Exploring the measurement profiles of socioeconomic background indicators and their differences in reading achievement: A two-level latent class analysis

Kajsa Yang Hansen and Ingrid Munck

Department of Education and Special Education, University of Gothenburg, Sweden

Applying a two-level mixture modeling technique, the study explored the psychometric profiles of socioeconomic status (SES) and examined reading achievement differences according to the latent SES profiles. The two-level latent class analysis (TLCA) takes into consideration the measurement error in the response patterns of the SES indicators, and the variation of the latent class indicators across different schools. It also controls for individual characteristics to assure precision in latent class estimation and differences in reading achievement between classes. The SES background variables and reading achievement variable were taken from the Swedish Grade 4 data of the Progress in Reading Literacy Study (PIRLS) 2006.

The analysis identified three latent classes of individuals, namely the economically and culturally affluent group, the culturally disadvantaged group, and the culturally well-off group. Reading achievement differed significantly across the three SES classes. About 16% of the differences in reading achievement could be attributed to the SES differences of individual students in different latent SES classes. The lowest achieving class was the immigrant-concentrated, culturally disadvantaged group. Only for this group, speaking the test language at home had a significant impact on reading achievement. The school-level continuous factor captured the variation in the SES composition of student intake across schools, and it explained almost half of the between-school differences in reading achievement. The findings in this study may imply that a mixed societal and school environment can compensate for students' disadvantaged family background. Educational investment in this group of students may reduce educational inequality and school segregation.

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BACKGROUND

Numerous studies have established the association between students' socioeconomic status (SES) and academic achievement, making SES one of the powerful predictors of student performance (see, for example, Coleman et al., 1966). Typically, family SES is represented by parental education, occupation, and income. However, there is no consensus on how SES is composited and measured by its indicators. A variety of alternative measurements of SES has also been developed, which has led to an inconsistency of predictive value of SES on, for example, academic achievement and cognitive development (see, for example, Sirin, 2003, 2005; White, 1982).

As a background variable, SES fulfills one of the following functions:

1. A control variable to statistically adjust for background differences and confounding effects with other factors;
2. A stratification variable to increase the precision of comparing treatment effects or interaction effects of different treatments within different SES groups;
3. An independent variable in causal models to examine its effects on educational outcomes;
4. A descriptive aggregated variable at classroom or school level in contextual, teaching effect, or school-effect studies (White, 1982; see also Willms, 1992).

Depending on the function it may carry, SES is defined according to differentiated psychometric properties. In most of the effect studies, SES is measured as a one-dimensional composition. This line of research adopts the Weberian tradition, regarding SES as a combination of property, power, and prestige, the components of which are well reflected by family material assets, income, and parental education and occupation on an integrated continuum (see, for example, Bradley & Corwyn, 2002).

White (1982) reviewed over 200 studies and found an overall average SES-achievement correlation of 0.35. He also observed that the relationship between SES and achievement varied greatly across studies, contingent upon the measures of SES and the unit of analysis. When SES is defined as a composite of father's income, education, and occupation, and the individual is used as the unit of observation, SES is only weakly correlated with academic achievement (r = 0.22). When the SES-achievement relationship is determined at aggregate levels, such as the school level, the correlation is higher (r = 0.73).

This aggregated-level SES-achievement correlation is an ecological correlation, which is based on school average of SES and achievement. And it tends to be much higher compared to the individual correlation, due to the fact that measurement errors of the school average in SES and reading achievement are reduced by the aggregation across units. Thus, "there needs to be no correspondence between the individual correlation and the ecological correlation" (Robinson, 1950, p. 354). Sirin (2005) also noted in his meta-analysis of SES effect that much of the variation in the magnitude of the SES-achievement relation is due to "methodological characteristics, such as the type of SES measures, and student characteristics, such as student's grade, minority status, and school location ... [all of which] moderated the magnitude of the relationship between SES and academic achievement" (p. 438).

However, a general trend, observed in the recent literature on measuring SES and its effects, is that of moving from a conception of SES as a single composition toward a multidimensional normally distributed continuous latent construct that imposes its effects differently at different levels of observation, for example, students and schools (Sirin, 2003, 2005). Bourdieu's cultural reproduction theory and forms of capital offer a conceptual framework with respect to defining the dimensionality and structure of SES and explaining educational inequality (see, for example, Lareau & Weininger, 2003).

According to Bourdieu (1997), social structure and function are impossible to explain unless all forms of capital are recognized. Capital in the monetary sense (i.e., economic capital) along with the intangible forms of capital, namely cultural capital and social capital, form the three fundamental manifestations of resources, and the possession of one form of capital can influence the chance to possess other forms of capital (Bourdieu, 1997). When explaining his cultural reproduction theory, Bourdieu argued that modern education systems transform the social hierarchies into academic hierarchies (Bourdieu, 1977; Bourdieu & Passerson, 1977). The transmission of status operates largely through cultural capital, by which the relative social advantages of individuals or groups are maintained and promoted. Lack of knowledge of institutionalized cultural norms, such as attitudes, preferences, formal knowledge, behaviors, goods, and credentials, negatively affects the academic outcomes of individuals and therefore hinders their upward mobility (Bourdieu & Boltanski, 1979; see also Lamont & Lareau, 1988).

Applying Bourdieu's capital concepts and a two-level structural equation modeling technique (see, for example, Muthén, 1989, 1991), Yang (2003) measured family and school SES simultaneously with a set of home possession items from the IEA survey studies. An economic capital factor and a cultural capital factor were identified at the individual level. However, only one general capital factor was found at the school level. The latent structure of SES differs across countries. Such differences are reflections of country-specific social, cultural, and economic factors, as well as differences in availability of SES data in IEA studies. It also was found that the cultural capital factor in general had a significant and positive impact on students' academic achievement, while the relationship between the economic capital factor and academic achievement was negative or non-significant. The school-level general capital factor, representing the SES composite of the school student bodies, alone explained a substantial amount of school differences in academic achievement (Yang, 2003; see also, Yang & Gustafsson, 2004). Such a multidimensional, multilevel measurement of SES can thus offer a more detailed understanding of the mechanisms through which SES exerts its impact on academic achievement.

Another major use of SES is, however, to classify individuals according to the level of family socioeconomic circumstances. In this context, SES is a categorical index that very often is based on the average of the observed SES indicators. Several issues are raised in respect of such an index. First, measurement errors and missing responses in the relatively few construct indicators may cause the construct index to have a low reliability. Second, the assumption that construct indicators contribute equally to the index they measure may not hold, since a construct can relate more or less strongly to different indicators. Third, little is known about the validity of the index.

One way to deal with these methodological problems is to adopt a multivariate latent variable modeling approach, whereby measurement models are used to represent the construct indicators (see, for example, Yang Hansen, Rosén, & Gustafsson, 2006). This approach allows testing of the hypothesized model against data, and it optimally weights the contribution of each of the indicators to its underlying latent variable. Measurement models also allow estimation of individual latent variable scores (i.e., factor scores) from partially missing data. Factor score estimates may be treated as observed variables and used both in regular analyses and categorization of individuals. However, because a factor score does not have a natural cut point for SES groups, the division of SES groups seems to be more arbitrary in the factor score approach.

The two-level latent class analysis (TLCA) approach offers new possibilities for exploring the psychometric profiles of SES (Vermunt, 2003). It is assumed that SES has a multinomial distribution and this assumption is conceptualized by forming discrete latent categories or typologies that are based on the prior and posterior probability distributions under conditional maximum likelihood estimation (Henry & Muthén, 2010; Muthén, 2007).

One of the advantages of TLCA is that it takes into consideration the measurement error (i.e., misclassification of individuals) in the response patterns of the SES indicators, and achieves more precise classification of individuals through estimated latent classes. The latent class membership can then be merged with the original data file and used as an estimated SES index. Another advantage of TLCA is that it allows researchers to adjust the biases caused by cluster sampling designs by modeling the hierarchical data structure and then simultaneously examining the SES effects on academic achievement at individual and collective levels.

The aim of the current study was to apply two-level latent class analysis in order to identify the unobserved categories of individuals according to a set of SES measures in the IEA Progress in Reading Literacy Study (PIRLS) 2006 data (Mullis, Martin, Kennedy, & Foy, 2007). A further aim was to examine the extent to which different latent SES classes and collective SES can account for differences in reading achievement.

METHOD

Sample and Variables

The current analysis drew on the Swedish data from the 2006 iteration of IEA PIRLS. The Swedish sample consisted of 4,393 Grade 4 students and 147 schools. Variables indicating family SES and school student-intake characteristics were selected from the study's student questionnaire (StQ) and home questionnaire (HQ), in order to identify latent SES classes of individuals while taking into account the clustering of individuals in different schools. A measure of student reading achievement (ASRREA01) was included so that the mean achievement differences among different latent classes could be examined. A set of student-level background variables was also included in order to describe the characteristics of the estimated latent classes.

Table 1 shows the descriptive statistics of SES indicators involved in identifying the latent classes, together with the covariate "use of the test language at home" (ASBGLNG1) and the distal reading outcome variable ASRREA01 at the individual level. The number of observations of certain categories in some of the SES indicators is fairly low, which may cause a sparse distribution of individuals in certain cells in the cross-tabulation among different variables. Because this, in turn, can affect maximum likelihood estimation, making it difficult for the statistical model to converge to the global maximum, categories with few observations were reclassified into a larger category of the variable.

As shown in Table 1, five SES indicators were taken from the HQ: highest level of parental education (ASBHHEDUP), number of books at home (ASBHBOOK), number of children's books at home (ASBHCHBK), family affluence (ASBHWELL), and highest level of parental occupation (ASBHHOCP). A sum score of the five items used in the StQ to denote possessions potentially found in students' homes (personal computer, desk, own books, newspapers, and own room) was also derived and then categorized into low, medium, and high levels. It was used to represent the level of educational aids at home (EDUAIDS). These six SES indicators were recoded into ordinal categorical variables, with the low or negative category being coded as 1 and the high or positive category being coded as 3.

Among these SES indicators, two categories of variables can be distinguished. One category, in line with Bourdieu (1984, 1997), is the objectified state of cultural capital, which signifies the cultural preferences of people in everyday life. Proxies for the concept of cultural capital are number of books at home and the educational level of the parents. Another category relates to family wealth (i.e., economic capital). Information about family affluence, parental occupation, and educational aids in the home for children functions as an indicator of the economic aspect of SES. Table 1 also presents frequencies of individuals in each category of the variables as well as the number of missing observations in each variable.

Table 1: Descriptive information on all variables included in the mixture modeling of SES

Variables	Label	Source	Scale	Value labels (percentage of individuals in each category)	Missing
ASBHHEDUP	Highest level of parental education	HQ	Ordinal	1 = finished upper-secondary school (29.2%) 2 = finished post-secondary but not university (36.6%) 3 = finished university or higher (34.2%)	696
ASBHBOOK	Number of books at home	HQ	Ordinal	1 = fewer than 25 (10.4) 2 = 26–100 (26.7%) 3 = more than 100 (62.9%)	303
ASBHCHBK	Number of children's books at home	HQ	Ordinal	1 = fewer than 25 (15.1%) 2 = 26–100 (57.2%) 3 = more than 100 (27.7%)	296
ASBHWELL	Family affluence status: being well-off family	HQ	Ordinal	1 = not well-off (7%) 2 = average (41%) 3 = well-off (52%)	
ASBHHOCP	Highest level of parental occupation	HQ	Ordinal	1 = skilled worker, general laborer, or never worked outside home for pay (8.6%) 2 = small business-owner or clerical (33.7%) 3 = professional (57.7%)	451
EDUAIDS	Level of educational aids in home: an index of summed scores of the five common home-possessions items (personal computer, desk, own room, newspaper, books)	StQ	Ordinal	1 = low 0–3 (8%) 2 = average 4 (27.5%) 3 = high 5 (64.5%)	65
ASBGLNG1	Use of the test language at home	StQ	Binary	1 = yes (94.8%); 0 = no (5.2%)	162
ASRREA01	Plausible value: overall reading achievement	StQ	Continuous	Mean = 548.7; *SD* = 63.5	0

Notes:
The percentages presented in the parentheses are valid percentages and the dataset was weighted by house weight (HOUWGT).
Sample size = 4,393.

The variable ASBGLAN1 (i.e., extent to which the language of the PIRLS test was being used at home) is an indicator of students' ethnic backgrounds. It was used as a covariate at the individual level to further describe the estimated latent SES classes in the latent class analysis (LCA) modeling.

An important aspect of LCA is that it allows researchers to investigate the characteristics of individuals within each latent class by relating the latent classes to auxiliary variables. Auxiliary variables can be, for example, covariates, concurrent outcomes, and distal outcomes that are not involved in the estimation of latent classes (see, for example, Clark & Muthén, 2009). Table 2 presents these auxiliary variables, all of which are, in their original scale, individual-level variables taken from the StQ or the HQ. These were used in the current study to further describe the latent SES classes.

Given the latent SES class membership, the class-specific means (i.e., conditional means) of the variables in Table 2 can be evaluated and compared by conducting a Wald test of mean equality using Mplus software (Muthén & Muthén, 2010a). The results of the comparison can then be used to validate the interpretation of the latent SES classes and further depict the class characteristics (Clark & Muthén, 2009; Muthén & Muthén, 2010a).

Table 2: Auxiliary variables of student characteristics used in the latent class analysis

Variables		Source	Highest category (no. of categories)	Missing
ASBHMJF	Main job of father	HQ	Professional (11c)	727
ASBHMJM	Main job of mother	HQ	Professional (11c)	682
ASBGTA5	Own room	StQ	Yes (dummy)	84
ASBHLEDF	Highest education of father	HQ	Beyond ISCED Level 5A (7c)	832
ASBHLEDM	Highest education of mother	HQ	Beyond ISCED Level 5A (7c)	861
ASBGBOOK	Number of books at home	StQ	Over 100 books (5c)	146
ASBGTA4	Daily newspaper	StQ	Yes (dummy)	97
ASDHHER	Index home educational resources	StQ	High (3c)	344
ASBGBRNM	Mother born in the country	HQ	Yes (dummy)	200
ASBGBRNF	Father born in the country	HQ	Yes (dummy)	159

Note: Sample size = 4,393.

Analytical Method

Latent class analysis (LCA, see, for example, Hagenaars & McCutcheon, 2002) was used in the first step to identify small numbers of unobserved homogenous groups of individual students inferred from the properties of the set of SES measures. A latent class is characterized by a pattern of conditional probabilities that indicates the degree of association of the observed dependent variables with each of the latent classes (i.e., SES indicators).

The conditional probabilities of SES indicators can be understood in the same way as the factor loadings in factor analysis. The conditional probability signifies the chance of a certain response pattern being chosen in the set of observed indicators, given the individual's membership within a latent class. In other words, conditional probabilities indicate the likelihood of an individual within a latent class giving a particular response on an observed measure. Like the factor loadings, the conditional probabilities offer measurement profiles that describe the latent classes. By looking at the pattern of responses for all SES measures, one obtains an overview of the nature of each latent class, thus assisting in interpreting the relationship between these latent classes and other outcome variables such as reading achievement.

As is the case with conventional covariance structure modeling, the observations are assumed to be independently sampled in LCA. However, the stratified multistage cluster sampling design used in PIRLS violates this assumption. For example, students in the same school will, when compared to students from different schools, achieve similarly and have a similar demographic background. For this reason, the multilevel technique was needed in the current study to account for such dependencies (Asparouhov & Muthén, 2008; Vermunt, 2003, von Davier, 2010).

The two-level latent class model applied in the current study not only allowed an examination of the multilevel structure of the data but also made it possible to detect subgroups of individuals according to the observed SES properties. In other words, the two-level latent class analysis took into account the nested structure of the data, thereby allowing the aggregated SES indicators to differ across second-level units (i.e., indicator-specific random effects; Henry & Muthén, 2010). This type of analysis can also detect whether, and if so how, the second-level units influence the lower-level latent classes. Here, the process involves comparing the latent class profiles of SES that were estimated by taking into account the indicator-specific random effects at school level with those that were estimated without (for a detailed example, see Henry & Muthén, 2010).

The parameters in the two-level latent class analysis were estimated by the maximum likelihood estimator with robust standard errors, with the combination of missing data analysis. The current analysis was carried out using Version 6 of the Mplus software program (Muthén & Muthén, 2010a).

The Modeling Process

In order to find the best-fitting latent class model, the modeling process followed an exploratory strategy (see, for example, Henry & Muthén, 2010b). The first step involved performing a one-level fixed-effect LCA using six SES measures: ASBHHEDUP, ASBHBOOK, ASBHCHBK, ASBHWELL, ASBHHOCP, and EDUAIDS. To determine the optimal number of latent classes, the LCA model was estimated stepwise, that is, a one-class LCA model was fitted first and an additional class was added sequentially until the model fitted the data well. These models were estimated by different sets of starting values to prevent any local maximum in the iteration processes and were compared with respect to the Bayesian information criterion (BIC). BIC is a popular indicator for determining the number of latent classes among the information criterion measures (Schwartz, 1978; see also Kass & Wasserman, 1995). The model with the lowest BIC was preferred.

The next step involved evaluating the correct number of classes chosen for each model. The Vuong-Lo-Mendell-Rubin likelihood ratio test (LRT) (Lo, Mendell, & Robin, 2001) was used to compare the loglikelihood differences of the model with *k* classes with the one with *k*-1 classes. A significant improvement in loglikelihood difference implies that the *k*-class model fits the data better (Muthén & Muthén, 2010b; Nylund, Asparouhov, & Muthén, 2007). Moreover, the substantive meaningfulness of the latent classes is yet another factor to consider when determining the number of latent classes. If the latent class size is small, a substantive rationale based on previous research and theories has to be offered to support the inclusion of the class. This need arises because the extremely small group may be a statistical artifact that reflects only the measurement character in the sample (Samuelsen & Dayton, 2010).

In the next step, the single-level LCA model was extended to a two-level latent class model to capture the randomness in the latent class indictors at school level (i.e., variation in the intercepts of SES indicators across different schools). A continuous latent variable was specified by these aggregated means of SES indicators. A chi-square test of conditional mean equality was then carried out for a set of potential latent SES class predictors and reading achievement.

Finally, the covariate "use of test language at home" (ASBGLNG1) was introduced to the two-level latent class measurement model in order to control for differences in students' ethnic background. The reading achievement ASRREA01 was regressed on the covariate ASBGLNG1 and the latent class membership at individual level so that the latent class differences in reading achievement level could be examined. At school level, the aggregated reading achievement was regressed on the indicator-specific random effect factor at the school level so that the collective SES effect on reading achievement could be examined.

FINDINGS

Results from the Single-Level LCA Analysis

The LCA model was fitted at the individual level in order to classify students into possible latent groups. Table 3 shows the Bayesian information criterion (BIC) and entropy values associated with each of the LCA models. The BIC estimate decreased dramatically from the one-class LCA model to the four-class LCA model, and stabilized between the four-class and the five-class models. The BIC increased, however, for the six-class model, which indicated that the five-class model should be chosen as the preferred solution.

Table 3 also shows the *p*-values for the LRT test and the adjusted LRT test[1] that were obtained from the series of LCA models. The *p*-values for LRT and adjusted

1 That is, adjusting the conventional likelihood ratio test for *k* versus *k* +1 classes for violation of regularity conditions (see Lo et al., 2001).

Table 3: Evaluation of the single-level LCA measurement models of socioeconomic status

Fit criteria	Individual-level latent class models (complex model type with weight)					
	One-class model	*Two-class model*	*Three-class model*	*Four-class model*	*Five-class model*	*Six-class model*
No. of free parameters	12	25	38	*51*	64	77
Loglikelihood	- 22288	-20915	-20631	*-20488*	-20430	-20406
BIC	44677	42041	41581	*41405*	41399	41458
Comparison between		1- vs. 2-class	2- vs. 3-class	3- vs. 4-class	4- vs. 5-class	5- vs. 6-class
p-value for LRT		.0000	.0002	.0006	*.7409*	*.8150*
p-value for adjusted LRT		.0000	.0002	.0007	*.7414*	*.8150*

Note: The Vuong-Lo-Mendell-Rubin test (LRT) showed a significant difference in the loglikelihood estimation between the four-class and five-class model, thus leading to the choice of the four-class LCA model of the individual-level SES (see fit criteria in italic) even though the Bayesian information criterion for the four-class model was not the lowest among the estimated models.

LRT between the four- and five-class LCA models were non-significant, suggesting that four classes would be the sufficient number of latent groups of individuals with respect to the combined characteristics of the SES measures. Scrutiny of the BIC estimates of the four- and five-class LCA models revealed the difference as marginal. The size of the fifth class was rather small for the five-class solution, being about seven per cent of the total sample size (see Appendix 1). The inclusion of the extra class did not contribute more substantive meaning to the classification of the sample students. The four classes achieved from the LCA model were therefore taken as the optimal solution.

Item probabilities were estimated for each category of the SES measures, given the SES latent class membership. Table 4 shows the item probability of answering Response Category "3" for each measure of SES in the different latent classes. The SES indicators for Response Category 3 are "finished university education or higher," "more than 100 books at home," "more than 100 children's books at home," "being a well-off family," "highest parental occupation is professional," and "have five home-possession items" (see Table 1 on page 54 for detailed descriptions of the variables and labels).

For Latent Class 1, the conditional probabilities were very high for all six SES indicators, implying that the individuals belonging to this latent class very likely came from an economically and culturally affluent family. Latent Class 1 can therefore be termed the "economically and culturally affluent group." The opposite pattern was evident in Latent Class 2, where the item probability was low on all six SES indicators. The individuals in this group were very likely to have come from an economically and culturally disadvantaged family. This latent class can thus be termed the "economically and culturally disadvantaged group."

Table 4: The conditional probability of answering "Category 3" of the SES indicators estimated by the four-class single-level LCA measurement model

Variables	Label (Category 3)	Latent Class 1: Economically and culturally affluent group	Latent Class 2: Economically and culturally disadvantaged group	Latent Class 3: Economically well-off group	Latent Class 4: Culturally affluent group
ASBHHEDUP (C)	Parental educational level (finished university or higher)	0.65	0.06	0.34	0.03
SBHBOOK (C)	Books at home (more than 100 books)	1.00	0.02	0.34	0.59
ASBHCHBK (C)	Children's books at home (more than 100 books)	0.51	0.00	0.09	0.21
ASBHWELL (E)	Family well-off	0.65	0.40	0.55	0.39
ASBHHOCP (E)	Parental highest occupation (professional)	0.93	0.16	0.93	0.09
EDUAIDS (E)	Index of the level of educational aids at home (5, high)	0.74	0.39	0.68	0.62

Notes:
C and E in parentheses denote cultural capital indicator and economic indicator respectively.

Although the pattern of posterior probabilities of the economic capital indicator for Latent Class 3 was rather similar to the pattern for Latent Class 1, the former's cultural capital was much lower than the latter's. Latent Class 3 was thus named the "economically affluent group." Finally, Latent Class 4 can be seen as the "culturally affluent group" because the number of books, children's books, and educational aids in the home accounted for the distinction between Latent Classes 2 and 4. (For the graphical profiles of each latent class, see Appendix 2.)

Each student in the sample was assigned to one of the four latent classes according to the most probable likelihood of him or her belonging to that class. Class 1 contained the most students in the sample; in all, 1,700 students (38.9% of the total sample). The second largest group was Class 4, with 1,314 individuals (30% of the sample). The number of individuals in Classes 2 and 3 was smaller, being 609 (13.9%) and 755 (17.2%), respectively.

In summary, the single-level LCA achieved a four-class solution for the classification of students according to the response patterns of SES indicators. However, the stratified cluster sampling design in PIRLS 2006 implies that the data have a hierarchical structure (Martin, Mullis, & Kennedy, 2007). But ignoring the cluster effect in the data may lead to misclassification of individuals. A two-level LCA model is thus needed to correct such misclassification.

In Sweden, the increasing degree of residential segregation and the fact that more and more parents are determining which school their child should attend has led to an increasing incidence of cross-school differences in school SES composition (Björklund, Clark, Edin, Fredriksson, & Krueger, 2005; Yang Hansen, Cliffordson, & Gustafsson, 2010). Consequently, the collective SES, represented by the aggregated means of SES indicators (i.e., an indicator-specific random effect), becomes more homogeneous within each school and varies largely across different schools.

Results from the Two-Level Mixture Modeling

Determining the Structure of the Two-Level Latent Class Model

To adjust for the cluster effect of the hierarchical data structure and to capture the between-school difference in the aggregated means of the SES indicators, a set of two-level latent class models was estimated and evaluated. Various researchers, including Asparouhov and Muthén (2008) and Vermunt (2003), recommend identifying a common factor to represent the SES indicator-specific random effects between schools (i.e., the random means and associated covariance). The assumption here is that the random means are highly correlated and have different loadings on the common factor.

Table 5 presents the evaluation of the set of two-level latent class models, with the four-class single-level LCA model (Model 1) providing the reference. Model 2 is a two-level latent class model with four latent classes at the individual level and a continuous factor *fu* at the school level (Model 2). This model has a better BIC estimation compared to that of the single-level LCA model.

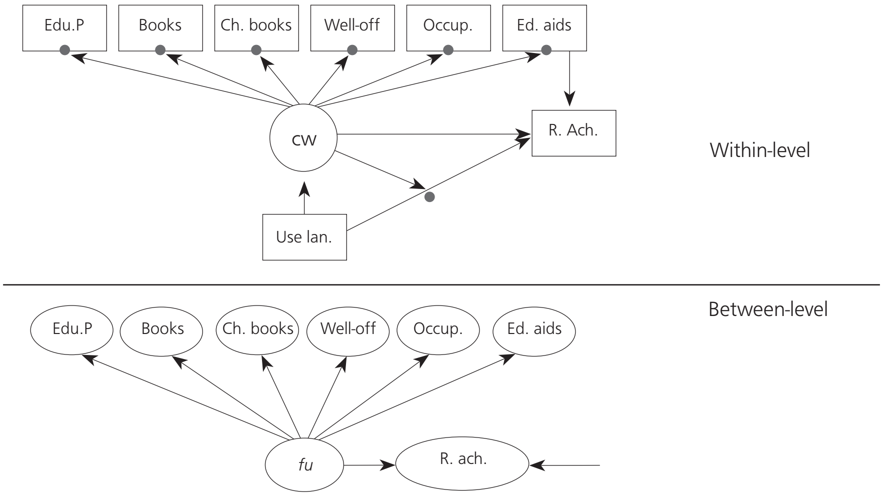
Table 5: Model evaluation for two-level LCA measurement models and two-level LCA models with a covariate and an outcome variable

	Model 1: Single-level four-class LCA	Model 2: Two-level LCA with cw4 & *fu*	Model 3: Two-level LCA with cw3 & *fu*	Model 4: Two-level mixture model with cw3, *fu*, x & y
No. of free parameters	51	57	44	57
Loglikelihood	- 20488	- 20063	- 20171	- 42587
BIC	41405	40604	40712	85650
Entropy	0.67	0.57	0.58	0.60
Lo-Mendell-Rubin test (LRT)	282.658	214.684	460.435	485.32
p-value for LRT	0.01	0.10	0.00	0.01
Test for H_0	3 vs. 4 classes	3 vs. 4 classes	2 vs. 3 classes	2 vs. 3 classes

Notes:
Model 1: Single-level LCA model with four latent SES classes;
Model 2: Two-level LCA with cw4 & *fu* = a two-level latent class model with four latent classes at individual level and a continuous factor *fu* at school level;
Model 3: Two-level LCA with cw3 & *fu* = a two-level latent class model with three latent classes at individual level and a continuous factor *fu* at school level;
Model 4: Two-level LCA with cw3, *fu*, x & y = a two-level mixture model with three latent classes at individual level and a continuous factor *fu* at school level.
An individual-level covariate x (use of the test language at home) and an outcome variable y (reading achievement) were also included in Model 4.

However, the non-significant *p*-value for LRT suggests that a three-class solution is satisfactory for classifying individuals, but only after the between-school differences in the collective SES of student intakes have been taken into account. A more parsimonious model was thus estimated, with a three-class latent SES variable at the individual level and the same between-school structure as in the previous model (Model 3). In the next step, Model 3 was extended to include an individual-level covariate "use of test language at home" (ASBGLNG1) and reading outcome (ASRREA01, Model 4). Figure 1 depicts the structure of the final two-level mixture model (see Appendix 2 for the Mplus model input).

Figure 1: Path diagram of the two-level mixture model with covariate and reading outcome (Model 4)



Notes:

Edu. P = Parental highest educational level (ASBHHEDUP); Books = number of books at home (ASBHBOOK); Ch. books = number of children's books at home (ASBHCHBK); Well-off = family affluence status, being well-off (ASBHWELL); Occup. = parental highest occupation (ASBHHOCP); Ed. aids = educational aids at home (EDUAIDS); R. Ach. = reading achievement; Use lan. = use of test language at home.

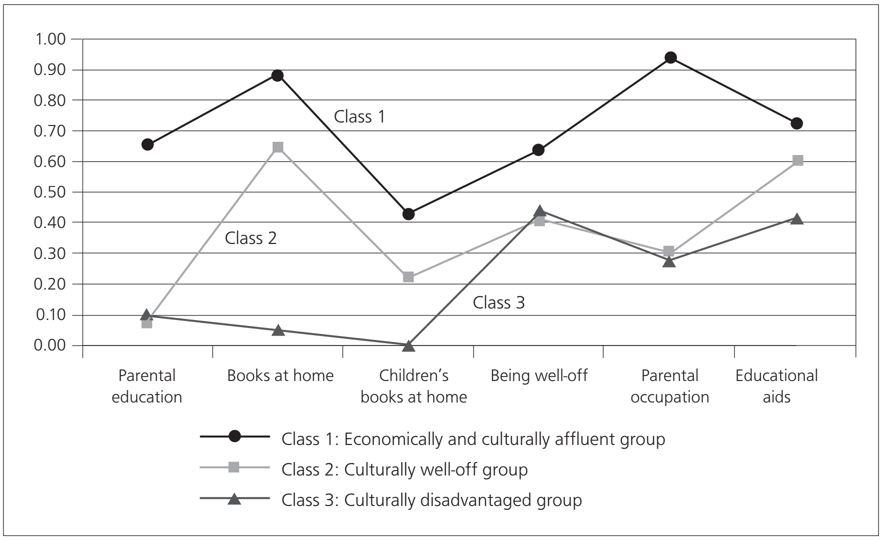
The filled dots under the SES indicators represent the randomness of aggregated mean across schools. *Fu* is a continuous latent variable reflecting the collective SES.

The continuous latent variable *fu* may be understood as the SES composite of all school intakes that captured the SES indicator-specific mean differences across schools and was assumed to affect average school reading achievement. In the within part of the model, the filled dots attached below the individual-level SES indicators represent the random means of the six indicators at the second-level unit, that is, the school. They were regarded as unobserved variables and are shown in circles in the school-level model. The within-level part of the model was relaxed, thus allowing for differences in ASBGLNG1 and reading achievement across latent classes, as well as the between-class differences in the impact of ASBGLNG1 on reading achievement ASRREA01. The latter was shown by the path from the latent class variable cw to the path between ASBGLAN1 to ASRREA01.

Latent Class Profiles Estimated from the Two-Level Latent Class Model

Three latent SES classes were chosen when comparing the fit of the different sequentially estimated two-level latent class models. The nature of these latent classes was determined by the posterior probabilities estimated for each of the SES indicators. Figure 2 depicts the latent class profiles based on item probabilities of students belonging to one of the latent SES classes when choosing the highest category in their response to the SES indicators.

Figure 2: Graphical description of the latent classes according to the profiles estimated in the two-level LCA model



Notes:

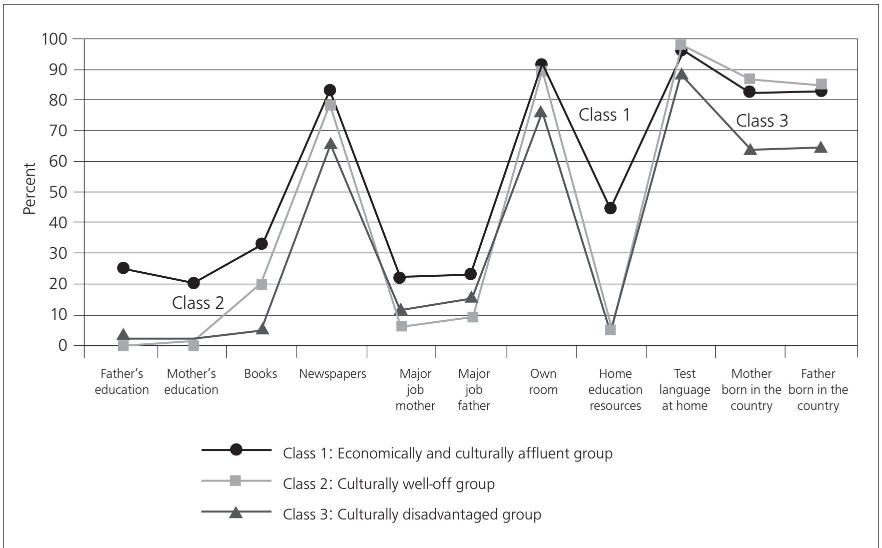
The y-axis represents the estimated mean probability of the third category (the highest category) in each given SES latent class indicator presented on the x-axis. The total number of individuals in each of the latent classes is as follows: Class 1: economically and culturally affluent group = 2,150 (49%); Class 2: culturally well-off group = 1,247 (28%); and Class 3: culturally disadvantaged group = 980 (22%).

It is evident in Figure 2 that the posterior probabilities of Class 1 were high in all SES indicators, meaning that the probability of being included in Class 1 was very high for those students whose parents graduated from university or gained a post-graduate qualification, had more than 100 books and children's books at home, were well-off and held a professional job, and could provide their children with basic educational resources. This latent class can thus be called the "economically and culturally affluent group." About half of the individuals in the sample belonged to this group (2,150 students).

Class 2 and Class 3 showed a fairly similar pattern with regard to the economic capital indicators and parental education level. However, Class 2 had relatively high probabilities for the books and educational aids at home variables. Class 3 had the lowest probabilities for almost all the SES indicators, especially with respect to the book and educational aids variables. Students in this class were therefore identified as the "culturally disadvantaged group" and students in Class 2 as the "culturally well-off group." There were 980 individuals in Class 2 (22% of the total student sample) and 1,247 (28% of the student sample) in Class 3.

So that the characteristics of the latent SES classes could be better understood, the proportions of individuals who chose the highest category in their response to a set of auxiliary variables (see Table 2) were plotted for each latent SES class. The outcome is shown in Figure 3.

Figure 3: Graphical description of students' characteristics in each of the latent SES classes by a set of background variables pertaining to their parents



Notes:

The y-axis represents the percentage of individuals who responded with the highest category in each given background variable presented on the x-axis. (For variable information, see Table 2.) The three latent classes referred to in this figure were estimated by the two-level LCA measurement model.

As shown in Figure 3, students in the economically and culturally affluent group (Class 1) were likely to be the ones who chose the highest category of the auxiliary variables. The proportion of such students is the highest among the three SES latent classes. The proportion of students in the culturally disadvantaged group (Class 3) is relatively low. However, of the students in Class 3, the percentages of individuals whose parents were born in the country and who spoke the test language at home were much lower than the corresponding percentages for the other two classes. This pattern suggests that the culturally disadvantaged group contained a large number of students with an immigrant background.

The pattern most distinguishing the culturally well-off group from the culturally disadvantaged group was the larger number of books that the former group had at home and the greater likelihood that these students had of being from a non-immigrant background. The low proportion of students in Class 2 (culturally well-off) with one or both parents having finished university and/or having a professional job may have reflected a large number of parents who began university at a relatively late age and who read a lot, both for themselves and to their children. Also, these parents may have still been in full-time study and/or engaged in only temporary or part-time employment. Being culturally well-off in Class 2 was relative to the SES pattern in Class 3. When compared to Class 1, however, the cultural capital, in terms of parental educational level and home educational resources, was much lower in Class 2.

The Wald chi-square test of conditional mean equality of the auxiliary variables across the latent SES classes confirmed the latent class profiles of the auxiliary variables in Figure 3. (For detailed Wald chi-square test results, see Appendix 4.) Reading achievement differed significantly among the three latent classes, with the economically and culturally affluent group achieving the highest average score on the reading test (565), the culturally disadvantaged group the lowest (528), and the culturally well-off group scoring at an intermediate level (544). Differences in conditional means between Class 2 and Class 3 in variables such as "mother's educational level," "father's educational level," and "mother's major job" were not significant, implying that these background variables were not strong latent class predictors, that is, able to distinguish Class 2 from Class 3. The same was true with respect to Class 1 and Class 2 for the variables denoting "use of the test language at home," "mother being born in the country," and "father being born in the country."

Typically, the greater the differences between these conditional means were across the different SES classes, the more likely it was that the predictors related to the latent SES classes (Muthén & Muthén, 2010). The SES indicators "parental highest educational level" and "parental highest occupation" in the current two-level latent class models were derived variables from mother's educational level and father's educational level, and from mother's and father's major job. Non-significant mean differences may increase the level of measurement error (i.e., misclassification in LCA) and therefore affect the quality of categorization of individuals—a possibility that may explain the low entropy level in the two-level latent class analysis, namely, 0.58 (see Table 5).

It should be noted that an auxiliary variable was not involved in the determination of the latent classes, but rather was used as a further description of the latent classes. The plot and Wald chi-square test, however, showed that reading achievement and ethnic background were two potential predictors of latent SES classes. Including these predictors may improve the precision of classification of individuals, thus improving the reliability in the estimates of SES effects on reading achievement at both individual and school levels. Therefore, a final two-level mixture model was developed by adding "use of test language at home" (ASBGLNG1) and reading achievement (ASRREA01) in the two-level latent class model (see Figure 1 and Appendix 3 for the model structure and Mplus input of the final model).

Results from the Two-level Mixture Model with a Covariate and Reading Outcome

In the final two-level mixture model, the latent class variable cw and reading achievement were regressed on the covariate ASBGLANG1 at the individual level in order to examine latent class differences in reading achievement, with ethnic background differences being controlled for. In order to take into account the between-school differences in SES and its effect on reading achievement, the reading achievement variable was regressed on the collective SES factor *fu* at the school level.

After the effects of the SES composite of the school intakes and the ethnic background of students had been accounted for, it was obvious that some of the individuals had moved from one latent SES class to another. This outcome implies that taking into account information on students' achievement levels and ethnic backgrounds further corrected misclassification of students. Compared to the distribution of individuals in the latent classes estimated by the previous two-level latent class model (Model 3), the proportion of individuals in the economically and culturally affluent group reduced from 49% to 43%, leaving 1,809 students in this group. The number of students in the culturally disadvantaged group dropped to 804, leaving only about 19% of the total student sample in this group. The culturally well-off group gained eight per cent of the individuals in the total sample, swelling the number of students in that group to 1,618. The entropy increased to a level of 0.60, indicating a more accurate classification. The move to another SES class for some individuals kept the nature of the SES latent classes intact, however.

Mean reading achievement differed significantly across the latent SES classes. The economically and culturally affluent group (Class 1) achieved the highest mean achievement score, 552, while the culturally disadvantaged group (Class 3) had the lowest, 499. For the culturally well-off group (Class 2), the average achievement in the reading test was at an intermediate level, 512. It is worth noting that the higher number of books and educational aids at home in Class 2 may function as compensation for the otherwise disadvantaged home background, therefore increasing the ability of students in this group to achieve a higher level of reading ability—13 points higher than the group of students with a similar level of SES but many fewer books (Class 3). It should also be emphasized that the three latent SES classes estimated in this final model became more distinguishable in terms of the between-class differences in reading achievement, especially the differences between Class 1 and the other two latent classes, a finding that again provides evidence of better classification.

Table 6 presents the between-class differences for the individual-level covariate variable "use of test language at home" (ASBGLNG1) and for the effects of ASBGLAN1 on reading achievement. The language used at home variable indicates students' ethnic background and so has a different impact on the latent class variable cw, that is, a different odds ratio for belonging to a different latent SES group. When the culturally well-off group (Class 2) was set as the reference group, the chance of a student from a non-immigrant background belonging to the culturally disadvantaged group was slightly more than one tenth of the likelihood of that same student being in Class 2. The chance of a student from a nonimmigrant background belonging to the economically and culturally affluent group was about three fifths of the chance of him or her being in Class 2. After the between-group differences in ethnic background had been controlled for, the only significant impact of language used at home on reading achievement was found for the culturally disadvantaged group, with a correlation coefficient of 0.13.

Table 6: Latent class differences in the individual-level covariate ASBGLNG1 and the effect of the covariate on reading achievement in the two-level mixture model

	Relation	Odds ratio
Class 1: Economically and culturally affluent	cw#1 ON ASBGLNG1	0.64
Class 2: Culturally well-off	Reference group	1.0
Class 3: Culturally disadvantaged	cw#3 ON ASBGLNG1	0.12
	Relation	Regression coefficient
Class 1: Economically and culturally affluent	ASRREA01 ON ASBGLNG1	0.07 (ns)
Class 2: Culturally well-off	ASRREA01 ON ASBGLNG1	0.07 (ns)
Class 3: Culturally disadvantaged	ASRREA01 ON ASBGLNG1	0.13

Note: ns = not statistically significant. cw#1 and cw#3 are thresholds for Latent Class 1 and Latent Class 3, respectively. Latent Class 2 is the reference group.

At the individual level, about 16% of the reading achievement differences between individuals could be attributed to the different SES profiles across the latent classes, according to the effect size measure eta-square. The collective SES factor *fu* at the school level that captured the differences in the SES composite of school intakes, and which mirrored the degree of segregation in Swedish compulsory schools, had a considerable impact on school achievement. The estimated regression coefficient was 0.70, which implied that almost half of the between-school reading achievement differences could be explained by the differences in collective SES across different schools. This result reflects, to a large extent, the selection mechanism and segregation in Swedish compulsory schools (Skolverket, 1996, 2012; Yang Hansen, Rosén, & Gustafsson, 2011).

DISCUSSION AND CONCLUSIONS

The current study explored the latent profiles of individuals according to their socioeconomic background and examined reading achievement differences among these latent profiles by applying two-level latent class modeling techniques. Unlike the previous view of SES as simply being an observed index, the current measurement approach allows the formation of distinct and homogenous categories or typologies of individuals by conceptualizing SES as unobserved classes conditional upon its indicators. One advantage of two-level latent class modeling is that it can achieve a SES index variable by estimating latent groups through a set of SES indicators. It can also take into account the measurement error in SES indicators, the hierarchical data structure, and the variation of the SES indicators across collective-level units (schools in the case of this study). Accordingly, it can eliminate the misclassification of individuals in different observed categories of SES indicators and thus assure the precision of the estimated class membership of individuals. The categorical latent class variable of SES can be saved and used as an ordinary variable in further analysis, such as that pertaining to the impact of SES differences on academic achievement, attitude, and motivation. It can also be used to test the interaction between SES and other personal traits, such as gender.

Another advantage is that two-level mixture modeling can simultaneously examine SES effects on reading achievement at individual and collective levels. The way in which students were classified into model-based latent classes makes it possible to further explore and improve understanding of the effects of educational inequality and school segregation.

Three latent classes of individuals with different SES profiles were found in the present study, namely, the economically and culturally affluent class, the culturally well-off class, and the culturally disadvantaged class. Reading achievement differed significantly among the three latent SES classes, with the economically and culturally affluent group achieving the highest and the culturally disadvantaged group the lowest scores. It was evident that these latent groups could potentially be ordered in terms of the item probabilities decreasing from Class 1 to Class 2 to Class 3.

Student's ethnicity, indicated by whether or not students spoke the test language at home, was significantly related to reading achievement only for the culturally disadvantaged immigrant-concentrated class (Class 3). This finding implies that immigrant background does not affect the reading achievement of students in Classes 1 and 2 because the language ability of these students is boosted by their peers and surrounding environments, such as family, neighborhood, and school. For students in the disadvantaged group, however, such support may not have been available to the same extent as it was for students in Class 1 and Class 2. This finding raises concerns about the increasing segregation along socioeconomic lines and immigrant background in Sweden's schools and society (Skolverket, 2009, 2012). The concern rests on the premise that students in the disadvantaged group are not being exposed to an integrated learning environment where deleterious aspects of their home background may be compensated for by other cultural and educational resources.

At the individual level, about 16% of the reading achievement differences could be attributed to membership of the different latent SES classes, while the relationship between collective SES and reading achievement at school level reached 0.70. These estimates not only agree closely with the findings of meta-analyses of SES effects on academic achievement conducted by such researchers as Sirin (2003, 2005) and White (1982, 2005) but also confirm the results from previous SES effect studies (conducted by the likes of Yang Hansen et al., 2011).

Previous studies measuring SES and its effects on reading achievement, using data from IEA's Reading Literacy Study (Elley, 1994), identified two dimensions in SES at the level of the individual—a cultural capital dimension and an economic capital dimension at (Gustafsson, 1998; Yang & Gustafsson, 2004). In Sweden, the studies just cited found no significant relationship between economic capital and reading achievement. However, the cultural capital factor had a strong positive impact on reading achievement.

The three latent SES classes identified in the current study indeed reflect the two underlying dimensions and their relationship with reading achievement. The composition of the latent SES groups highly mirrors the level of cultural capital and its importance to reading achievement. Muthén (2001) observed that data that have a good fit with a *k*-class model often have a good fit with a *k*-1 dimensional factor analysis model, in terms of the LCA's ordering of the latent classes. An observation of the same relationship was also found in a latent profile analysis conducted by Bartholomew (1987). The empirical evidence from the current study provides yet another proof of this relationship.

One may argue that factor scores achieved by multilevel factor analysis can be used to divide individuals into groups of different SES levels. Moreover, compared to the two-level mixture model used in the current study, multilevel factor analysis has relatively less computation load and is much easier to converge. However, because a factor score does not have a natural cut point for SES groups, the division of SES groups seems to be more arbitrary. As Muthén concluded, latent class analysis is a better means than factor analysis of finding clusters of individuals (see, for example, Muthén, 2001).

The current analysis clearly shows that ignoring the cluster effect of data structure and multiple-level variation will bias the classification of individuals, whereas bringing in covariates and distal outcome variables to the two-level mixture model can further improve the quality of latent class estimation. However, including too many SES indicators in the model may cause a heavy computation and latent class patterns that are difficult to interpret. Selecting optimal SES indicators is therefore important, and this can be done with the help of a Wald chi-square test of mean equality. Results from a Wald test of a set of auxiliary variables in this study showed that ethnic background and reading achievement were two important sources of variation among the latent SES classes that were controlled for in the later stage of the two-level mixture model. The outcome was an improvement in the quality of the classification of individuals.

Unfortunately, the indicators of ethnic background in PIRLS 2006 were limited. "Use of test language at home," "father born in the country," and "mother born in the country" were the only available alternatives. As shown in the Wald test, however, these variables did not distinguish between the students in SES Class 1 and those in SES Class 2. This finding could be one of the reasons why the entropy level in the current study, although being improved, stayed at a relatively low level.

In order to gain a better understanding of this problem, and to gain confirmation about the feasibility and accuracy of the method of classifying students into unobserved SES groups, multiple countries with either similar (e.g., other Nordic countries) and/or rather different circumstances (e.g., England, Germany, and the United States) and societal and school characteristics need to be brought into the analysis.

Finally, a sensitivity study may be needed to test the stability of the results. In the current study, SES indicators were recoded into ordinal variables with three categories. It might be argued that the cut point of the recoding can affect the latent class estimation. Testing of the impact of recoding has been carried out during our analysis, using dummy variables of the SES indicators. The results were consistent with the findings presented in this paper. Further testing in which the SES indicators were treated as continuous variables in a latent profile analysis, in order to avoid the self-inflicted problem of having only a few categories in each variable, would also be useful.

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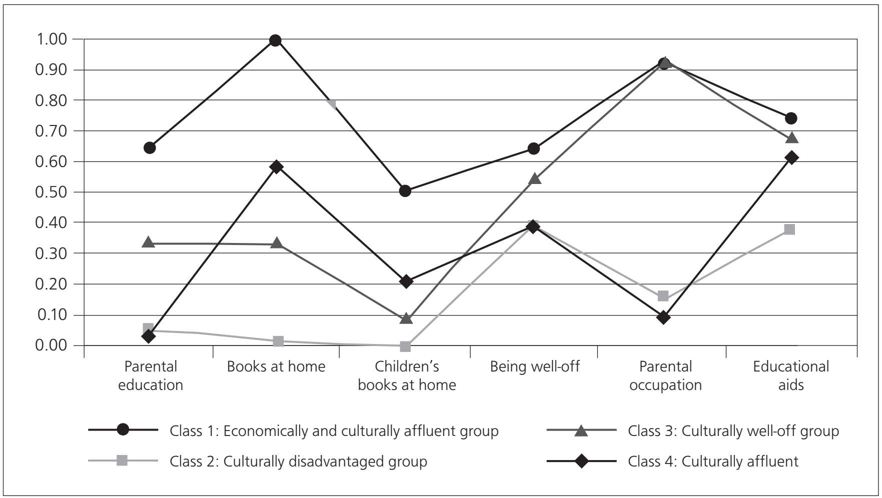
Appendix 1: Average latent class probabilities for most likely latent class membership (row) by latent class (column)

Four-class solution						
Subgroup of individuals belonging to:	Class 1	Class 2	Class 3	Class 4	Class size	
Class 1	.859	.011	.086	.044	755	
Class 2	.106	.827	.061	.006	1,700	
Class 3	.049	.073	.807	.072	1,314	
Class 4	.045	.012	.125	.818	609	
Five-class solution						
Subgroup of individuals belonging to:	Class 1	Class 2	Class 3	Class 4	Class 5	Class size
Class 1	.773	.127	.027	.065	.007	1,522
Class 2	.010	.856	.097	.016	.021	813
Class 3	.000	.061	.842	.033	.064	877
Class 4	.045	.042	.098	.812	.003	828
Class 5	.017	.031	.162	.025	.766	339

The table shows a matrix of the average probabilities of the most likely latent class membership in each latent class, as well as the latent class size based on estimated posterior probabilities for both the four- and five-class solutions. For the subset of students with the most likely class membership of 1, for example, the posterior probabilities for each class are averaged, and presented in row 1 of Table 4. The average posterior probabilities should be high on-diagonal of the matrix, and the probabilities off-diagonal should be as low as possible, indicating precision of the latent class membership estimation. For the four-class solution, the average posterior probabilities on-diagonal are over .80, and the sizes of each latent class are rather large, being over 10% of the sample size. For the five-class solution, the average on-diagonal posterior probabilities are lower than .80 for Class 1 and Class 5. The size of Class 5 is relatively small, being about seven per cent of the total sample (4,393 individuals).

Appendix 2: Graphical depiction of the latent classes according to the profiles estimated in the single-level LCA model



Notes:

This is a graphic depiction of the conditional probabilities presented in Table 4. The y-axis represents the conditional probability level, and the x-axis represents the SES indicators. The first three variables on the x-axis are cultural capital indicators; the last three are economic capital indicators. The total number of individuals in each of the latent classes is as follows: economically and culturally affluent group = 1,700 (38.9%); culturally disadvantaged group = 609 (13.9%); economically well-off group = 755 (17.2%); culturally affluent group = 1,314 (30%).

Appendix 3: Mplus input of the final two-level mixture model with covariates and outcome variable

```
USEVARIABLES ARE u1-u6 y x;
       CATEGORICAL ARE u1-u6;
       MISSING ARE u1-u6 x(99);
       CLUSTER=IDSCHOOL;
       WEIGHT=HOUWGT;
           CLASSES = cw(3);
           WITHIN = x;
   ANALYSIS:   TYPE = TWOLEVEL MIXTURE;
           PROCESSORS = 4(STARTS);
           STARTS = 100 10;
           STITERATIONS = 20;
   MODEL:
           %WITHIN%
           %OVERALL%
          cw ON x (cw_x);
          cw#1 ON x;
          cw#2 ON x;
          y ON x;
          %cw#2%
          y
          y ON x;
          %cw#3%
          y ON x;
          y;
           %BETWEEN%
           %OVERALL%
           fu BY u3@1;
           fu BY u1;
           fu BY u2;
           fu BY u4;
           fu BY u5;
           fu BY u6;
           [fu@0];
           fu*0.043 (8);
           y ON fu;
    %cw#1%
    [u1$1 u1$2 u2$1 u2$2 u3$1 u3$2 u4$1 u4$2 u5$1 u5$2 u6$1 u6$2];
    %cw#2%
    [u1$1 u1$2 u2$1 u2$2 u3$1 u3$2 u4$1 u4$2 u5$1 u5$2 u6$1 u6$2 ];
    %cw#3%
    [u1$1 u1$2 u2$1 u2$2 u3$1 u3$2 u4$1 u4$2 u5$1 u5$2 u6$1 u6$2];

    OUTPUT: STANDARDIZED;
         TECH1 TECH11;
    SAVEDATA:
           FILE IS Model 4_cw3_fu_xy.dat;
                     SAVE = CPROBABILITIES;
```

Note:

Note: Variables u1 to u6 are the SES indicators ASBHWELL, ASBHHEDUP, ASBHBOOK, ASBHCHBK, ASBHHOCP, and EDUAIDS. "x" is the covariate at student level—"use of test language at home" (ASBGLNG1). The covariate at school-level "w" is "school intake characteristics" (INTAKECH). Outcome variable "y" is the standardized reading achievement ASRREA01

Appendix 4: Comparison of mean equality across latent SES classes by Wald chi-square test

Classes	Conditional mean									
	ASBHLEDF	ASBHLEDM	ASBGBOOK	ASBGTA4	ASBHMJF	ASBHMJM	ASBGTA5	ASBGLNG1	ASBGBRNF	ASBGBRNM
Class 1	4.9	5.3	3.8	0.83	8.1	8.8	0.91	0.96	0.83	0.83
Class 2	3.4	3.7	3.4	0.77	5.8	5.5	0.88	0.96	0.83	0.84
Class 3	3.4	3.6	2.8	0.70	6.2	5.8	0.80	0.90	0.66	0.66
Classes	*p*-values for Wald test of mean equality									
Overall	*	*	*	*	*	*	*	*	*	*
1 vs. 2	*	*	*	*	*	*	*	ns	ns	ns
1 vs. 3	*	*	*	*	*	*	*	*	*	*
2 vs. 3	ns	ns	*	*	*	ns	*	*	*	*

Classes	Conditional mean
	ASREA01
Class 1	565
Class 2	544
Class 3	528
Classes	*p*-values for Wald test of mean equality
	ASREA01
Overall	*
1 vs. 2	*
1 vs. 3	*
2 vs. 3	*

Note:

For more information on the auxiliary variables, see Table 2. Most of these variables have more than five ordinal categories or are dummy variables. They are taken as continuous variables in the Wald test of mean equality.

ns = not significant; * p-value < 0.05.

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