $\alpha = 0.05$, **significant at $\alpha = 0.01$.

Finally, differential effects were found on four school practices, on two of which the evidence was strong. The association between fair discipline practices and learning varied significantly across groups ($\chi^2_{df=2} = 12.57$, $p < 0.01$), having a strong positive association in the low group, a marginally significant negative association in the middle group, and a nonsignificant association in the high groups. Principal ratings of the proportion of teachers who are excellent varied across groups ($\chi^2_{df=2} = 4.88$, $p < 0.10$), with a significant negative association with learning in the low social class group and a marginally significant negative association in the middle group but a nonsignificant association in the high group. The proportion of students who reported feeling unsafe at school had a significant negative association with student learning in the middle social class composition group, but a non-significant association with the low and high group. Surprisingly, the proportion of students in the academic track had a negative relationship with learning in the low social class composition group, but a nonsignificant relationship in the middle and high social class composition groups.

The proportion of the between-school variance in learning explained by school-level variables differed substantially across groups. School variables explained more than double the percentage of the variance in mean learning rates in the low social class composition subpopulation (54%) compared with the middle (23%) and more than three times compared with the high (17%). Moreover, while the amount of unexplained variation in mean learning rates was not significantly greater than zero in the low social class composition subpopulation ($t = 0.97$, $p > 0.10$), substantial and highly significant amounts of variation remained in the middle ($t = 3.47$, $p < 0.01$) and high ($t = 2.97$,

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$p < 0.01$) subpopulations. These findings suggest that school factors have far stronger relationships with learning in the context of low social class composition schools than in the context of middle or high. This finding is discussed below. Furthermore, the full sample school model explained only 8% of the between-school variance in learning – less than one sixth of the percent explained in the low subpopulation and less than half of the percent explained in the high – providing further evidence that failing to differentiate the school effectiveness model on social class composition greatly reduces its explanatory powers.

Global differential effects were found for both school inputs and school practices. The likelihood ratio test results (Table 3b) indicated that both the unconstrained input model ($\chi^2_{df=18} = 39.79$, $p < 0.01$) and the unconstrained practice model ($\chi^2_{df=8} = 16.58$, $p < 0.05$) fit the data significantly better than the constrained models. These findings suggest that, taken together, the association between school inputs and learning as well as between school practices and learning differ significantly across social class composition subpopulations.

Discussion

The results of this study provide strong evidence of both individual and global differential effects for school inputs and school processes but not for student background characteristics. These findings are re-examined below in terms of their substantive and methodological implications.

Widespread disparities in educational milieu

As outlined in the results section and documented in Appendix Table B, the vast majority of the school characteristics examined in this study – 30 of 39 – exhibited mean differences across social class composition subpopulations at the $\alpha = 0.05$ level. Moreover, the pattern of mean differences was both predictable and consistent; school characteristics consistently indicated less favorable conditions for learning in the low social class schools and more favorable conditions in the high social class schools. These mean differences provide a depiction of the breadth of disparity in the educational milieu of schools across subpopulation. The broad differences include characteristics of the student body, school resources (including indicators of teacher quality), structural characteristics of schools, and the practices that are employed.

While the results suggest that many of these measures are not directly associated with learning in any social class composition group, they may work collectively to influence the educational environment. For example, in the low social class schools, teachers who tend to have less experience and training work in a more chaotic environment (e.g., more

Table 3b. Global test of differential effects for school inputs and school practices.

Model	*Df*	χ^2	$\Delta\chi^2$	Δdf	RMSEA	CFI
1. Input unconstrained	104	608.57	–		0.052	0.971
2. Input constrained	120	637.15	28.58*	16	0.049	0.970
3. Practice unconstrained	116	627.52	–	–	0.050	0.970
4. Practice constrained	124	646.72	19.20*	8	0.049	0.970

*significant at $\alpha = 0.05$.

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disruptions and safety issues, lack of environmental control, lack of curricular alignment) with students who more commonly have a history of underachieving and disciplinary problems. This constitutes a set of conditions that may collectively overwhelm the learning environment, yet any single factor may be inconsequential. Scheerens and Bosker (1997, p. 65) refer to this theory as a "synergetic interpretation" of school effects. Rather than having additive effects on learning, several variables with weak associations with learning have a complex interactive effect which, while difficult to model when there are a large number of variables involved, can collectively have a substantial impact on learning.

Initial achievement and learning rates differ across subpopulations

Mean initial achievement and mean learning rates at public high schools varied significantly across social class composition subpopulations of schools. On average, students attending low social class composition schools entered with lower achievement and learned less over 4 years of high school than students attending high social class composition schools. These differences are now quantified using a grade-level metric to accentuate their magnitudes. Compared with students attending high social class composition high schools, students at low social class composition schools entered with achievement levels an average of 4.5 grade levels behind. Over 4 years of high school, the gap increased another 1.2 grade levels to 5.7 grade levels.[13] While adjusting for differences in student background characteristics and school inputs does reduce the initial achievement gap 27% to 3.3 years, and the learning disparity 17% to 1.0 years, substantial discrepancies remain – and adjusting for differences in school practices does little to reduce it further. Even after adjusting for a large number of student characteristics and school inputs and practices, the mean learning rate at high social class composition schools is 30% higher than at low social class composition schools.

School factors matter most in the low subpopulation

School inputs and practices account for a far greater percentage of the between-school variance in learning in low social class composition schools than in middle or high. After controlling for student background differences across schools, school inputs account for 34% of the between-school variance in the low subpopulation but only 8% in the middle and 11% in the high. This trend continued with school practices, which explained an additional 20% of the between-school variance beyond school inputs in the low social class composition subpopulation but only 15% in the middle and 6% in the high. Furthermore, after accounting for school inputs and practices, the between-school variation in learning rates is not significantly greater than zero in the low social class composition sample, while the vast majority of the between-school variance in both the middle and high samples – more than three quarters – remains unaccounted for. These findings suggest that student learning in socially disadvantaged schools is more sensitive to school factors, as compared with middle and high social class schools where differences in learning rates are more random and unrelated to the extensive set of school variables examined in this study.

Differential effects of school inputs and practices

Strong evidence for global differential effects for both school inputs and school practices on learning was found. Beyond the global effects, several individual variables had strong

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evidence of differential effects on learning. Compared with middle-size schools, the effects of attending extra large schools varied significantly across subpopulations: students attending low social class composition schools learned significantly more, which was not the case in the middle and high social class composition subpopulations. This finding may be related to differences in course-taking patterns across settings. In the low social class composition subpopulation, extra large schools may offer a broader curriculum including more college prep courses, because they have more students to take them and more teachers to teach them. However, in the high social class composition subpopulation, the majority of the students may enroll in a college prep curriculum regardless of the school size, suggesting that there is no shortage of students to fill advanced courses even in small schools. A review of the data revealed some empirical evidence supporting this hypothesis. In the low social class composition subpopulation, students attending extra large schools, compared with middle-size schools, took more college prep courses during high school (mean = 12.4 vs. 11.8) and, perhaps as a result, spent more time on homework per week (4.0 hr vs. 3.1 hr). The exact opposite trend was observed in high social class composition schools, where the mean number of college prep courses taken at extra large schools was less than at middle-size schools (14.7 vs. 15.4) as was the average amount of time spent on homework (5.6 hr vs. 6.0 hr).

The results also provided strong evidence of a differential effect for salary, which had a significant positive association with learning in low social class schools, but was not associated with learning in middle and high. The largest school expenditure – teacher salaries[14] – was also significantly lower in the low social class subpopulation ($29,684) compared with the high ($31,942) (see Appendix Table B). These results address a debate that has been ongoing since the Coleman Report (1966) as to whether or not school resources impact learning. Together, the salary findings of this study seem to suggest that at low social class composition schools, monetary resources do matter – at least those that are spent on teacher salaries.

These findings are intriguing, since they suggest that increasing salaries in low social class composition schools may have a positive impact on learning and may also reduce the learning gap between low and high social class composition schools. This is not to suggest that raising salaries in low social class composition schools would immediately result in higher learning rates. A more plausible scenario is that raising salaries would enable low social class composition schools to recruit and retain higher quality teachers, which would have a positive impact on learning over time. These interpretations imply a causal relationship between salary, teacher quality, and learning in the low social class subpopulation, which is difficult to substantiate with large-scale survey data such as NELS.

Strong evidence of a differential effect was also found for the proportion of students who agree that discipline is fairly administered at the school. This measure had a highly significant positive association with learning in the low social class composition subpopulation but nonsignificant associations in the middle and high. Given that the mean values for classroom disruptions and the incidence of students feeling unsafe were significantly higher in the low social class composition subpopulation (see Appendix Table B), it is likely that discipline problems are also more prevalent. Preceived fairness of the discipline practices may be a proxy for using practices that are effective for reducing events and behaviors that disrupt the learning environment. It may also be a proxy for faculty-student relational trust, which is believed to impact the learning environment (Bryk & Schneider, 2002).

As outlined above, the *contingency theory* of organizational functioning, which essentially states that the best way to organize in terms of structures and processes depends

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on the conditions or contingency factors present (Scheerens & Bosker, 1997), provides an explanation for the differential effects based on social class composition noted above. That is, the effect of school factors on learning is contingent upon the social class composition of the school, which may impact the educational milieu of the school. The widespread mean differences that were noted in Appendix Table B suggest that the educational milieu of these three subpopulations do differ substantially.

Methodological implications

Large-scale survey datasets have played an important role in school effectiveness research. However, studies using these datasets typically employ generic models, ignoring differential school effects. Recent scholarship has begun advocating for the use of specific models to examine differential effects, because the generic models can lead to inferences that do not apply in certain subpopulations (Aitkin & Zuzovsky, 1994; Lee & Burkam, 2003; Luyten et al., 2005; Muijs et al., 2005; Teddlie et al., 2000; Thrupp & Lupton, 2006), and may be counterproductive when used to inform school improvement efforts. The findings of this study certainly verify that concern.

While the results of this study show that the school effects models differ for low, middle, and high social class composition subpopulations of schools, many other potential differential effects went unexplored. An important issue related to this is how to determine which subpopulations to examine in a given study. At one extreme is a fully exploratory strategy which essentially mines the data for statistical effects without regard to theory. Aitkin and Zuzovsky (1994) seemed to advocate that approach when they argued that, in the multilevel context, all two-way interactions[15] among student-level variables and between student- and school-level variables should be explored. When a large number of variables are available, such an approach can be impractical. Moreover, even when the number of variables is manageable, this approach has been criticized for being entirely exploratory and atheoretical, which heightens the likelihood that results are conditioned on sample characteristics (Raudenbush, 1994).

At the other end of the spectrum is the option of rejecting empirically based exploratory analyses altogether, limiting model specification to those designed to test well-defined theory. This approach is most likely to lead to durable findings that hold up to cross validation. Yet, taken to an extreme, this approach precludes the potential contributions that elements of exploratory analyses can make to school effectiveness research. Therefore, some balancing of these two extremes seems advisable when using large-scale survey data. Researchers should strive for a sensible compromise of these two extremes that focuses on theory testing without completely stifling the exploratory elements – those elements that large-scale survey data are particularly suitable for and that can be catalysts for theory formulation. However, the arbitrary selection of groupings should be avoided, because it can lead to a large number of inexplicable interactions. The groupings through which differential effects are examined should be judicially selected and limited to characteristics that are of central importance to the topic.

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Notes

1. This sample was restricted to respondents with valid school IDs in 1990, who had valid test scores in 1988 and 1990 and who attended schools with at least five respondents. These restrictions were necessary so that students could be linked to a high school and so that the reliability of the individual growth trajectory estimates and the within-school parameter estimates could be improved.
2. The social class groups were constructed using this criterion to address two competing concerns. The most important was ensuring that the groups differed substantially in terms of mean social class composition. Dividing the sample into three equal size categories, for example, would result in groups that were relatively similar because the distribution of social class composition is approximately normal, which dictates that the majority of the schools are clustered close to the mean. The other concern was that all groups had sufficient sample sizes to ensure adequate power for the statistical tests. A more extreme criterion (e.g., two standard deviations) was not used because it would have resulted in very small samples for the low and high groups, and likely insufficient power.
3. In an effort to include sufficiently large samples of certain student subpopulation (e.g., ethnic minority groups), NCES oversampled student members of those subpopulations. To correct for this design and yield a nationally representative sample of American high-school students, NCES developed sample weights. While these weights are typically appropriate for uses in descriptive analyses, their appropriateness for sophisticated multivariate analyses such as the models used in this study is controversial and some econometrists strongly recommend against it (DuMouchel & Duncan, 1983; Goldhaber & Brewer, 2001). There are two reasons for this. One is the variables that were oversampled may be included in the model as statistical controls, as is the case in the present study. Another reason is that the sample weights are designed for use with specific samples, which may not match the sample used in specific analyses. For example, none of the NELS weight variables match the subsample of students attending public schools that was used in the present study. For these reasons, sample weights were not used in the present study.
4. While the classroom level of analysis was excluded in this study, it is a potentially important source of variance in student outcomes. One reason for excluding the classroom level is that, on average, the NELS data surveyed only 1.5 teachers/classrooms per student, which is insufficient for reliable estimation of classroom effects and variance components. Moreover, studying classroom effects with such a growth model would require a multilevel cross-classified model of extraordinary complexity, since students are not nested within a single classroom over the 4-year period but rather are potentially members of dozens of classrooms.
5. Although many studies of school effects use achievement in one or two academic subjects, particularly mathematics (e.g., Lee et al., 1997; Morgan & Sorensen, 1999), a four-subject composite was used in this study because it provides a more comprehensive measure of achievement that consists of components that are common elements of the core academic curriculum in most high schools. An alternative strategy would be to analyze the four academic tests separately.
6. Standardized achievement tests in math, science, reading, and social science were administered to students in the spring of 1988, 1990, and 1992, when most students were enrolled in Grades 8, 10, and 12, respectively. Three tests of varying difficulty were developed for each subject and were vertically equated to ensure that students were administered tests of appropriate difficulty.
7. Another way of conceptualizing this is to consider that *time* is fixed or balanced across students in the classical Latent Growth Curve (LGC), while it is a random variable in the multilevel regression growth model.
8. A small percentage of the students – those who were retained in a grade level or dropped out of school – may not have been in the 10th and 12th grades in 1990 and 1992, respectively.
9. Because addressing the research questions of this study involved estimating multiple models and conducting multiple statistical tests, p values are likely inflated. However, since model selection was guided by prior research and the number of models estimated was relatively small, the inflation may also be very small. A Bonferroni adjustment was considered to address this, but was not used because of the growing controversy surrounding its statistical adequacy (Perneger, 1998).

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10. The intra-class correlation coefficient is computed by taking the ratio of the variance in a random coefficient at the between-school level to the total variance (between-school + within-school variance).
11. Because the social class composition subpopulations were defined based on the distribution of the mean SES variable, within any subpopulation family SES is expected to have a more limited range and variability compared to the whole sample. This undermines the statistical significance of the family SES variable in any subpopulation.
12. The school input model was first estimated without school practice variables. However, adding school practice variables did not moderate the effects of any input variables. Therefore, to save space, only the results from the final model are presented, which included both school inputs and practices, as shown in Table 3a. Note that this model also included the student background control variables shown in Table 2a.
13. The mean achievement growth over 4 years of high school is 7.61 units for the full sample, which is approximately 1.9 units per year, on average. The mean initial achievement of the low socioeconomic composition school subpopulation is 40.87 compared with 49.45 for high. The difference is 8.58 units, which equals approximately 4.5 years of learning ($8.58/1.9 = 4.5$).
14. Of the approximately $388 billion spent during the 2002-03 school year for American K-12 public education, $238 billion (61% of total) went to instruction, $169 billion (44% of total) of which was spent on teacher salaries and another $46 billion (12% of total) of which was spent on teacher benefits. Data retrieved on July 20, 2006, from http://nces.ed.gov/ccd/pubs/npefs03/findings.asp.
15. The multilevel, multiple group, latent growth curve model used in this study can be considered as an elegant form of an interaction model where all variables in the model can be interacted with the grouping variable, including random coefficients, factor scores, and residuals.

Notes on contributor

Gregory J. Palardy is a faculty member in the Graduate School of Education at the University of California, Riverside. His research addresses methodological issues related to school effectiveness research as well as how families, teachers, and schools impact educational outcomes and opportunity.

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Appendix Table A
Variable definitions

Variable Name	Description and (NELS variables)
	STUDENT VARIABLES
Test composite	Mean of math, science, reading, history tests
Female	(F1SEX = 2)
Asian	(F1RACE = 1)
Black	(F1RACE = 2)
Hispanic	(F1RACE = 3)
Native	(F1RACE = 5)
SES	Composite of family income, parents' educational and occupational prestige (F1SES)
Nontraditional family	Does not live with both mother and father (F1S92A $\neq$ 1 or F1S92D $\neq$ 1)
Grades 6–8	GPA composite (BYGRAD)
Misbehavior 8th	Standardized principal component of student questions on how often during first semester (0 = never, 2 = more than twice) they were sent to the office for misbehaving (BYS55A), parents received warning about their behavior (BYS55E), they got into a physical fight with another student (BYS55F). Factor has an eigenvalue of 2.02 and explains 67% of combined variance
College aspirations 8th	Planned to earn at least a 4-year degree (BYS45 = 5 or 6)
Friends dropped out 10th	Close friend(s) who dropped out of school (F1S69 = 1, 2, or 3)
Retained 8th	Ever held back a grade in school as reported by student (BYS74 = 2) or parent (BYP44 = 1).
Transfer	Transferred schools between 10th and 12th grade (F2F1SCFG = 1)
Dropout	Dropped out at any time (F2DOSTAT = 3 or 5)
	SCHOOL VARIABLES
Inputs	
Student Body Composition	
SES variation	Within school standard deviation on SES
Proportion minority	School mean of dummy variable indicating Black and Hispanic student (F1RACE = 2 or 3)
Proportion nontraditional families	School mean of student variable, nontraditional family

(*continued*)

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Appendix Table A. (*Continued*).

Variable Name	Description and (NELS variables)
Mean 8th grade grades	School mean of student variable, Grades 6–8th
Mean 8th grade misbehavior	School mean of student variable, misbehavior 8th
Mean parental college aspirations	How far in school parent wants teen to go (F2P61); ranges from 1 = LT HS grad to 10 = PHD/MD/OTH PROF
Proportion retained Grades 1–8	School mean of student variable, retained 8th
Structure	
Small	School enrollment = 0–600 (F1C2)
Large	School enrollment = 1201–1800 (F1C2)
Extra large	School enrollment = 1801 + (F1C2)
Urban	School located in urban setting (F1URBAN = 1)
Rural	School located in rural setting (F1URBAN = 2)
Magnet	(F1C4AB)
Resources	
Student–teacher ratio	(F1SCENRL/F1C35)
Proportion excellent teachers	Proportion of teachers rated excellent by principal (F1C92D)
Prop. teachers w/advanced degrees	Proportion of teachers with advanced degrees ((F1C44C + F1C44D)/F1C35)
Mean salary	School mean teacher salary (F1C42A + F1C42B)/2)
Subject certified	Proportion of teachers certified to teach in their teaching subject area (depending on their teaching area, one of F1T3_8A-D = 1)
Teacher experience	Proportion of teachers with four or more years of secondary level teaching experience (F1T3_4B = 2–9)
Standard credential	Proportion of teachers who have a standard teaching credential (F1T3_7 = 1)
BA in teaching subject	Proportion of teachers with at least a BA in their primary teaching subject (depending on their teaching area, one of F1T310B2-E2 = 1)
Highly qualified teacher	BA in subject area, 4+years of experience, and standard credential
Processes	
Parent involvement	Proportion of parents who agree or strongly agree that they have adequate say in school policy (F2P42M = 1 or 2)
Fair discipline	School mean of dummy variable indicating student agrees the discipline is fair at the school (F1S7D = 1 or 2)
Homework time	School mean number of hours spent on homework per week (F1S36A2)
Teacher negativity	Composite of (F1C93K and F1C93L) measuring principal assessment of teachers having negative attitudes about students and difficulty motivating students.
Teaching quality	Standardized principal component
Teacher efficacy	Standardized principal component
Teacher locus of control	Standardized principal component
Class disruptions	Standardized principal component
Teacher sense of community	Standardized principal component
Teacher sense of control	Standardized principal component
Teacher curriculum coordination	Standardized principal component
Principal leadership	Standardized principal component
Percent teacher attrition	Teacher attrition rate 1990 (F1C50/F1C35)

(*continued*)

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Appendix Table A. (*Continued*).

Variable Name	Description and (NELS variables)
Poor learning environment	Principal rating of school learning environment based on physical conflicts, gang activity, drug use, etc. (composite of F1C95D, E, F, G, J, K, L, M)
Academic track	Proportion of students in academic track (F1HSPROG = 2)
Unsafe	Proportion of students who report they feel unsafe at school (F1S7M = 1 or 2)
NAEP composite	Mean number of Carnegie units in Math, Science, English, and Social Science earned in H.S. (F2rall1_C + al2_C + geo_C, tri_C + pre_C + cal_C + bio_C + che_C + phy_C + soc_C + his_C)

Appendix Table B

Variable means, standard deviations, and tests of equality of means and deviation from linearity

Variable Name	Full Sample	Low	Middle	High
Student Level	12,334	1,547	1,865	1,914
Test composite 8th**	46.18 (7.64)	41.05 (6.57)	45.42 (7.40)	49.34 (7.21)
Test composite 10th**	50.39 (9.05)	44.28 (7.73)	49.35 (8.58)	54.39 (8.51)
Test composite 12th**	54.72 (9.25)	48.69 (7.95)	53.76 (8.50)	58.88 (8.54)
Female	0.51 (0.50)	0.51 (0.50)	0.50 (0.50)	0.51 (0.50)
Asian**	0.06 (0.24)	0.05 (0.23)	0.05 (0.22)	0.11 (0.32)
Black**	0.09 (0.29)	0.20 (0.40)	0.08 (0.27)	0.04 (0.20)
Hispanic**	0.12 (0.32)	0.34 (0.47)	0.09 (0.29)	0.05 (0.22)
Native**	0.01 (0.11)	0.02 (0.12)	0.01 (0.08)	0.00 (0.06)
SES**	−0.07 (0.77)	−0.74 (0.69)	−0.11 (0.68)	0.62 (0.63)
Nontraditional family**	0.35 (0.48)	0.41 (0.49)	0.37 (0.48)	0.25 (0.43)
Grades 6–8**	2.98 (0.73)	2.82 (0.73)	2.95 (0.76)	3.17 (0.67)
Misbehavior 8th**	−0.09 (0.92)	−0.07 (0.95)	−0.09 (0.93)	−0.18 (0.85)
College Aspirations 8th**	0.68 (0.47)	0.55 (0.50)	0.65 (0.48)	0.85 (0.36)
Friends dropped out 10th**	0.23 (0.42)	0.35 (0.48)	0.23 (0.42)	0.12 (0.32)
Retained 8th**	0.13 (0.33)	0.19 (0.39)	0.12 (0.33)	0.08 (0.28)
Transfer	0.06 (0.24)	0.07 (0.26)	0.06 (0.24)	0.06 (0.23)
Dropout**	0.08 (0.27)	0.13 (0.34)	0.09 (0.28)	0.02 (0.15)
School Level	779	112	115	117
Context				
Mean SES**	−0.08 (0.43)	−0.74 (0.20)	−0.12 (0.23)	0.61 (0.22)
SES variation**	0.65 (0.14)	0.66 (0.15)	0.65 (0.14)	0.60 (0.15)
Proportion minority**	0.23 (0.28)	0.61 (0.35)	0.19 (0.25)	0.10 (0.13)
Proportion nontraditional families**	0.35 (0.15)	0.43 (0.20)	0.38 (0.16)	0.26 (0.12)
Mean 8th grade grades**	2.96 (0.27)	2.79 (0.28)	2.96 (0.26)	3.17 (0.26)
Mean 8th grade misbehavior**	−0.07 (0.29)	−0.01 (0.33)	−0.08 (0.29)	−0.18 (0.27)

(*continued*)

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Appendix Table B. (*Continued*).

Variable Name	Full Sample	Low	Middle	High
Mean parental college aspirations**	7.68 (0.79)	7.62 (0.90)	7.51 (0.74)	8.41 (0.53)
Proportion retained Grades 1–8**	0.16 (0.11)	0.20 (0.13)	0.12 (0.10)	0.08 (0.08)
Structure				
Small**	0.21 (0.40)	0.15 (0.36)	0.22 (0.42)	0.04 (0.20)
Large**	0.29 (0.45)	0.27 (0.44)	0.26 (0.44)	0.43 (0.50)
Extra large†	0.14 (0.35)	0.25 (0.44)	0.14 (0.35)	0.22 (0.42)
Urban**	0.19 (0.40)	0.45 (0.50)	0.21 (0.41)	0.24 (0.43)
Rural**	0.39 (0.49)	0.34 (0.48)	0.42 (0.50)	0.11 (0.32)
Magnet**	0.04 (0.21)	0.15 (0.36)	0.01 (0.09)	0.02 (0.13)
Resources				
Student–teacher ratio	16.61 (5.79)	17.56 (4.05)	17.04 (7.05)	16.52 (4.69)
Proportion excellent teachers	0.33 (0.19)	0.32 (0.19)	0.35 (0.21)	0.37 (0.22)
Prop. teachers w/advanced degrees**	0.53 (0.21)	0.51 (0.19)	0.49 (0.19)	0.62 (0.20)
Mean salary**	29529 (4492)	29684 (4421)	28878 (4166)	31942 (4717)
Subject certified*	0.86 (0.21)	0.85 (0.26)	0.89 (0.26)	0.93 (0.17)
Teacher experience**	0.91 (0.20)	0.82 (0.25)	0.82 (0.26)	0.92 (0.17)
Standard credential†	0.89 (0.21)	0.84 (0.26)	0.87 (0.26)	0.91 (0.18)
BA in teaching subject*	0.40 (0.18)	0.38 (0.19)	0.38 (0.17)	0.43 (0.18)
Highly qualified teacher**	0.36 (0.18)	0.33 (0.19)	0.33 (0.16)	0.41 (0.18)
Process				
Parent involvement**	2.46 (0.18)	2.43 (0.18)	2.50 (0.18)	2.35 (0.20)
Fair discipline	0.63 (0.14)	0.60 (0.15)	0.61 (0.16)	0.63 (0.14)
Homework time**	4.19 (1.49)	3.50 (1.22)	3.76 (1.22)	5.71 (1.73)
Teacher negativity**	4.62 (1.61)	5.17 (1.43)	4.59 (1.61)	4.21 (1.63)
Teaching quality **	0.08 (0.31)	−0.07 (0.37)	0.10 (0.32)	0.05 (0.30)
Teacher efficacy	−0.04 (0.54)	0.05 (0.66)	−0.06 (0.46)	−0.01 (0.45)
Teacher locus of control**	−0.08 (0.64)	−0.35 (0.52)	−0.15 (0.49)	0.25 (0.48)
Class disruptions**	−0.05 (0.29)	−0.14 (0.31)	−0.07 (0.28)	0.06 (0.30)
Teacher sense of community†	−0.08 (0.67)	−0.18 (0.70)	−0.08 (0.63)	0.00 (0.55)
Teacher sense of control**	−0.02 (0.72)	−0.34 (0.67)	−0.12 (0.71)	0.06 (0.61)
Teacher curriculum coordination**	−0.04 (0.58)	−0.14 (0.59)	−0.08 (0.48)	−0.02 (0.52)
Principal leadership	−0.05 (0.74)	−0.07 (0.72)	−0.03 (0.73)	0.05 (0.63)
Percent teacher attrition	0.04 (0.06)	0.04 (0.06)	0.04 (0.07)	0.03 (0.03)
Poor learning environment**	12.09 (2.45)	13.14 (3.25)	11.86 (2.32)	12.14 (2.28)
Academic track**	0.30 (0.18)	0.23 (0.16)	0.30 (0.21)	0.35 (0.19)
Unsafe**	0.08 (0.08)	0.13 (0.09)	0.07 (0.08)	0.05 (0.06)
NAEP composite**	13.38 (1.91)	12.16 (2.28)	13.06 (1.67)	15.10 (1.68)

†group means differ significantly at 0.10; *group means differ significantly at 0.05; **group means differ significantly at 0.01.

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Appendix Table C

Principal component descriptions, path loadings, and variance explained

Factor and Items Labels	Item Descriptions	Item Loadings
Teacher Quality	4-point Likert scale (1 = *strongly agree*, 4 = *strongly disagree*)	
F1S7G	TEACHING IS GOOD AT SCH	0.702
F1S7H	TEACHERS ARE INTERESTED IN STUDENT	0.789
F1S7I	WHEN R WORKS HARD TEACHERS PRAISE EFFORT	0.681
F1S7J	IN CLASS OFTEN FEEL PUT DOWN BY TEACHERS (reverse coded)	0.591
F1S7L	MOST TEACHERS LISTEN TO R	0.747
F1S66G	TEACHERS EXPECT R TO SUCCEED AT SCHOOL	0.697
Variance Explained		49.5%
Teacher Efficacy	6-point Likert scale (1 = *strongly disagree*, 6 = *strongly agree*)	
F1T4_5A	CAN GET THROUGH TO MOST DIFFICULT STUDENTS	0.666
F1T4_5B	TCHER RESPONSIBLE FOR KEEPING STUDENTS FOR DROPPING	0.622
F1T4_5C	CHANGE APPROACH IF STUDENTS NOT DOING WELL	0.626
F1T4_5D	DIFFERENT METHODS CAN EFFECT ACHIEVEMENT	0.730
F1T4_5E	LITTLE I CAN DO TO ENSURE HIGH ACHIEVEMENT (reverse coded)	0.610
F1T4_5F	R MAKING DIFFERENCE IN STUDENTS LIVES	0.595
F1T4_11F	CREATE LESSONS STUDENTS WILL ENJOY LEARNING	0.516
Variance Explained		39.3%
Teacher Locus of Control	6-point Likert scale (1 = *strongly disagree*, 6 = *strongly agree*)	
F1T4_1D	SUCCESS/FAILURE DUE TO FACTORS BEYOND ME	0.569
F1T4_1E	STUDNT MISBEHAVIOR INTERFERES W/TEACHING	0.678
F1T4_1I	STUDENTS INCAPABLE OF LEARNING MATERIAL	0.631
F1T4_2J	FEEL WASTE OF TIME TO DO BEST AT TEACHNG	0.648
F1T4_2N	STUDENTS ATTITUDES REDUCE ACADMC SUCCESS	0.755
Variance Explained		43.4%
Class Disruptions	4-point Likert scale (1 = *strongly agree*, 4 = *strongly disagree*)	
F1S7F	OTHER STUDENTS OFTEN DISRUPT CLASS	0.673
F1S7K	OFTEN FEEL PUT DOWN BY STUDENTS IN CLASS	0.501
F1S7N	DISRUPTIONS IMPEDE R'S LEARNING	0.712
F1S7O	MISBEHAVING STDNS OFTEN GET AWAY WITH IT	0.696
Variance Explained		42.4%
Teacher Sense of Community	6-point Likert scale (1 = *strongly disagree*, 6 = *strongly agree*)	
F1T4_1B	CAN COUNT ON STAFF MEMBERS TO HELP OUT	0.741
F1T4_1C	COLLEAGUES SHARE BELIEFS ABOUT MISSION	0.720
F1T4_2E	GREAT DEAL COOPERATVE EFFORT AMONG STAFF	0.846
F1T4_2F	BROAD AGREEMNT AMONG FACULTY ABOUT MISSN	0.771
F1T4_2H	SCHOOL SEEMS LIKE A BIG FAMILY	0.753
Variance Explained		58.9%

(*continued*)

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Appendix Table C. (*Continued*).

Factor and Items Labels	Item Descriptions	Item Loadings
Teacher Sense of Control	5-point Likert scale (1 = *no influence*, 5 = *great deal of influence*)	
F1T4_9A	TEACHRS INFLUENCE OVER DISCIPLINE POLICY	0.767
F1T4_9B	TEACHRS INFLUENCE OVER INSERVICE PROGRAMS	0.714
F1T4_9C	INFLUENCE GROUPING STUDENTS BY ABILITY	0.774
F1T4_9D	INFLUENCE OVER ESTABLISHING CURRICULUM	0.748
Variance Explained		56.4%
Teacher Curriculum Coordination	6-point Likert scale (1 = *strongly disagree*, 6 = *strongly agree*)	
F1T4_1A	COORDINATE COURSE CONTENT W/DEPT TEACHRS	0.783
F1T4_1N	COORDINATE CONTENT W/TCHRS OUTSIDE DEPT.	0.666
F1T4_2P	FAMILIAR W/CONTENT TAUGHT BY DEPT. TCHRS	0.657
Variance Explained		49.6%
Principal Leadership	6-point Likert scale (1 = *strongly disagree*, 6 = *strongly agree*)	
F1T4_1F	PRINCIPAL POOR AT GETTING RESOURCES (reverse coded)	0.711
F1T4_1G	PRINCIPAL DEALS WITH OUTSIDE PRESSURES	0.669
F1T4_1H	PRINCIPAL MAKES PLANS and CARRIES THEM OUT	0.798
F1T4_1J	GOALS/PRIORITIES FOR THE SCHL ARE CLEAR	0.709
F1T4_1L	STAFF MEMBRS RECOGNIZD FOR JOB WELL DONE	0.644
F1T4_1O	PRINCIPL KNOWS WHAT KIND OF SCH HE WANTS	0.848
F1T4_1P	ADMINISTRATN KNOWS PRBLMS FACED BY STAFF	0.756
F1T4_2I	PRINCIPAL LETS STAFF KNOW WHAT'S EXPECTD	0.861
F1T4_2K	PRINCIPAL IS INTERESTED IN INNOVATION	0.778
F1T4_2M	PRINCIPAL CONSULT STAFF BEFORE DECISIONS	0.723
Variance Explained		56.6%

Note: All variables were coded on 4-6 Likert-type scales. Factor loadings were computed using all cases from the F2 sample of NELS with a valid F1sch_id ($N = 19{,}392$).