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The socio-spatial dimension of educational inequality: A comparative European analysis

Kaspar Burger

University of Minnesota, University College London

Abstract

Given recent evidence of rising levels of social segregation in European countries, this study uses standardized data from the Program for International Student Assessment (*n* = 171,159; 50.5% male) to examine the extent to which education systems in Europe are socially segregated and whether social segregation in the school system affects achievement gaps between students of different social origin. Results suggest that the degree of social segregation within education systems varied substantially across countries. Furthermore, multilevel regression models indicate that the effect of socioeconomic status on student achievement was moderately but significantly stronger in more segregated education systems, even after controlling for alternative system-level determinants of social inequality in student achievement. These findings provide original evidence that social segregation in education systems may contribute to the intergenerational transmission of educational (dis)advantage and thus serve to exacerbate wider problems of socioeconomic inequality in Europe.

Keywords

Cross-national comparison; Social segregation; Standardized assessment; European education systems; Multilevel

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Correspondence should be addressed to Kaspar Burger, 1014 Social Sciences Building, Department of Sociology, 267 19th Avenue South, University of Minnesota, Minneapolis, MN 55455, USA, E-mail: burgerk@umn.edu

The Socio-Spatial Dimension of Educational Inequality: A Comparative European Analysis

1. Introduction

In recent years, the level of social segregation in European countries has increased (Marcinczak, Musterd, van Ham, & Tammaru, 2016). It is therefore crucial to examine whether, and to what extent, education systems in Europe are also segregated along social lines, and whether social segregation between schools shapes individual student achievement and social inequality in educational outcomes.

Social segregation in education systems refers to the uneven distribution across schools of students from different socioeconomic backgrounds (Jenkins, Micklewright, & Schnepf, 2008). Where students are highly segregated by socioeconomic origin between schools, resources that contribute to students' educational success—such as social, economic, and cultural capital—are more unequally distributed (Owens, 2018; Reardon & Owens, 2014). An unequal distribution of such resources among student populations typically leads to disparities in educational opportunities, because schools draw on these resources informally in educating their students (Chiu, 2015; Croxford & Paterson, 2006). For instance, schools serving socioeconomically advantaged students receive more support from parents (Lee & Burkam, 2002). Their students come from families who tend to have higher educational expectations for their children (Davis-Kean, 2005; Neuenschwander, Vida, Garrett, & Eccles, 2007); and these families often have more knowledge of the education system (e.g., about its written and unwritten rules, what and how students should learn, or what educational decisions to take; Crosnoe & Muller, 2014; Jackson, Erikson, Goldthorpe, & Yaish, 2007). Moreover, schools that serve advantaged students benefit from the fact that their students typically attach great value to education and use similar forms of communication and interactions in school and in their family environment (Lareau & Weininger, 2003). As a result, their student populations constitute functional communities particularly conducive to learning (Lee & Bowen, 2006). Children learn from each other, and peer achievement affects achievement growth (Hanushek, Kain, Markman, & Rivkin, 2003; Lavy, Paserman, & Schlosser, 2012). Consequently, an uneven distribution of students of diverse social origins within an education system may affect not only student achievement but also social disparities in achievement.

So far, research on the relationship between social segregation within education systems and social class gradients in student achievement across European countries is scarce. This is despite researchers and policymakers increasingly acknowledging the need to address common challenges, such as ensuring social cohesion and fairness in education, at a European level (e.g., Pépin, 2011).

In light of the above, this study pursues two main objectives. First, it assesses the links between social segregation and socioeconomic gradients in student achievement within European education systems. Second, it examines whether social segregation in these education systems moderates the micro-level associations between socioeconomic status and educational achievement, when controlling for further country- as well as school-, and individual-level variables. The study thereby extends cross-national comparative research on the mechanisms underlying "socioeconomic inequality in educational achievement," which (for brevity) we also refer to simply as "educational inequality."

2. Prior research on social segregation and educational inequality

2.1. System-level links between social segregation and educational inequality

Prior research indicated a positive correlation between social segregation within education systems and socioeconomic disparities in student achievement (Felouzis & Charmillot, 2013). However, this research compared education systems at subnational levels in Switzerland. To date, there is no research analyzing specifically whether, across Europe, more socially segregated education systems are those in which student achievement is more closely linked to socioeconomic status.

2.2. Effects of social segregation on educational inequality

Some studies sought to examine whether social segregation in education systems affects educational inequality. McPherson and Willms (1987) found that moving from a selective to a comprehensive secondary school system in Scotland minimized social class segregation between schools and improved the educational achievement, in particular, of poor children. A more recent study suggests that educational inequality was more pronounced in OECD countries whose education systems exhibited higher levels of social segregation (Holtmann, 2016). However, this study did not control for any other country-level determinants of educational inequality, thus making it difficult to conclude that segregation was the actual driver of this inequality. Furthermore, evidence from the United States indicates that income segregation between school districts exacerbated achievement gaps between privileged and underprivileged students (Owens, 2018; Reardon, 2011). However, it remains unclear whether social segregation also increases socioeconomic inequality in educational outcomes in European countries where the levels of social segregation are estimated to be substantially lower (Marcinczak et al., 2016; see also Sortkær, 2018).

More generally, there is relatively little cross-national comparative research on the consequences of system-level segregation on educational inequalities. Prior research on socio-spatial inequalities in education typically focused on school social composition effects (Borman & Dowling, 2010; Dumay & Dupriez, 2008; Fekjær, & Birkelund, 2007; Opdenakker & van Damme, 2007; Palardy, 2013; Rumberger & Palardy, 2005), rather than system-level segregation effects. In fact, in a review of research, Reardon and Owens (2014) concluded that "much of the research purporting to assess the links between segregation and student outcomes instead measures the association between school composition and student outcomes" (p. 200). Research on school composition effects tests the impact of segregation in only a limited sense, under the assumption that segregation affects educational achievement and/or inequality predominantly through school composition mechanisms, rather than through other mechanisms such as the uneven distribution of resources and the corresponding disparities in learning opportunities on a broader system level. Moreover, research on school composition effects does not allow for analyzing system-wide segregation effects. Within a country, a given set of schools may exhibit low levels of social segregation, although the degree of segregation at the overall system level might be substantial. Cross-national comparative research allows for distinguishing between school composition and system-wide segregation effects and thus may provide a more comprehensive picture of the consequences of socio-spatial clustering of students. In addition, cross-national research provides the opportunity to examine systematic patterns of covariation between social segregation and educational inequality across countries by taking into account potential system-level confounders. Prior research focusing on school composition effects was conducted in diverse countries that differed not only in the overall level of social segregation within the system, but also in other macro-level variables (e.g., Belfi et al., 2014; Driessen, 2002; Lauen & Gaddis, 2013; Strand, 2010; Televantou et al., 2015; Van Ewijk & Sleegers, 2010). In this research, effects of the socio-spatial clustering of students may have been confounded with those of further, unmeasured, country-specific influences. Specifically, this prior research may have overlooked alternative country-level explanations of educational inequality, such as the overall level of national inequality (Chmielewski & Reardon, 2016), the economic development of a country (Yaish & Andersen, 2012), or the comprehensiveness of the education system (Burger, 2016a).[1] Given that standardized cross-national data on student achievement are now available, it is now possible to analyze effects of social segregation within comparative designs that also consider further potential country-level determinants of educational inequality. We develop such a design here.

3. Contribution to the literature

This study extends knowledge of social segregation and inequality in European countries (Benito et al., 2014; Bernelius, & Vaattovaara, 2016; Böhlmark, Holmlund, & Lindahl, 2016; Musterd, Marcińczak, van Ham, & Tammaru, 2017; Yang Hansen, & Gustafsson, 2016, in press; Yang Hansen, Rosén, & Gustafsson, 2011). First, it uses cross-national standardized data to analyze the link between social segregation within education systems and socioeconomic gradients in student achievement across European countries. Second, because socioeconomic gradients in achievement could be a consequence of further system-level influences (rather than the result of segregation within the education system), the study investigates whether segregation moderates these gradients when alternative system-level influences are considered. Our strategy is to examine major system-level influences comprehensively while keeping the models parsimonious. Thus, we concentrate on five economic and education policy dimensions that have been identified as major system-level determinants of educational inequality in prior research: (1) economic development, (2) population-level socioeconomic inequality, (3) annual schooling time, (4) preschool enrollment rate, and (5) public expenditure on education.

Economic development and *socioeconomic inequality* have long been recognized as potential drivers of educational inequality (Heyneman & Loxley, 1983; Jerrim & Macmillan, 2015). Specifically, research has shown that the level of *economic development* correlates negatively with educational inequality because more economically developed societies tend to be more open societies in which the importance of ascriptive ("non-merit") factors such as social origin for individual educational attainment gradually decreases (Ferreira & Gignoux, 2014; Gustafsson, Nilsen, & Yang Hansen, 2018; Marks, 2009; van Doorn, Pop, & Wolbers, 2011). Moreover, evidence suggests that *socioeconomic inequality* is related positively to educational inequality (Campbell, Haveman, Sandefur, & Wolfe, 2005; Chmielewski &

[1] A few studies used cross-national comparative designs, but they did not specifically consider country-specific determinants of educational achievement and inequality (Alegre & Ferrer, 2010; Benito, Alegre, & Gonzàlez-Balletbò, 2014; Yang Hansen, Gustafsson, & Rosén, 2014).

Reardon, 2016; Kearney & Levine, 2014). One explanation for this is that schools may reproduce or even exacerbate the inequalities that children bring with them (Downey & Condron, 2016).

In addition, the comprehensiveness of education systems—in terms of the *annual schooling time*, *preschool enrollment rate*, and *public expenditure on education*—may affect educational inequality (Burger, 2016a; Pfeffer, 2008; Schütz, Ursprung, & Wössmann, 2008; Stadelmann-Steffen, 2012). A longer *annual schooling time* can reduce educational inequality because children from all social classes share similar learning environments at school, benefit from similar learning opportunities, and thus make similar learning progress (Ammermüller, 2005; Schlicht, Stadelmann-Steffen, & Freitag, 2010). *Preschool enrollment* may equalize educational outcomes among children because children of low socioeconomic status, who often lag behind in their academic development, typically make greater developmental progress in preschool programs than their more advantaged peers (Burger, 2010, 2013, 2015, 2016b; Cebolla-Boado, Radl, & Salazar, 2017). Finally, *public expenditure on education* is commonly thought to reduce educational inequality (OECD, 2012; Schütz et al., 2008). Where public expenditure on education is low, a shift in responsibility from the public to the private sector may occur, resulting in diverging educational opportunities among social classes, with more advantaged families being likely to spend more on their children's education (Schlicht et al., 2010; Schmidt, 2004).

To identify the unique contribution of social segregation to educational inequality, the current study distinguishes between social segregation and the above-mentioned economic and education policy dimensions as potential country-specific sources of educational inequality.

Furthermore, it is essential to recognize that social segregation in education systems may be related in part to educational tracking (Felouzis & Charmillot, 2013; Pfeffer, 2015), or allocation of students to different types of schools or curricula that are vertically structured by student performance and typically prepare students either for further academic or for vocational programs. This is because a student's likelihood of transitioning to a given track is to some extent associated with family background characteristics (Brunello & Checchi, 2007; Lucas, 2001). However, associations between tracking and social segregation differ considerably across education systems (Alegre & Ferrer, 2010; Chmielewski, 2014; Maaz, Trautwein, Lüdtke, & Baumert, 2008). Moreover, the degree to which education systems are socially segregated varies significantly, even among those systems that use comparable tracking regimes (see Appendix A). For instance, several education systems display comparatively high levels of social segregation, although they use little or no tracking, which is in part explained by the fact that social segregation is often a result of choices made, whether consciously or unconsciously, by families who tend to live in socially homogeneous school catchment areas, or may decide to enroll their children in particular high-performing or private schools (Lockheed, Prokic-Bruer, & Shadrova, 2015; Saporito & Sohoni, 2007). In addition, research also suggests that de-tracking schools may lead to an increase in residential segregation (De Fraja & Martinez Mora, 2012). Consequently, school tracking might actually have a de-segregating effect, or at least prevent further increases in segregation. In a similar vein, a study from Japan found that de-tracking reforms can yield unintended consequences, as they may drive better-performing students out of public schools, and thus exacerbate the divide between students from different socioeconomic backgrounds (Kariya & Rosenbaum, 1999). In conclusion, these findings suggest that social segregation within education systems can affect educational inequality independent of tracking (Esser & Relikowski, 2015; Waldinger, 2006). Nevertheless, the educational track that a student attends should be considered in any study designed to assess social disparities in educational outcomes. Thus, we consider whether a student attended a general *academic program* (designed to give access to further academic studies at the next educational level), or a *pre-vocational or vocational program* (designed to give access to vocational studies or the labor market).

To conceptualize segregation effects, we draw on the distinction between “Type A” and “Type B” effects (cf., Raudenbush & Willms, 1995). Type A effects refer to the effects that school systems have on individual student achievement through both mechanisms they control (e.g., educational resources) and mechanisms they do not control (contextual effects such as peer influences). By contrast, Type B effects refer to the controllable effects alone (Castellano, Rabe-Hesketh, & Skrondal, 2014). We study Type A effects of school system segregation, which represent both controllable and uncontrollable influences on student achievement. This allows us to assess the net effect of segregation, which corresponds to the sum of positive and negative effects of segregation, adjusted for observable potential confounders.

It is clear that non-experimental research examining segregation effects typically cannot exclude selection bias. Social segregation in education systems may generate disparities in student achievement. However, achievement disparities may as well reflect preexisting differences between students (i.e., differences *not* related to the exposure to socially segregated schools). For instance, family characteristics such as social and economic resources contribute to residential and school district choice *and* to children’s educational achievement, which complicates the estimation of genuine segregation effects. Previous research from the United States used measures of local government fragmentation prior to the observation period as instruments for segregation, indicating that segregation does have a causal effect on inequalities in educational attainment (Quillian, 2014). However, identifying robust instruments is difficult (Owens, 2018). Here we use a comparative approach and standardized international student assessment data to study whether social segregation within education systems moderates micro-level associations between socioeconomic status and educational achievement under *ceteris paribus* conditions—when observable country-, school-, and individual-level determinants of student achievement are taken into account. We argue that social segregation within education systems contributes to social disparities in educational achievement by increasing inequalities between disadvantaged and advantaged schools. Schools draw on social, economic, and cultural resources of families informally, and we expect that an unequal distribution of such resources will intensify disparities in learning environments and educational opportunities, ultimately exacerbating social inequality in student achievement. In view of the challenges that potential selection effects present, the results of our study provide empirical evidence consistent with, but not definitively demonstrating, a causal association between social segregation in education systems and social inequality in educational achievement.

4. Method

4.1. Data

The data are drawn from the 2012 wave of the Program for International Student Assessment (PISA), a cross-national comparative survey that has analyzed 15 year olds' achievement in mathematics, science, and reading in a three-year cycle since 2000, with a special focus on one of these subjects in each wave, which was here mathematics. PISA uses a stratified sampling procedure and, in the first stage, schools with 15-year-old students are selected with a probability proportional to the size of the school (primary sampling units). In the second stage, students are selected at random within schools. The sample used here comprises 29 European countries with 171,159 students (50.5% male) from 7,301 schools.[2] Table 1 summarizes the

[2] Thirty-one European countries participated in the 2012 PISA wave. Liechtenstein was excluded owing to its small sample size. Italy was excluded because it contained 6.2% of schools in which fewer than 20 students participated in the survey, but analyses including Italy yield virtually identical results and lead to the same conclusions. It should also be noted that schools are not necessarily comparable across all countries. This is exemplified by the fact that, in some countries, schools were defined as administrative units that can consist of several buildings. In others, individual buildings were defined as schools. Of the 29 countries included in our

number of students and schools for each country. The PISA final student weights are applied so that the sample of each country reflects the total population of 15-year-old students within each country (see OECD, 2009b, p. 47ff.). These weights are inversely proportional to the probability of selecting a given student into the PISA sample, which considers the probability of selecting the school within a country as well as the individual student within a school.

Table 1
Number of schools and students in the sample.

Country	*N* schools	*N* students
Austria	191	4,251
Belgium	287	7,452
Bulgaria	187	4,952
Croatia	163	4,846
Czech Republic	297	5,072
Denmark	341	6,546
Estonia	206	4,562
Finland	311	8,447
France	226	4,178
Germany	230	3,632
Great Britain	507	11,524
Greece	188	4,816
Hungary	204	4,633
Iceland	134	3,275
Ireland	183	4,770
Latvia	211	4,071
Lithuania	216	4,278
Luxembourg	42	4,282
Netherlands	179	4,089
Norway	197	4,338
Poland	184	4,372
Portugal	195	4,933
Romania	178	4,983
Serbia	153	4,438
Slovakia	231	4,452
Slovenia	338	5,578
Spain	902	24,037
Sweden	209	4,155
Switzerland	411	10,197
Total	7,301	171,159

sample, 23 used individual schools as the primary sampling unit, whereas six used educational programs or tracks within schools as the primary sampling units (BEL, HRV, HUN, NLD, ROU, SVN).

4.2. Measures

This section describes the variables used in this study. Table 2 displays the descriptive statistics of these variables, pooled across countries; Table 3 displays the descriptive statistics of the individual- and school-level variables for each country separately; Table 4 displays the descriptive statistics of the dependent variable (5 plausible values) for each country.

Table 2
Descriptive statistics.

Predictor variables	Mean	SD	Min.	Max.
Individual level				
Male	0.50	---	0	1
First-generation immigrant	0.05	---	0	1
Language spoken at home: same as test language	0.88	---	0	1
School grade relative to modal grade	-0.07	0.58	-3	2
Pre-vocational or vocational program [(a)]	0.20	---	0	1
Socioeconomic status (SES)	0.02	0.94	-5.95	3.27
School level				
School type: private school [(b)]	0.19	---	0	1
Proportion of first-generation immigrants in school	0.05	0.04	0	1
School socioeconomic composition	-0.17	0.28	-1.11	1.24
Country level				
Gross domestic product (GDP) per capita	104.15	43.00	38.00	264.00
Income inequality: Gini coefficient [(c)]	30.09	3.84	23.50	38.00
Annual taught time in compulsory education	816.13	103.13	555.00	1010.40
Preschool enrollment rate	93.05	6.72	69.53	99.50
Educational expenditure (as % of the GDP)	1.76	0.34	1.00	2.53
Social segregation within the education system	0.24	0.08	0.09	0.46
Dependent variable	**Mean**	**SD**	**Min.**	**Max.**
Student achievement: Plausible value 1	493.26	93.30	95.19	896.80
Student achievement: Plausible value 2	493.22	93.36	43.78	857.85
Student achievement: Plausible value 3	493.31	93.31	83.28	865.56
Student achievement: Plausible value 4	493.18	93.37	102.98	867.20
Student achievement: Plausible value 5	493.32	93.41	88.34	849.36

Note: N = 171,159. Descriptive statistics of binary and un-centered continuous variables. The continuous variables were grand-mean centered for the analyses. [(a)] The reference category is “general academic program”. [(b)] As opposed to public schools, private schools are funded by fees paid by parents (entirely if they are government-independent, partially if they are government-dependent). [(c)] Gini coefficient of equivalized disposable income (higher values of indicate greater inequality in disposable household income).

4.2.1. Dependent variable. The dependent variable is student achievement, estimated using the PISA measurement of math proficiency. In PISA, math proficiency is conceptualized as an individual's capacity to formulate, interpret, and deploy mathematics in a variety of contexts, which involves the application of important mathematical concepts, knowledge, and skills to solve everyday problems (OECD, 2013). Although math proficiency constitutes only one aspect of student achievement, it is considered as a particularly suitable subject for comparative purposes across educational systems, in particular because several educational systems contain large proportions of immigrant students whose language proficiency may vary considerably (Levels, Dronkers, & Kraaykamp, 2008). Math proficiency is also used as a proxy for student achievement to compare with findings from previous studies (Schlicht et al., 2010; Stadelmann-Steffen, 2012). Math proficiency is estimated in the form of five plausible values, which represent the range of abilities that a student can be expected to have, given the student's responses to the PISA test items (Wu, 2005). To determine population statistics, each plausible value is first used separately in any analysis. Using Rubin's rule (1987), the results of these analyses are then averaged in order to produce the final statistics (OECD, 2009a). By employing plausible values instead of raw estimates of student achievement, we minimize the effect of measurement error bias in the outcome variable.

4.2.2. Independent variable. The independent variable is students' socioeconomic status (SES), measured using an index that considers parents' occupational status (the international socioeconomic index of occupational status, HISEI), parents' educational level (number of years in education according to the international standard classification of education, ISCED), and home possessions (a construct consisting of items assessing family wealth, cultural possessions, educational resources, and the number of books at home). In the PISA dataset, this is known as the index of economic, social, and cultural status (ESCS). This index is comparable across countries, as determined by similar scale reliabilities (Cronbach's α) across countries, as well as through principal component analyses, performed separately for each country, indicating that across countries the three components—parental occupational status, parental education, and home possessions—had very similar loadings on the index of economic, social, and cultural status, and thus correlated to a very similar degree with this index (OECD, 2014, p. 352).

4.2.3. Central moderator variable. The key variable assumed to moderate the individual-level relationship between SES and educational achievement is an index of social segregation within national education systems (see Table 5). This index is estimated by means of intra-class correlations of SES, using a multilevel modeling approach in line with previous studies (Ferrer-Esteban, 2016; Goldstein & Noden, 2003; Mayer, 2002). The intra-class correlation (ICC) measures the degree to which SES varies between, as opposed to within, schools. A high ICC indicates high within-school similarity of students, meaning that students within a given school are more similar in terms of SES to students within their school than to those in other schools. The ICC can also be interpreted as the proportion of variance in SES that lies between schools. Mathematically, it corresponds to the ratio of the school-level variance in SES to the total variance in SES within a country. In order to partition the total variation in SES within a country into two variance components—within schools and between schools—we use an unconditional multilevel regression model with SES as the outcome and with a random intercept at the student level and a random intercept at the school level, performed separately for each country. This model is specified as

$$\text{SES}_{ij} = \beta_{0j} + \varepsilon_{ij} \qquad \text{(eq. 1)}$$

$$\text{with } \beta_{0j} = \alpha_{00} + \mu_{0\text{j}} \qquad \text{(eq. 2)}$$

where, at the individual level, SES_{ij} is the socioeconomic status of student i in school j, β_{0j} is the mean SES in school j, and ε_{ij} is the deviation of the SES of student i from the school mean, or the residual error (eq. 1). At the school level, α_{00} is the grand mean, and $\mu_{0\text{j}}$ is the deviation of the mean SES of school j from the grand mean, or the residual error (eq. 2). The variances of the residual errors ε_{ij} and $\mu_{0\text{j}}$ are assumed to have a normal distribution with a mean of zero and to be mutually independent. They are denoted as $\sigma^2_{\varepsilon 0ij}$ and $\sigma^2_{\mu 0j}$, respectively, and are also referred to as variance components. As noted above, the ICC corresponds to the ratio of the school-level variance in SES to the total variance in SES within a country. Thus, it is calculated as $\rho = \sigma^2_{\mu 0j}$ / $(\sigma^2_{\mu 0j} + \sigma^2_{\varepsilon 0ij})$, where $\sigma^2_{\mu 0j}$ is the school-level variance and $\sigma^2_{\varepsilon 0ij}$ is the individual-level variance in SES.

The intra-class correlation of SES is a standard index of social segregation within education systems (Agirdag, Van Avermaet, & van Houtte, 2013; Goldstein & Noden, 2003; Modin, Karvonen, Rahkonen, & Östberg, 2015; Palardy, Rumberger, & Butler, 2015). There are various other indices of segregation available (Duncan & Duncan, 1955; Gorard & Taylor, 2002; Hutchens, 2004; Jenkins et al., 2008; Reardon & Bischoff, 2011). However, typically, and in contrast to the applied index, they are a function of observed proportions, such as poor versus non-poor children in schools, and thus based on dichotomous measures (Leckie, Pillinger, Jones, & Goldstein, 2012). The intra-class correlation relies on a continuous scale, which captures the entire distribution of socioeconomic origin. This allows us to determine to what extent students are socially dissimilar (segregated) between schools without determining a cut-off value to differentiate students into broad socioeconomic categories. As any other index of segregation, the intra-class correlation of SES provides an estimate of the unevenness in the distribution of students across schools.

4.2.4. Alternative country-level influences on educational inequality. In addition to the index of social segregation, the analysis includes the following country-level variables to evaluate their effects on student achievement and whether they moderate the relationship between SES and student achievement. As a measure of a country's economic development, we consider the *gross domestic product (GDP) per capita* in purchasing power standard (averaged across the years 2003 through 2011, the period preceding the PISA assessment during which the students attended compulsory school; data from Eurostat, 2017). As a measure of socioeconomic inequality, we consider the level of *income inequality* within the population, notably the Gini coefficient of equivalized disposable income (averaged across the years 2005 to 2012, given the availability of data for this period; data from Eurostat, 2018).[3] To take into account the amount of time that children spent in school annually in a given education system, we use the *annual taught time* (in hours of 60 minutes), averaged across the compulsory education years (2003—2011; data from Eurydice, 2013).[4] The *preschool enrollment rate* is estimated based on data from the PISA database. It refers to the proportion of students who had been enrolled in preschool (ISCED 0) for any given duration, in contrast to students who had never been enrolled. Finally, we assess the public *educational expenditure* on compulsory education (ISCED 1—4) as the percentage of the gross domestic product (GDP; averaged across the period 2003—2011; data from Eurostat, 2017) (see Table 2). To avoid model overspecification, we also perform models with only selected country-level variables, as explained in Section 6.

4.2.5. Control variables at the individual and school level. At the *individual level*, the analysis controls for gender, immigrant status, language spoken at home, the school grade in which a student is enrolled at the time of the assessment (school grade level), and whether a student attended (0) a general academic program or (1) a pre-vocational or vocational program, because

[3] Data for Serbia refer to 2013, owing to missing values for the preceding years.

[4] Data for Serbia are derived from OECD (2011), data for Switzerland from UNESCO (2011).

these variables have a direct effect on student achievement (Burger & Walk, 2016; Schlicht et al., 2010). At the *school level*, the analysis controls for school type (public vs. private), the proportion of first-generation immigrants in school, and school socioeconomic composition (the aggregate SES of a school's student population) in order to account for their hypothesized effects on student achievement. All control variables are derived from the PISA database.

Table 3
Descriptive statistics for the individual- and school-level variables, by country.

Country	Individual level						School level		
	Male	First-generation immigrant	Language at home: same as test language	School grade relative to modal grade	(Pre-) vocational program	Socioeconomic status (SES)	School type: private school	Proportion of first-generation immigrants in school	School socioeconomic composition
	Mean	Mean	Mean	Mean (SD)	Mean	Mean (SD)	Mean	Mean (SD)	Mean (SD)
Austria	0.50	0.05	0.89	-0.51 (0.57)	0.37	0.11 (0.83)	0.09	0.04 (0.02)	-0.26 (0.21)
Belgium	0.50	0.08	0.78	-0.42 (0.65)	0.18	0.18 (0.91)	0.21	0.05 (0.02)	-0.14 (0.29)
Bulgaria	0.52	0.01	0.90	0.00 (0.33)	0.00	-0.23 (1.02)	0.08	0.04 (0.02)	-0.26 (0.21)
Croatia	0.50	0.04	0.99	0.20 (0.34)	0.23	-0.35 (0.85)	0.08	0.04 (0.02)	-0.29 (0.19)
Czech Republic	0.50	0.02	0.97	0.41 (0.57)	0.09	0.06 (0.76)	0.22	0.05 (0.02)	-0.13 (0.30)
Denmark	0.50	0.07	0.87	-0.18 (0.42)	0.00	0.28 (0.91)	0.27	0.05 (0.03)	-0.10 (0.30)
Estonia	0.50	0.01	0.94	-0.21 (0.45)	0.02	0.15 (0.13)	0.10	0.04 (0.02)	-0.24 (0.22)
Finland	0.51	0.08	0.83	-0.19 (0.43)	0.00	0.35 (0.83)	0.23	0.05 (0.02)	-0.12 (0.29)
France	0.49	0.05	0.92	-0.27 (0.56)	0.14	-0.02 (0.80)	0.11	0.04 (0.02)	-0.22 (0.22)
Germany	0.51	0.03	0.93	0.27 (0.67)	0.02	0.19 (0.93)	0.12	0.04 (0.02)	-0.20 (0.26)
Great Britain	0.50	0.05	0.93	0.16 (0.40)	0.98	0.24 (0.81)	0.35	0.06 (0.04)	-0.02 (0.32)
Greece	0.50	0.06	0.95	-0.05 (0.27)	0.15	-0.05 (0.99)	0.09	0.04 (0.02)	-0.27 (0.20)
Hungary	0.47	0.01	0.99	0.16 (0.54)	0.15	-0.20 (0.94)	0.09	0.04 (0.02)	-0.23 (0.22)
Iceland	0.50	0.03	0.96	0.00 (0.00)	0.00	0.78 (0.81)	0.07	0.05 (0.02)	-0.30 (0.18)
Ireland	0.49	0.04	0.95	0.46 (0.73)	0.24	0.13 (0.85)	0.09	0.04 (0.02)	-0.27 (0.20)
Latvia	0.49	0.00	0.90	-0.12 (0.45)	0.00	-0.18 (0.87)	0.09	0.04 (0.02)	-0.25 (0.21)
Lithuania	0.51	0.00	0.97	0.05 (0.43)	0.00	-0.13 (0.91)	0.10	0.04 (0.02)	-0.22 (0.22)
Luxembourg	0.51	0.17	0.14	0.27 (0.67)	0.06	0.08 (1.10)	0.10	0.06 (0.03)	-0.28 (0.15)
Netherlands	0.52	0.03	0.94	0.44 (0.57)	0.53	0.21 (0.78)	0.08	0.05 (0.02)	-0.28 (0.20)
Norway	0.51	0.05	0.92	0.00 (0.07)	0.00	0.47 (0.76)	0.09	0.05 (0.02)	-0.26 (0.21)
Poland	0.48	0.00	0.99	-0.04 (0.23)	0.00	-0.16 (0.92)	0.09	0.04 (0.02)	-0.28 (0.20)
Portugal	0.50	0.04	0.97	-0.56 (0.76)	0.16	-0.48 (1.17)	0.09	0.05 (0.02)	-0.25 (0.21)
Romania	0.49	0.00	0.98	0.00 (0.32)	0.95	-0.46 (0.93)	0.09	0.04 (0.02)	-0.28 (0.19)
Serbia	0.49	0.02	0.96	0.01 (0.16)	0.76	-0.30 (0.90)	0.08	0.04 (0.02)	-0.30 (0.19)
Slovakia	0.52	0.00	0.93	-0.46 (0.68)	0.09	-0.15 (0.92)	0.12	0.04 (0.02)	-0.22 (0.26)
Slovenia	0.54	0.03	0.93	0.02 (0.21)	0.63	-0.02 (0.85)	0.27	0.05 (0.02)	-0.10 (0.28)
Spain	0.50	0.09	0.86	-0.38 (0.64)	0.01	-0.11 (1.00)	0.35	0.07 (0.09)	-0.06 (0.37)
Sweden	0.50	0.06	0.90	-0.02 (0.23)	0.00	0.29 (0.81)	0.10	0.04 (0.02)	-0.24 (0.22)
Switzerland	0.50	0.08	0.83	-0.02 (0.53)	0.03	0.11 (0.87)	0.35	0.05 (0.04)	-0.05 (0.30)

Note: SD = Standard deviation. Descriptive statistics for pooled data across countries reported in Table 2.

Table 4
Descriptive statistics for the dependent variable 'student achievement' (5 plausible values), by country.

Country	Plausible values (PV) PV1 Mean (SD)	PV2 Mean (SD)	PV3 Mean (SD)	PV4 Mean (SD)	PV5 Mean (SD)
Austria	507.71 (91.16)	507.53 (90.85)	507.84 (90.64)	507.76 (91.25)	508.05 (90.32)
Belgium	520.38 (101.49)	519.52 (101.13)	519.61 (101.54)	519.92 (101.48)	519.25 (101.97)
Bulgaria	442.16 (92.64)	442.38 (92.78)	442.95 (92.52)	442.70 (93.23)	442.16 (93.50)
Croatia	469.83 (86.70)	469.98 (87.52)	470.10 (88.02)	469.74 (87.50)	470.21 (87.43)
Czech Republic	519.77 (96.69)	520.76 (96.86)	520.12 (96.90)	520.32 (96.90)	519.31 (97.03)
Denmark	486.19 (86.59)	486.35 (85.71)	486.23 (86.10)	486.39 (86.70)	486.05 (86.25)
Estonia	521.81 (80.26)	522.36 (81.18)	522.48 (81.01)	522.11 (79.82)	522.95 (81.21)
Finland	507.53 (89.86)	506.94 (89.75)	506.94 (89.34)	507.16 (89.45)	507.30 (89.56)
France	499.47 (96.98)	497.73 (96.58)	498.26 (96.64)	497.97 (96.32)	498.44 (96.58)
Germany	513.93 (96.74)	513.79 (96.26)	513.55 (96.94)	514.12 (96.66)	513.97 (96.39)
Great Britain	489.65 (91.12)	489.52 (91.22)	489.55 (91.11)	489.67 (91.30)	490.24 (91.11)
Greece	453.89 (87.57)	453.23 (87.97)	453.77 (87.13)	453.07 (87.85)	453.61 (87.81)
Hungary	485.39 (91.34)	485.19 (91.38)	484.41 (91.27)	484.56 (91.01)	484.79 (90.64)
Iceland	493.15 (92.38)	492.21 (91.13)	492.62 (91.31)	493.22 (91.61)	493.43 (92.84)
Ireland	500.90 (84.51)	500.98 (84.20)	501.55 (84.51)	501.32 (84.85)	501.61 (84.78)
Latvia	495.45 (80.97)	495.70 (80.95)	495.34 (80.31)	495.68 (80.66)	495.52 (81.32)
Lithuania	478.68 (88.70)	479.12 (89.33)	479.58 (88.74)	479.45 (88.82)	479.37 (89.11)
Luxembourg	490.27 (95.33)	491.63 (95.67)	490.24 (95.31)	490.20 (96.05)	490.08 (95.05)
Netherlands	518.13 (92.60)	518.11 (92.56)	518.43 (92.58)	518.80 (92.27)	519.22 (92.18)
Norway	489.75 (89.84)	489.37 (89.45)	489.12 (90.07)	489.29 (89.68)	489.20 (90.41)
Poland	520.59 (91.15)	520.38 (90.75)	520.46 (91.15)	520.37 (91.21)	520.82 (91.23)
Portugal	484.56 (93.93)	484.89 (93.97)	485.73 (93.99)	485.34 (93.76)	485.09 (93.41)
Romania	445.78 (80.36)	444.28 (80.46)	445.48 (80.67)	445.36 (80.60)	445.53 (80.41)
Serbia	447.74 (89.43)	447.90 (90.18)	447.23 (89.75)	447.29 (89.70)	447.14 (89.99)
Slovakia	485.64 (102.24)	485.49 (101.42)	486.35 (101.85)	485.32 (100.73)	485.54 (102.06)
Slovenia	484.48 (89.50)	484.55 (89.88)	484.33 (89.95)	484.33 (90.28)	484.96 (90.15)
Spain	495.36 (88.43)	495.63 (88.67)	495.59 (88.35)	495.25 (88.43)	495.36 (88.50)
Sweden	479.15 (90.66)	478.79 (91.53)	479.40 (91.32)	479.23 (91.58)	479.62 (90.89)
Switzerland	520.67 (92.62)	521.25 (92.73)	520.94 (92.99)	520.83 (92.80)	521.15 (92.85)

Note: SD = Standard deviation.

4.3. Analytic strategy

First, we apply bivariate analysis to assess the extent to which social segregation is related to social inequality in student achievement at the macro level of European education systems. In this analysis, we calculate a country-specific index of social inequality in achievement, which corresponds to the coefficient of an ordinary least-squares (OLS) regression predicting math achievement as a function of SES, while controlling for gender, home language, immigrant background, and school grade (coefficients reported in Table 5). To obtain this index, we perform an OLS regression (for each country separately), because we focus solely on individual-level variables, whereas in further analyses we will perform multilevel regressions, which also include additional—school- and country-level—variables. The PISA final student weights are applied in this regression analysis, resulting in coefficients that are representative for each country.

Second, we perform multilevel (linear mixed-effects) models to ascertain whether social segregation moderates individual-level associations between SES and educational achievement. Multilevel models take into account that the data are hierarchically clustered—students in schools, and schools in countries—meaning that the observations in the sample cannot be considered as being independent (Snijders & Bosker, 2012). Standard (OLS) regression models rely on the assumption of independence of the observations. With a hierarchical data structure, this assumption is violated and hence the estimates of the standard errors of standard models will be too small, which may lead to spuriously significant results (Hox, 2010). Multilevel models allow for the simultaneous estimation of the direct effects of individual-, school-, and country-level variables on student achievement, as well as to evaluate whether social segregation within education systems strengthens the micro-level associations between social origin and student achievement. The final model is represented as:

$$y_{ijk} = \beta_{000} + \sum_{h=1}^{l} \beta_{\mathrm{h}}\, x_{\mathrm{h}ijk} + \sum_{m=1}^{o} \alpha_{\mathrm{m}}\, S_{\mathrm{m}jk} + \sum_{p=1}^{u} \delta_{\mathrm{p}}\, C_{\mathrm{p}k} + \sum_{v=1}^{z} \gamma_{v}\, (x_{\mathrm{l}ijk} \cdot C_{\mathrm{v}k}) \qquad \text{(eq. 3)}$$

$$+(\beta_{010} + \mu_{1jk})\, x_{\mathrm{l}ijk} + \nu_{0k} + \eta_{0jk} + \varepsilon_{0ijk}$$

The educational achievement Y of a student i in school j in country k is estimated as a function of the overall mean achievement across countries (β_{000}), a vector of individual-level variables ($X_{\mathrm{h}ijk}$ to $X_{\mathrm{l}ijk}$) with their coefficients (β_{h} to β_{l}), a vector of school-level variables ($S_{\mathrm{m}jk}$ to $S_{\mathrm{o}jk}$) with their coefficients (α_{m} to α_{o}), and a vector of country-level variables ($C_{\mathrm{p}k}$ to $C_{\mathrm{u}k}$) with their coefficients (δ_{p} to δ_{u}). The model also includes a vector of cross-level interactions between the individual-level variable ‘socioeconomic status’ and the country-level variables ($X_{1ijk} \cdot C_{vk}$), with the respective coefficients (γ_v to γ_z). Furthermore, by including a random slope $\mu_{1jk} \sim N(0, \sigma^2_{\mu\,1jk})$ on ‘socioeconomic status’ (X_{1ijk}) at the school level, the model considers that the association between socioeconomic status and student achievement differs between schools. The random slope is determined by a fixed effect for the school average on socioeconomic status and a random effect that defines the variance in the slopes between schools, as denoted by the term $(\beta_{010} + \mu_{1jk})\, X_{1ijk}$, where β_{010} represents the slope on socioeconomic status (X_{1ijk}) for the average school and $\sigma^2_{\mu\,1jk}$ represents the between-school variance in this slope. Three random terms are associated with the intercept and fixed effects, reflecting the remaining or residual variation at the country level, $v_{0k} \sim N(0, \sigma^2_{v\,0k})$, at the school level, $\mu_{0jk} \sim N(0, \sigma^2_{\mu\,0jk})$, and at the student level, $\varepsilon_{0ijk} \sim N(0, \sigma^2_{\varepsilon\,0ijk})$. These random terms are assumed to have zero means given the independent variables, to be drawn from normally distributed populations, and to be mutually independent. The model allows for a correlation between the school-level variance in math achievement (random intercept), v_{0k}, and the random slope on socioeconomic status at the school level, μ_{1jk}, thereby taking into account that any relationship between socioeconomic status and student achievement may vary across schools. We use un-centered binary variables and grand-mean centered continuous variables. There were no collinearity issues in the model, with all variance inflation factors being below 2.39.

In conclusion, our aim is to exploit variation in the level of social segregation within education systems across countries to describe systematic patterns of covariation between social segregation and educational inequality, when observable potential confounders are considered. Our models do not differentiate statistically between the effects of the systematic underlying processes that lead to segregated schools (such as the intertwined residential and school choice decisions of families and schools’ decisions regarding which students to admit), and the effects of exposure to segregated schools (cf., Leckie et al., 2012). We argue that student achievement and educational inequality are shaped by both such underlying processes and exposure to segregated schools. Accordingly, the estimates of the models reported hereafter may be interpreted as estimates of the combined influence of ‘selection’ into schools and ‘treatment’, or exposure to socially homogeneous or heterogeneous student populations, in these schools, under *ceteris paribus* conditions.[5]

[5] Given the cross-sectional nature of PISA, there is no direct measure of prior student achievement in the dataset. Following prior research using PISA data, we include school grade at assessment as a rough (in fact, the only available) proxy for prior student performance, presuming that 15 year olds who were enrolled in lower grades at

5. Results

Table 5 displays the index of social segregation within education systems and the index of social inequality in achievement for each country.

The index of social segregation varies between 0.090 and 0.456. Greater values indicate that students of a given socioeconomic-status group were found to a greater degree in distinct schools and thus isolated from students of a different socioeconomic-status group. Levels of social segregation were relatively low in Norway, Finland, and Sweden, whereas they were considerably higher, for instance, in Slovakia, Hungary, and Bulgaria.

The index of social inequality in achievement is a measure of the relationship between SES and the level of student achievement. It ranges from 15.60 in Spain to 51.67 in the Czech Republic. That is, on average across European countries, a one-unit increase in SES was related to a 31.48-point better achievement, or roughly a 0.31 standard-deviation improvement in achievement. The variation in the indices of social inequality in achievement between countries contributes to discussion on the degree to which student achievement is a result of inherited ability, providing the basis for a predisposition to learning, and/or of socialization and environmental influences (e.g., Nielsen, 2006). The degree of social inequality in achievement varied considerably across countries, which implies that any predisposition derived from the family context or otherwise cannot be the sole determinant of educational achievement. Because country-specific differences in educational inequality cannot be ascribed to any genetic or social inheritance, the macro environment seemed to play a decisive role in shaping this inequality.

the time of the assessment had performed worse in previous years (Chiu, 2010; Lee, Zuze, & Ross, 2005). We acknowledge the limitations of our approach in Section 6.

Table 5
Index of social segregation within the education system, index of social inequality in educational achievement.

Country	Index of social segregation	Index of social inequality in achievement (SE)
Austria	0.311	33.60 (1.54)
Belgium	0.282	27.84 (1.00)
Bulgaria	0.456	38.12 (1.12)
Croatia	0.229	34.44 (1.36)
Czech Republic	0.276	51.67 (1.53)
Denmark	0.187	32.56 (1.06)
Estonia	0.197	28.76 (1.37)
Finland	0.101	28.62 (1.05)
France	0.278	34.34 (1.46)
Germany	0.277	32.09 (1.46)
Great Britain	0.182	39.26 (0.94)
Greece	0.292	32.40 (1.17)
Hungary	0.379	41.45 (1.21)
Iceland	0.150	29.34 (1.90)
Ireland	0.211	38.70 (1.30)
Latvia	0.254	30.23 (1.29)
Lithuania	0.246	33.75 (1.33)
Luxembourg	0.280	23.71 (1.10)
Netherlands	0.183	31.80 (1.64)
Norway	0.090	30.48 (1.73)
Poland	0.312	39.61 (1.32)
Portugal	0.288	19.22 (0.86)
Romania	0.401	37.20 (1.10)
Serbia	0.218	32.33 (1.40)
Slovakia	0.357	45.16 (1.47)
Slovenia	0.242	34.87 (1.30)
Spain	0.232	15.60 (0.47)
Sweden	0.139	29.48 (1.58)
Switzerland	0.146	26.24 (0.95)
Average	0.248	31.48 (0.19)

Note: Information about the indices in section 4.2.

The correlation between the index of social segregation within education systems and the index of social inequality in achievement ($r(27) = 0.372$, $p < .05$) provides an estimate of the extent to which social segregation in education systems was related to social gradients in student achievement at the aggregate level of European education systems (see also Fig. 1). The moderate positive relationship identified here supports theory in respect to social class inequalities in education being more pronounced in those education systems where socioeconomically diverse students are less evenly distributed across schools.

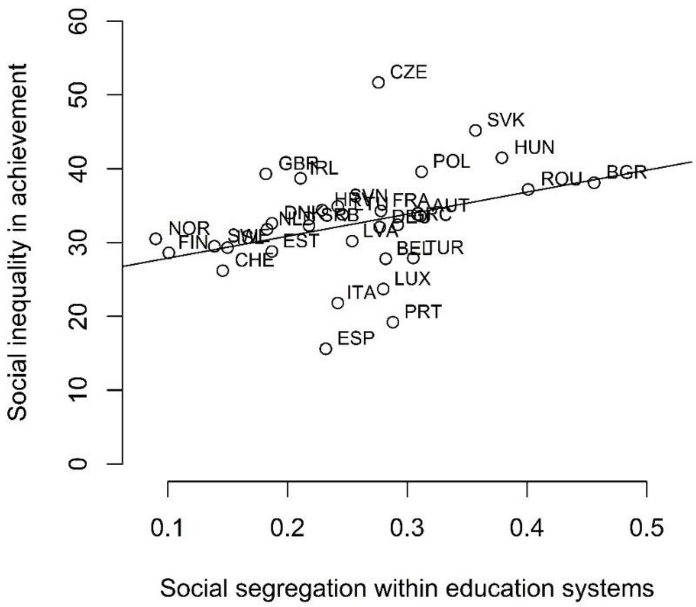

Figure 1. Scatterplot of the index of social segregation and the index of social inequality in achievement. Abbreviations: AUT: Austria, BEL: Belgium, BGR: Bulgaria, CHE: Switzerland, CZE: Czech Republic, DEU: Germany, DNK: Denmark, ESP: Spain, EST: Estonia, FIN: Finland, FRA: France, GBR: Great Britain, GRC: Greece, HRV: Croatia, HUN: Hungary, IRL: Ireland, ISL: Iceland, LTU: Lithuania, LUX: Luxembourg, LVA: Latvia, NLD: Netherlands, NOR: Norway, POL: Poland, PRT: Portugal, ROU: Romania, SRB: Serbia, SVK: Slovakia, SVN: Slovenia, SWE: Sweden.

However, the bivariate relationship between social segregation within education systems and social inequality in achievement does not allow us to gauge whether social segregation moderates social inequality in educational achievement. Thus, we also estimated a series of multilevel models to determine whether the strength of the relationship between SES and educational achievement at the individual level varies across education systems that exhibit different levels of social segregation, when potential alternative influences are considered at the individual, school, and country levels.

The dependent variable had complete data for all of the students in the sample; however three individual-level covariates contained missing values—school grade (0.4%), immigrant status (2.6%), and SES (1.9%). Assuming that the probability of a missing value on these variables was not conditional on unobserved values of these variables, given the observed values (Rabe-Hesketh & Skrondal, 2008; Rubin, 1976), we performed multilevel analyses using full maximum likelihood estimation, which is widely considered to provide robust estimations if the assumed model is accurate. Furthermore, this allowed us to compare the goodness of fit of several models through likelihood ratio tests (Muthén & Shedden, 1999; Schafer & Graham, 2002). In robustness analyses, we also replaced missing data with imputed data, computing maximum likelihood estimates through the expectation-maximization algorithm, which allows for estimation of parameters in a probabilistic model (Do & Batzoglou, 2008). These additional analyses confirmed the conclusions that we draw from the analyses presented hereafter.

Table 6 summarizes the results of four increasingly complex multilevel models. The unconditional (or null) model—with only intercepts at the individual, school, and country level, and student achievement as the outcome—reveals that 5.6% of the variance in student achievement was at the country level, whereas 12.7% was at the school-within-country level. However, variance components between schools and countries can only be reasonably interpreted when school grade level is considered, given that school grade level explains a large proportion of the variance in student achievement. Thus, in a quasi-unconditional model (not shown), which included school grade as the only predictor, we found that 9.9% of the variance in student achievement was at the country level, whereas 15.3% was at the school-within-country level. This result implies that student achievement scores varied systematically not only at the individual level, but also between schools and countries.

Table 6. Multilevel models predicting student achievement.

	Model 0		Model 1		Model 2		Model 3	
	Coefficient	(SE)	Coefficient	(SE)	Coefficient	(SE)	Coefficient	(SE)
Fixed effects								
Intercept	491.94***	(4.34)	489.30***	(4.83)	491.61***	(4.64)	491.70***	(4.71)
Individual level								
Male			16.67***	(0.37)	16.67***	(0.37)	16.69***	(0.37)
First-generation immigrant			-5.69***	(1.05)	-5.68***	(1.05)	-6.06***	(1.05)
Language spoken at home: same as test language			12.28***	(0.80)	12.29***	(0.80)	12.57***	(0.80)
School grade relative to modal grade			58.04***	(0.38)	58.04***	(0.38)	58.45***	(0.38)
Pre-vocational or vocational program			-70.63***	(0.75)	-70.63***	(0.75)	-71.14***	(0.75)
Socioeconomic status (SES)			25.64***	(0.53)	25.64***	(0.53)	25.89***	(0.53)
School level								
School type: private school			0.52	(0.55)	0.52	(0.55)	0.53	(0.55)
Proportion of first-generation immigrants in school			-2.27	(12.13)	-2.31	(12.13)	-6.85	(12.09)
School socioeconomic composition			15.67***	(2.38)	15.67***	(2.36)	16.54***	(2.37)
Country level								
Gross domestic product (GDP) per capita					-0.13	(0.14)	-0.11	(0.14)
Income inequality: Gini coefficient					-0.54	(1.45)	-0.47	(1.47)
Annual taught time in compulsory education					0.10	(0.05)	0.10	(0.05)
Preschool enrollment rate					0.57	(0.68)	0.59	(0.70)
Educational expenditure (as % of the GDP)					-5.59	(17.41)	-6.09	(17.68)
Social segregation within the education system					-57.43	(73.93)	-51.66	(75.08)
Cross-level interactions								
SES x GDP per capita							-0.05***	(0.01)
SES x Income inequality							0.33***	(0.10)
SES x Annual taught time							-0.03***	(0.00)
SES x Preschool enrollment rate							0.37***	(0.05)
SES x Educational expenditure							11.70***	(0.91)
SES x Social segregation in the education system							24.35***	(5.21)
Random effects	Variance	(SD)	Variance	(SD)	Variance	(SD)	Variance	(SD)
Individual-level variance (SD)	7,977.4	(89.32)	129,723.2	(360.17)	129,723.3	(360.17)	129,481.3	(359.84)
School-level variance (SD)	644.1	(25.38)	398.6	(19.96)	398.6	(19.96)	394.4	(19.86)
Country-level variance (SD)	514.7	(22.69)	613.4	(26.15)	512.3	(22.63)	528.6	(22.99)
Random slope on SES at the school level (SD)			108.3	(10.41)	108.3	(10.41)	95.5	(9.77)
Correlation between the school-level variance (random intercept) and the random slope on SES			0.14		0.14		0.14	
Log-likelihood	-1,100,952		-1,034,846		-1,034,843		-1,034,660	

Note: Unstandardized coefficients with standard errors (SE) are reported for the fixed effects. Variances with standard deviations (SD) are reported for the random effects. Maximum-likelihood estimation was used. The significance of the coefficient estimates of the fixed effects was determined using Wald tests. To partition the variance in student achievement into three components (at the individual, school and country level), model 0 was calculated with unweighted data. Models 1 to 3 were calculated with weighted data, as explained in section 4.1.
*** $p < .001$ (two-tailed tests).

In Model 1, we added the individual- and school-level predictors. The results of this model corroborate findings of earlier studies regarding the statistically significant relationships between student-level characteristics and educational achievement (Levels et al., 2008; Schlicht et al., 2010). On average, male students outperformed female students, while immigrant students underperformed. Moreover, students whose home language corresponded to the PISA test language, and students who were enrolled in higher grades at school, outperformed their peers who spoke a foreign language at home and were enrolled in lower school grades, respectively. The relationship between students' socioeconomic status and their educational achievement was positive and highly significant. We modeled between-school variation in the relationship between socioeconomic status and educational achievement by adding a random slope on socioeconomic status at the school level. That is, because the relationship between socioeconomic status and educational achievement varied across schools, we allowed the slope on socioeconomic status to vary across schools. Including this random slope improved the model fit significantly, as indicated by a likelihood ratio test based on a comparison of the log-likelihoods of a model without a random slope and a model with a random slope, χ^2 (2, N = 171,159) = 1481.5, $p < .001$ (see Raudenbush & Bryk, 2002, on likelihood ratio tests to compare the fit of nested models based on model deviance statistics). At the school level, school type (public vs. private) and the proportion of first-generation immigrants in school were not significantly related to student achievement, whereas school socioeconomic composition was. On average, each one-unit increase in school socioeconomic composition was associated with a 15.67-point improvement in student achievement, controlling for student socioeconomic status at the individual level and the other covariates in Model 1. This corresponds roughly to an increase in achievement of a 0.16 standard deviation. Thus, the average difference in achievement between students attending the most socioeconomically disadvantaged schools and students attending the most advantaged schools was approximately 36.97 points, or approximately a 0.37 standard deviation. Figure 2 further illustrates this relationship by revealing that the school average achievement level was higher in those schools with more privileged student populations. This finding does not allow for the conclusion that school socioeconomic composition necessarily caused an improvement in student achievement, given that PISA did not assess student ability prior to school entry. The higher achievement levels of schools that draw a majority of their population from more privileged backgrounds could be a consequence of greater student ability or of peer effects or a combination of both. Hence, Figure 2 does not provide evidence of a school composition effect (see also Pokropek, 2015), but it does provide descriptive evidence of a positive association between school socioeconomic composition and student achievement levels. Note that the box plots are based on pooled data from all countries included in the study (countries with a greater number of participating schools contribute more data points to the analysis; each school has equal weight).

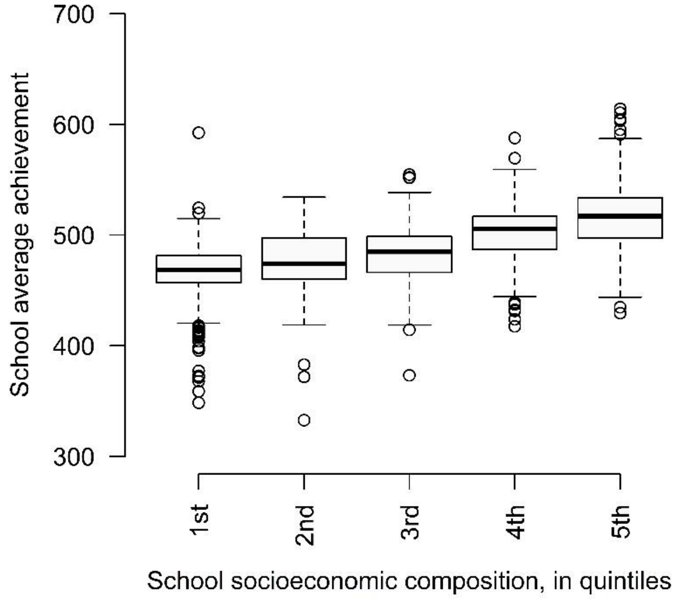

Figure 2. Box plots of the distribution of school average achievement across schools with varying socioeconomic compositions, divided into quintiles. The horizontal line within the boxes shows the median. The box edges represent the 1st and the 3rd quartile. The end of the upper whisker equals (Q3 + 1.5 * IQR), the end of the lower whisker equals (Q1 – 1.5 * IQR). Observations outside the whiskers are plotted as circles.

In Model 2, we added all of the country-level variables. This model shows that none of these variables had a statistically significant direct effect on student achievement. This includes a non-significant main effect of social segregation within the education system, suggesting that the level of social segregation within an education system was not significantly related to the average level of student achievement in a country.

In Model 3, we further included the cross-level interactions between SES and the country-level variables. Although our main focus here is on the interaction between SES and social segregation, we briefly summarize the findings regarding the other interactions in a first step, because all of these interactions were statistically significant. They indicate that the association between SES and student achievement was weaker in countries with a higher GDP and a longer annual taught time; however, this association increased with income inequality, preschool enrollment rates, and educational expenditure. The main finding of Model 3 was that social segregation moderated educational inequality in that the effect of SES on student achievement was stronger in countries with higher levels of social segregation within the education system, even when the alternative system-level influences were considered. To assess the contribution of the moderating effect of social segregation, we performed a likelihood ratio test, comparing the log-likelihoods of a model that included the cross-level interaction between socioeconomic status and social segregation, and a model without this interaction term. This test indicated that adding the cross-level interaction to the model significantly improved the model fit, χ^2 (2, N = 171,159) = 21.7, p < .001. Figure 3 illustrates the interaction between SES and social segregation, showing how the marginal effect of SES on student achievement changed as the degree of social segregation within education systems did, when all of the other variables in the model were kept constant (cf. Preacher, Curran, & Bauer, 2006). The black line indicates that, on average, a one-unit increase in SES was associated with an increase in student achievement of approximately 29 points in the least segregated education systems (Norway and Finland), and of approximately 40 points in the most segregated system (Bulgaria). Expressed in standard deviation units, an increase in SES by one standard deviation was associated with, approximately, a 0.29 standard-deviation increase in student achievement in the least segregated systems, and a 0.40 standard-deviation increase in student achievement in the most segregated systems. The 95% confidence interval shows that the statistical uncertainty associated with the coefficients increased slightly as the degree of social segregation within education systems grew, which can be explained by the smaller number of countries that exhibited a comparatively high degree of social segregation.

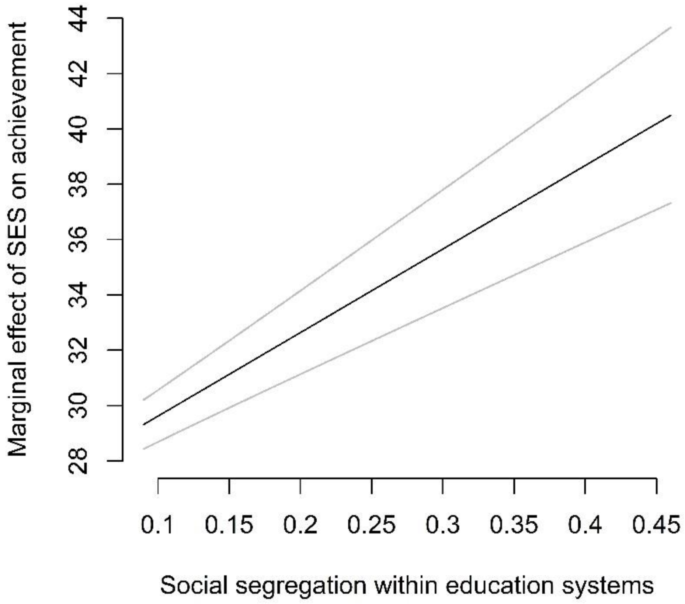

Figure 3. Change in the marginal effect of SES on student achievement as the degree of social segregation within education systems increases.

The individual-, school-, and country-level variances shown in Table 6 represent the effects of any unobserved covariates at the respective levels. In line with previous empirical studies and theory (Dronkers, 2010; Schlicht et al., 2010), the unexplained individual-level variance remained larger than the unexplained variances at the school and country levels. The weak positive correlation between the school-level variance (random intercept) and the random slope on SES at the school level (*r* = 0.14) indicates that the association between SES and student achievement was slightly stronger in schools with higher levels of average student achievement; however, differences between schools were negligible given the weak correlation.

We performed robustness tests to check for omitted variable and overspecification bias, and for variation in the results when using subsets of countries in the analysis. First, we assessed the sensitivity of the results to changes in model specification by entering additional, potentially confounding, country-level covariates: (1) an indicator of whether countries used centrally administered examinations to test student performance, (2) the proportion of schools that used assessments in order to compare students with national performance, (3) the variance in parental education attainment (as an inequality measure), and (4) an index of vocational specificity of the education system (dual system)—using data from PISA, Eurostat (2015), and Bol and Van de Werfhorst (2013). These variables were not included in the main models because of the unavailability of data for some of the sampled countries. Second, we ran several models in which we removed country-level variables because theoretically we might risk overspecifying our model by including six country-level variables simultaneously, although statistically we did not identify any multicollinearity issues. Third, we performed a type of cross-validation by replicating the analysis based on reduced datasets, sequentially excluding (1) one country, or (2) random pairs of countries (50 combinations), or (3) countries with comparatively strongly decentralized education policies (Austria, Belgium, Germany, Hungary, Switzerland; cf., Schlicht et al., 2010) from each replication. All of these additional tests corroborated the results reported here and lead to the same conclusions.

6. Discussion

Complementing prior research on correlates of socio-spatial separation of students, this study assessed to what extent social segregation occurred within education systems in Europe, and it examined patterns of covariation between social segregation within education systems and social inequality in educational achievement, using a cross-national comparative design that considered observable potential confounders at the individual, school, and country levels.

The findings indicate that schools were segregated along socioeconomic lines across European countries, albeit to varying degrees. Although the extent of social segregation was comparatively small in Scandinavian countries, it was substantially greater in some Central and Eastern European countries. For instance, it was approximately five times greater in Bulgaria than in Norway. Moreover, findings suggest that social segregation within education systems was related to social inequality in student achievement—the higher the level of social segregation within an education system, the stronger the aggregate-level relationship between SES and student achievement in a country. However, social gradients in student achievement could be the result of inequalities within society at large, or of the economic and education policy context, rather than the consequence of social segregation within the education system. We therefore examined whether social segregation in education systems moderates social inequality in student achievement when such country-level influences are considered (see Appendix B for a discussion of how the alternative country-level influences moderated educational inequality).

We found that, *ceteris paribus*, the effect of SES on student achievement was significantly stronger in education systems with higher levels of social segregation, suggesting that social segregation within education systems may contribute to the intergenerational transmission of educational (dis)advantage. This finding is in line with research from the United States revealing that spatial inequalities created by social segregation increase achievement gaps between advantaged and disadvantaged students (Owens, 2018). Moreover, the finding casts doubt on the view that the consequences of school segregation are “at the limit of our detectability” (Gorard, 2006, p. 87). Rather, the present investigation of nationally representative samples in a cross-national design measurably points toward the fact that social segregation may amplify inequality in educational outcomes. However, the moderating effect of social segregation on educational inequality was relatively modest. In the least socially segregated education systems, a one standard-deviation (SD) increase in SES was associated with an increase in student achievement by approximately 0.29 SDs, whereas in the most segregated systems it was associated with an increase in achievement of roughly 0.40 SDs. By way of comparison, this 0.11-SD difference was somewhat smaller than the 0.18-SD difference in the effect of SES on achievement that was attributable to variations in the annual taught time—in those education systems with the least time spent on teaching per year, a 1-SD increase in SES was associated with an increase in student achievement by 0.37 SDs, whereas in those systems with the most time spent on teaching per year, a 1-SD increase in SES was associated with an increase in achievement by 0.19 SDs, keeping all other covariates constant. However, the 0.11-SD difference attributable to social segregation was larger than the roughly 0.05-SD difference that was attributable to variations in economic development (GDP). It was also larger than the 0.05-SD difference attributable to variations in income inequality (Gini) and the 0.06-SD difference attributable to variations in preschool enrollment rates; finally, it was comparable in magnitude with the 0.10-SD difference ascribable to variations in educational expenditure.

Multiple sensitivity analyses confirmed the robustness of our findings (see Section 5). However, it must be acknowledged that estimates of segregation indices based on sample surveys tend to be biased upward because they capture both the uneven distribution of students across schools that results from actual segregation processes (i.e., the systematic underlying processes of segregation such as school choice decisions and residential choices of families) and the uneven distribution of students across schools that arises as a result of randomness. Even if students were allocated to schools completely at random, we would measure some unevenness in the distribution of diverse students across schools simply as a consequence of random allocation (Leckie et al., 2012; Ransom, 2000). Consequently, differences in the index of social segregation between countries are in part the result of sampling variability and must therefore be interpreted with caution. However, an index of segregation that would measure deviations from randomness, rather than deviations from evenness in the distribution of students across schools (Allen, Burgess, Davidson, & Windmeijer, 2015), would lead to a highly similar ranking of countries by school segregation, given that PISA sampled approximately the same number of students per school across countries (we have removed Italy from our analyses because it contained a relatively large proportion of schools in which fewer than 20 students participated in the survey). We recognize that for countries with a large average school size the index of social segregation between schools is expected to be smaller because larger schools will lead to smaller socioeconomic differences between schools, and greater differences within schools.[6] However, any measure of segregation that is based on a sample survey, such as PISA, is subject to sampling variation, and previous research has demonstrated that the number of schools sampled per country in the PISA survey is sufficiently large to minimize bias to negligible levels (Jenkins et al., 2008).

It should not be disregarded that social segregation within education systems may be a consequence of residential segregation, for instance, where particular schools are in more affluent catchment areas, while others are found in districts with a high level of social housing (Croxford & Paterson, 2006; Dupriez & Dumay, 2006; Ferrer-Esteban, 2016). Moreover, the reputation of the school may well give rise to residential segregation, with property markets responding to demand from families (Gorard, 2000; Kane, Riegg, & Staiger, 2006; Leech & Campos, 2001). Thus, the relationship between school social segregation and residential segregation may be theoretically conceived of as a reciprocal relationship of mutual determination between school and housing "markets" (Taylor & Gorard, 2001). There are currently no standardized cross-national data that could be cross-referenced at a European level with the data on the schools from the PISA survey. Our research therefore cannot distinguish between residential and school segregation. The essential question that it does address, however, is whether the clustering of children along social background lines—as observed in education systems—strengthens the relationship between social origin and educational achievement, with the results indicating that this is the case.

Finally, and as previously mentioned, it is important to be aware that effects of social segregation between schools on social inequality in achievement may be mediated by school characteristics, such as academic entry requirements or overall ability levels (e.g., Harris & Williams, 2012; Liu, Van Damme, Gielen, & Van Den Noortgate, 2015). Experimental

[6] Analyses in which the countries with the largest average school sizes were excluded (LUX, NLD, ROU, GBR; Eurydice, 2012) provided evidence of a slightly stronger interaction effect between socioeconomic status and social segregation within education systems than was the case with the interaction effect presented here.

longitudinal studies would provide the opportunity to examine causal mediation effects. However, such studies may pose significant ethical challenges and are therefore not necessarily feasible. With this in mind, the value of the PISA data for cross-national comparative analyses is substantial. Parallel data extending across European countries are rare. Thus, the standardized international assessments provide unique data for analyzing educational inequalities, where otherwise only smaller and non-representative samples were available (Hanushek & Wössmann, 2014). These large-scale assessments allow for exploring variation that exists only across countries. Even if the degree of social segregation may vary across areas within countries, variation between European countries is considerable and therefore particularly worthy of investigation (Fig. 1 and Tab. 5). In conclusion, and in the absence of longitudinal or experimental data, the current study provides robust descriptive evidence in support of theory that social segregation within European education systems is detrimental to equity in education.

7. Conclusion

Extending research on the geography of opportunity (Logan, Minca, & Adar, 2012), this cross-national comparative study shows that the degree of social segregation within education systems varied considerably across European countries. It also highlights a relationship at the system level between social segregation and the degree of social inequality in student achievement. The average level of student achievement in a country was not affected by the level of social segregation within the education system. However, the effects of social origin on student achievement were stronger in more socially segregated systems, although the respective differences between systems were relatively small. These findings provide new evidence of the potentially damaging effect of a socio-spatial separation of students, indicating that socioeconomic segregation in European education systems may contribute to some extent to the perpetuation of educational and, by extension, social disadvantage from one generation to the next.

Research ethics

This study involves analysis of publicly available, de-identified data. Any information presented here is such that study participants cannot be identified.

Conflicts of interest

None.

Appendix A

The scatter plots in Figure A.1 and Figure A.2 illustrate that the degree of social segregation in European education systems is to some extent related to the number of years that children spent in a tracked regime (Fig. A.1) and to the number of tracks that are implemented in a given system (Fig. A.2). However, there is also considerable variation in the degree of social segregation among education systems that use similar or even identical tracking regimes. Note that the data on the tracking regimes are derived from Eurydice (2010) which provides official information about the structure of European education systems. The Organization for Economic Co-operation and Development (OECD, 2013) reports data that differ slightly for certain countries (e.g., 4 tracks in Germany, 3 tracks in Hungary). Analyses based on OECD data confirm the results presented in this article and lead to the same conclusions.

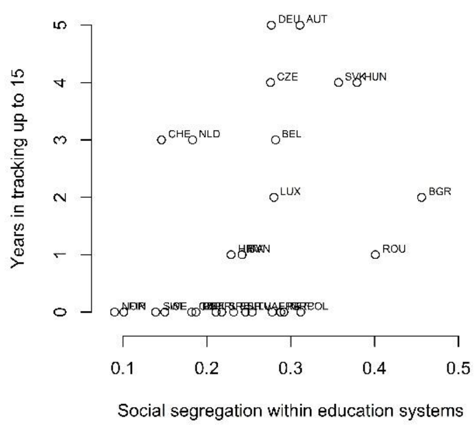

Figure A1.

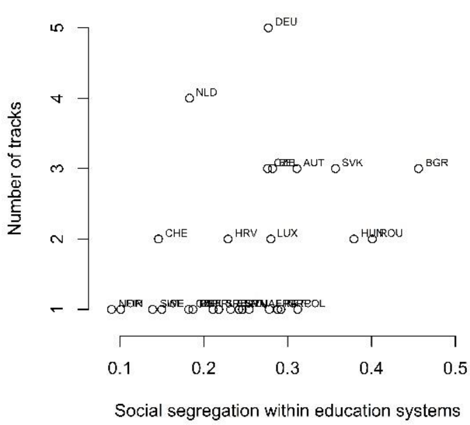

Figure A2.

Appendix B

All cross-level interactions in our model were statistically significant, indicating that all country-level variables moderated the individual-level relationship between socioeconomic status and student achievement (i.e., educational inequality). First, levels of educational inequality were lower in countries with a higher GDP. This supports the theory that social inequality in educational outcomes declines with economic development (Marks, 2009), suggesting that in the context of economic growth a transition occurs "from ascriptive rules of social mobility to mobility patterns based on personal achievements and meritocratic ideas" (van Doorn et al., 2011, p. 97). Second, income inequality was positively associated with the degree of educational inequality, which ties in with recent findings from a study of selected OECD countries (Chmielewski & Reardon, 2016). Although policy documents emphasize the role of education in "breaking the link between socioeconomic background and life prospects" (OECD, 2012, p. 18), school systems in Europe seem to face significant challenges in breaking this link. Instead, they might even reproduce and exacerbate pre-existing family income-related inequality between children (cf., Downey & Condron, 2016). Third, educational inequality was weaker in countries with a longer annual taught time. This corroborates prior research whereby a more intense schooling may diminish socioeconomic differentials in educational outcomes (Schlicht, Stadelmann-Steffen, & Freitag, 2010). Fourth, the preschool enrollment rate was positively associated with the degree of educational inequality. This unexpected finding might be explained by socioeconomic differentials in the duration of preschool attendance across Europe, with children of higher-SES families attending preschool for longer periods of time (authors, 2016). As a consequence, a higher preschool enrollment rate may increase, rather than decrease, social inequality in educational outcomes. Fifth, a higher level of educational inequality was observed in countries with greater educational expenditure. This result challenges the view that an increase in public spending on education might prevent the occurrence of educational inequality. Instead, it suggests that public expenditure on education may benefit in particular socioeconomically advantaged students who are potentially better able to capitalize on public education. Finally, the degree of educational inequality was stronger in countries with a higher level of social segregation in the education system, as explained in detail in the article.

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