

School Socioeconomic Composition as a Factor of Educational Inequality Reproduction

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Abstract. It can be inferred from international findings that school socioeconomic composition (SEC) is a major factor of educational inequality in secondary education. Along with individual student characteristics, SEC is believed to have a direct impact on student achievement. However, a review of research methods used in most studies calls the existence of a direct influence into question.

A study was carried out to evaluate causal relations between school SEC and student achievement. Multilevel regression analysis and propensity score matching (PSM) methods were applied to the data obtained in the panel study Trajectories in Education and Careers in order to measure the effects of one year of attending a low- vs. high-SEC school.

Correlational and quasi-experimental effect sizes were compared.

Analysis results confirm that school SEC is a key factor of educational inequality in Russian secondary education. The inequality effects of school composition overlapping only partially with those of school location. Within a year of schooling, ninth-graders with similar individual characteristics may lose up to a quarter of standard deviation in their PISA-2012 scores if attending a low-SEC school, while attending a high-SEC school is associated with improvements in educational outcomes by the end of the ninth grade. Negative effects were observed for two subject areas, which allows suggesting a systematic impact of SEC on student achievement. The final part of the article describes the theoretical and practical significance of the findings and presents the main directions of further research in the field.

Keywords: social inequality, educational inequality, school socioeconomic composition, quasi-experimental research designs, propensity score matching, academic achievement.

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Today, social mobility gradually becomes not just an advantage of a fair democratic system but also a prerequisite for development. Low upward social mobility, closely associated with inequality of opportunity, hinders national human capital accumulation, retards econom-

ic growth, and undermines social cohesion and engagement [Aiyar, Ebeke 2019; World Economic Forum 2019].

In 2020, the World Economic Forum provided an assessment of 82 global economies according to their performance on social mobility. The Russian Federation ranks 39th [World Economic Forum 2020]. This is no tragedy, yet it follows from the assessment results that the life chances of Russians are largely contingent on their sociodemographic characteristics, such as place of residence, social status, parental education, etc. Children born into less socially advantaged circumstances encounter a number of high barriers to moving up the social ladder.

Education is a powerful “equalizer” of chances [Esping-Andersen 2015; World Economic Forum 2020]. Ensuring that individuals have equal opportunities to access quality education is a key goal of an effective social system [Field, Kuczera, Pont 2007]. A school’s ability to give its students a chance for upward social mobility through learning becomes an indicator of quality education [Konstantinovskiy et al. 2006]. However, equity does not mean that all students obtain equal educational outcomes, but rather that differences in students’ outcomes are unrelated to their background or to economic and social circumstances over which students have no control.

The real situation in education is somewhat different from the ideal. A lot of countries have witnessed a sharp increase in educational inequality in recent years [OECD2018]. Russia, too, demonstrates significant sociodemographic disparities in student performance. Social and regional inequalities in school education are quite salient [Amini, Nivorozhkin 2015; Kapuza et al. 2017; Konstantinovskiy 2010; Froumin, Pinskaya, Kosaretsky 2012]. Students with different levels of socio-economic capital differ not only in their academic achievement but also in their post-school educational trajectories [Khavenson, Chirkina 2018; Kosyakova et al. 2016].

A number of studies examine the role of school in promoting educational inequality [Blossfeld et al. 2016; Borman, Dowling 2010; Condrón 2009; Duncan, Murnane 2011; Oppedisano, Turati 2015]. However, researchers often find it challenging to distinguish the direct effects of school from the influence of individual student characteristics on the learning outcomes. No clear answers have been found so far. This state of affairs in sociology of education being sometimes described as a “theoretical vertigo” [Condrón, Downey 2016]. According to various studies schools can reproduce preexisting inequalities, magnify them, or help reduce them.

On average 41% of outcome variance may be explained by covariates at the school level [Brunner et al. 2018], of which socioeconomic composition (SEC) is the strongest predictor [Coleman 1966]. School composition is normally expressed in studies as a school- or class-level aggregated socioeconomic status (SES) data [Perry 2012]. Social class composition of a student’s school can be 2.5 times more

important than a student's individual social class for understanding educational outcomes [Borman, Dowling 2010].

International findings obtained in studies assessing the impact of school SEC on student performance are controversial. In most publications, the effects of SEC are qualified as positive [Bartholo, Costa 2016; Belfi et al. 2014; Chesters, Daly 2017; Danhier 2017; Opdenakker, Damme 2007; Palardy, Rumberger, Butler 2015; Perry, McConney 2010; Agirdag 2018; Langenkamp, Carbonaro 2018; Niu, Tienda 2013; Palardy 2013; Rjosk et al. 2014]. Students in high-SEC schools exhibit higher attainment and are more likely to choose academic-track pathways after graduation. These results have been confirmed across a variety of countries: the United States, Belgium, Australia, Brazil, and others.

At the same time, some scholars believe that the compositional effect does not exist and represents a statistical artifact resulting from methodological pitfalls [Boonen et al. 2014; Flouri, Midouhas 2016; Marks 2015; McCoy, Quail, Smyth 2014; Televantou et al. 2015; Armor, Marks, Malatinszky 2018]. In particular, opponents emphasize the importance of using multilevel modelling for longitudinal data and taking account of prior attainment in the models. Addition of some indicators of prior attainment on individual level can make compositional effect insignificant.

Nearly all studies on the school composition effect use correlational designs based on regression analysis or structural equation modelling. A major limitation of these methods is the self-selection of students into different types of schools [Murnane, Willett 2011]. High-SEC schools are chosen by students who differ in their individual characteristics from those who enroll in low-SEC schools. As a result, the observed compositional effect may be overestimated due to unaccounted individual differences. Experimental and quasi-experimental designs should be applied to overcome the self-selection bias and evaluate the causal relationship between school type and academic achievement. Of all the literature reviewed, only one publication used a quasi-experimental framework and revealed a positive impact of primary school SEC on students' mathematics achievement growth [Belfi, Haelermans, De Fraine 2016]. There are no findings on the influence of school composition on academic performance in middle or high school yet.

This study, designed with consideration of criticism for prior research and its methods, seeks to assess the impact of school SEC on student achievement that is independent from individual student characteristics. Along with regression analysis, traditionally applied in most publications, this study also uses a quasi-experiment to compare the results. The main research question is articulated as follows: what is the effect of one year of attending a low- vs. high-SEC school on academic achievement?

**1. Research
Methodology****1.1. Data**

The study uses data from the panel study Trajectories in Education and Careers (TrEC)¹. This project started in 2011, when eighth-graders from 210 schools in 42 regions of Russia participated in the Trends in International Mathematics and Science Study (TIMSS). The sample, composed of 4,893 respondents, was representative of Russian eighth-graders in 2011. The survey assessed student achievement in mathematics and science and also collected contextual data on school and family characteristics. At the end of the 9th grade, the same sample participated in the Programme for International Student Assessment (PISA), which measured literacy in mathematics, science, and reading. The original sample for the present study included 4,399 students who were respondents in both assessments. The final sample consists of those who did not change school in grades 8–9.

1.2. Variables

Information for the longitudinal study was gathered at two levels: student (including student's family) and school. The study makes use of variables corresponding to both levels. All interval variables included in analysis were standardized to a mean of 0 and standard deviation (SD) of 1. Descriptive statistics for non-standardized variables is presented in Appendix 1.

1.2.1. Covariates

A few variables reflecting the school characteristics and the main sociodemographic parameters of students were used as control variables.

At the student level, gender was controlled for by coding girls as '1' and boys as '0'. Student age in grade 8 was treated as an interval variable derived from the month and day of birth. Ethnicity was conventionally assessed through the prevalence of speaking Russian at home, where "Always" was coded as '1', and "Almost always", "Sometimes", and "Never" were coded as '0'.

Making allowance for previous-year achievement is indispensable to ensure accurate estimation of the compositional effect [Armor, Marks, Malatinszky 2018]. For this purpose students' performance in TIMSS-2011 mathematics and science was considered in analysis. TIMSS uses a 1,000-point scale with five plausible values (PV), which were assigned to every student and averaged to calculate the mean achievement score in two subjects.

Individual SES has been traditionally considered to have a tripartite nature that incorporates parental income, parental education, and parental occupation [Sirin 2005]. Studies examining the school composition effect often use parental education alone, as it appears to be the strongest predictor of SES [Buckingham, Wheldall, Beaman-Wheldall 2013]. Besides, questions about this component are unlikely to remain unanswered by respondents, compared to the other components of SES. For this reason, parental education is used in the

¹ <http://trec.hse.ru/>

present study as a characteristic of SES at both student and school levels. The TIMSS variable describing parents' highest level of education was used as a basis for constructing a variable coded as '1' if a student had at least one parent with higher education and '0' if both parents had no degree.

School SEC is represented as a school-level aggregated SES (parental education), specifically as a percentage of students with at least one parent with a degree. A higher percentage means a higher proportion of advantaged students, hence a higher level of SEC. Since the sample consisted of students from the same cohort, the indicator of school composition was based on observations within that cohort only. Here it is assumed that different cohorts within the same school don't differ significantly in their social composition. In addition to the percentage of high-SES students, SD for this variable at school was added as a source of additional information about the influence of student heterogeneity on the school composition effect.

At the school level, allowance was made for the size of locality. Three types of localities were identified: cities ($\geq 100,000$ inhabitants), towns (15,000–100,000), and rural settlements ($< 15,000$). All the three types were included in analysis as individual dichotomous variables. School type was also registered as a dichotomous variable with '1' for gymnasiums, specialized schools, and regular schools offering gymnasium classes, and '0' for other types of schools. School size was treated as an interval variable reflecting the total number of students enrolled in a school. Additionally, analysis took account of ethnic school composition, expressed as a percentage of eighth-graders who always speak Russian at home.

- 1.2.2. Dependent variable Academic achievement at the end of the 9th grade was assessed through performance in PISA-2012. Students' scores in two subjects, mathematics and science, were used in analysis. Each subject was analyzed separately. Students' performance was assessed on a 1,000-point scale with five PVs. As with TIMSS, the PVs were used to calculate the mean.
- 1.2.3. Treatment variable The treatment variable, based on school SEC, was used for the quasi-experiment. Distribution of the variable at the school level was used for identifying low-SEC (the bottom 40%) and high-SEC (the top 40%) schools. Attending a low-SEC school in the 9th grade was coded as '1'. It means that in this study learning at school with a low-SEC is considered as intervention. Hence, ninth-graders attending a high-SEC school formed the control group, and the treatment variable in this case was equal to 0. Students enrolled in schools in the middle 20% of the distribution were excluded from analysis at the stage of quasi-experimental effect assessment. In this research, the treatment variable is treated as complex, in a broad sense meaning that a student attends a specific type of school with certain composition. As

a result, all the learning process characteristics that may be associated with school composition in the 9th grade are qualified as treatment. Which learning characteristics exactly are associated with the effect of school composition on outcome variable is beyond the scope of this article.

1.3. Analysis strategy

Assessment of the compositional effect is methodologically different from merely searching for achievement differences related to differences in the social composition of students [Harker, Tymms 2004]. A compositional effect exists when the school-level aggregated variable makes a significant contribution to the explanation of outcome variance after controlling for the same variable at the individual level. In contrast to studies that measure the relationship between school composition and student achievement [Yastrebov et al. 2014; Kosaretsky, Grunicheva, Pinskaya 2014], this one follows methodology for the compositional effect assessment.

At the first stage of data analysis, linear multilevel regression models were used to measure the compositional effect for the whole sample of schools. Two groups of models were constructed, one for mathematics scores and one for science scores in PISA-2012. The interval variable of the percentage of students with at least one parent with higher education was used as an indicator of school composition. Since measurement of the compositional effect required adding individual SES and prior attainment to the model, these parameters were used as control variables along with the other covariates. TIMSS scores in mathematics and science had been attained by students before the 9th grade, so they could serve as an indicator of prior achievement for the respective subjects in PISA-2012. A random intercept fixed slope model was applied to assess the compositional effect. Explained proportion of the variance was estimated using the formula proposed by Tom A. B. Snijders and Roel J. Bosker [Snijders, Bosker 1994]. Regression models of the first and second levels looked as follows:

$$(1) Y_{ij} = \beta_{0j} + B_1 \times (\text{individual characteristics})_{ij} + \varepsilon_{ij},$$

where Y_{ij} is the i -th student's PISA-2012 score of school j in mathematics or science; β_{0j} is school's mean PISA-2012 score, unrelated to the covariates included in the model; B_1 is regression coefficients reflecting the relationship between students' individual characteristics and their PISA-2012 performance; and ε_{ij} is level 1 residual.

$$(2) \beta_{0j} = Y_{00} + C_{01} \times (\text{school characteristics})_j + \mu_{0j},$$

where β_{0j} is the same as in (1); Y_{00} is mean PISA-2012 score in the school sample; C_{01} is regression coefficients reflecting the relationship between school characteristics and PISA-2012 performance; and μ_{0j} is level 2 residual.

Next, the propensity score matching (PSM) method was applied. The basic idea of the matching method consists in finding, for each observation in the treatment group (low-SEC school students), statistical “twins” in the control group (high-SEC school students), i. e. students who are as similar as possible in their observable characteristics. The method is used to balance the sample by partially solving the problem of self-selection into high- and low-SEC schools and to measure the achievement gap based on observations that only differ in the type of school. Performance disparities in the matched sample will show the compositional effect that is unrelated to the individual and school characteristics included in the model.

Matching begins with selecting the covariates—the variables that will be used to find similar observations. There are various strategies and no uniform procedure for covariate selection. One of the widely used strategies consists in selecting variables that demonstrate a significant correlation with the dependent variable even if they are not related to the distribution between the control and treatment groups. Inclusion of factors associated with distribution into groups alone may increase the standard error of the variable of interest [Cuong 2013]. Being enrolled in a school with a certain SEC by the 9th grade—that is, distribution into groups—can be determined by initial school choice or school change before the 8th grade. School choice may be affected, in some way or another, by family’s socioeconomic status, place of residence, ethnicity, student’s abilities, and the type and ethnic composition of the school. Academic achievement (separately in mathematics and science) may be related to all the control variables used at the previous stage of analysis. According to the strategy adopted, the final set of covariates contained the following characteristics that were significantly related to academic achievement and distribution into groups: gender, age, family SES, prior attainment, and school size.

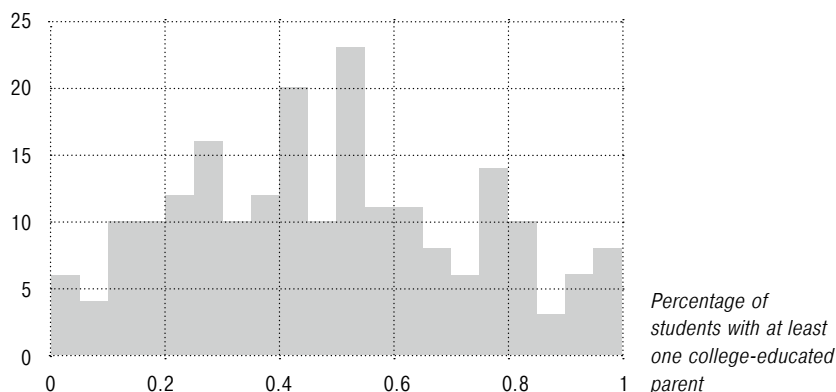
Further matching, with due regard for the variables selected, was carried out by constructing a logistic regression model reflecting the likelihood of a student being assigned to the treatment group based on that student’s covariate information, and by calculating the propensity score (PS). Similar observations were found using the methods of radius matching and Mahalanobis distance matching [Guo, Fraser 2014]. Covariate balance after matching was assessed using *t*-tests that measured differences between the control group and the treatment group before and after matching. *T*-test was also used to measure the effect of attending a low-SEC school as compared to attending a high-SEC school (average treatment effect on the treated) in the matched sample.

2. Results

2.1. Assessing the relationship between school SEC and academic achievement

Russian schools differ quite markedly in their socioeconomic composition (Figure 1). The indicator of school composition (percentage of students with at least one parent with higher education) is on aver-

Figure 1. **Socioeconomic composition of Russian schools, based on TIMSS-2011**



age 48% across 210 educational institutions, ranging from 40 to 60% for most schools. Meanwhile, it exceeds 95% in eight schools, and six institutions have no high-SES students at all.

Regression analysis shows that, despite a considerable variation in scores at the individual level, the distribution of students among schools explains 38 to 41% of the variance in PISA-2012 performance (Table 1). Nearly half of the differences in academic achievement can be explained by student's belonging to a particular type of educational institution. The variance patterns in Russia are similar to those reported in international literature.

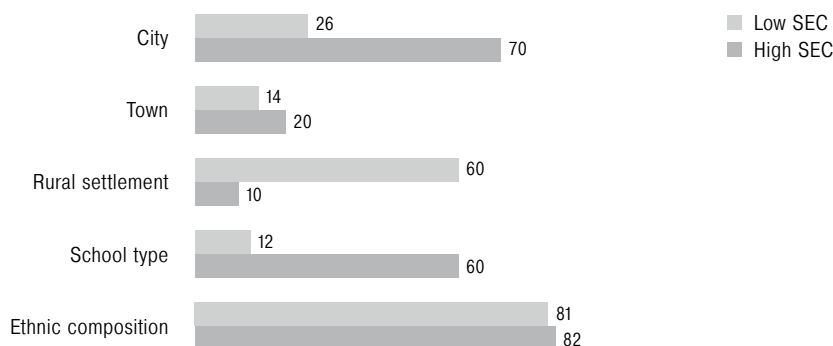
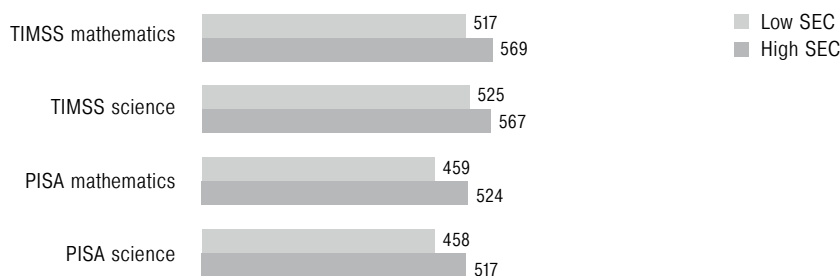
The next models also included control variables but made no allowance for previous-year achievement. TIMSS-2011 scores in mathematics and science were added to the last two models. Using the indicator of prior attainment in the subject improves the model quality significantly, percentages of explained variance reaching 55% in mathematics and 50% in science. Meanwhile, the effects of other student and school characteristics on academic achievement become noticeably weaker for all parameters.

The positive correlation between school SEC and PISA performance in mathematics shrinks almost twice when previous-year TIMSS scores are added to the model. Nevertheless, school composition remains a significant characteristic in both subjects, being related to academic performance stronger than any other school or individual factor. On average, a 25% increase in school SEC improves PISA-2012 performance by 58 score points in mathematics and by 53 points in science. Schools SD in students SES was found to be insignificant: homogeneity has no impact on success in either of the two subjects. In addition, territorial inequality becomes insignificant or changes the direction of correlation when school composition is controlled for.

Table 1. Results of multilevel regression modelling of relationship between school SEC and PISA-2012 performance in mathematics and science

	PISA-2012 mathematics			PISA-2012 science		
Gender (1—female)		-0.13*** (0.03)	-0.10*** (0.02)		-0.04 (0.03)	0.05** (0.02)
Age		-0.07*** (0.02)	-0.04*** (0.01)		-0.07*** (0.02)	-0.06*** (0.01)
Ethnicity (1—always speaking Russian at home)		0.06 (0.05)	0.05 (0.04)		0.07 (0.05)	0.03 (0.04)
Socioeconomic status (1—at least one parent with degree)		0.21*** (0.03)	0.07*** (0.02)		0.23*** (0.03)	0.07*** (0.02)
TIMSS-2011			0.65*** (0.02)			0.61*** (0.02)
Socioeconomic composition		1.25*** (0.18)	0.71*** (0.14)		1.09*** (0.19)	0.68*** (0.15)
SEC SD		-0.80** (0.37)	0.07 (0.31)		-0.71* (0.38)	0.04 (0.3)
City (1—over 100,000 inhabitants)		-0.12 (0.1)	-0.20** (0.08)		-0.04 (0.1)	-0.08 (0.08)
Town (1—15,000 to 100,000 inhabitants)		0.02 (0.12)	-0.08 (0.08)		0.05 (0.12)	0.00 (0.09)
School type (1—gymnasiums, regular schools offering gymnasium classes, specialized schools)		0.18*** (0.05)	0.04 (0.03)		0.16*** (0.05)	0.03 (0.03)
School size		0.02 (0.05)	0.06* (0.03)		-0.02 (0.05)	0.02 (0.03)
Ethnic composition		0.02 (0.04)	0.02 (0.03)		0.10** (0.05)	0.06* (0.04)
Constant	-0.06 (0.05)	-0.32 (0.2)	-0.28* (0.17)	-0.06 (0.04)	-0.40* (0.23)	-0.40** (0.19)
Between-group variance	0.41	0.21	0.12	0.38	0.20	0.14
Within-group variance	0.59	0.56	0.32	0.62	0.58	0.35
ICC	0.41	0.27	0.28	0.38	0.26	0.28
R^2 (Level 1)		0.21	0.55		0.19	0.50
R^2 (Level 2)		0.42	0.66		0.39	0.60
Number of students	4,399	2,963	2,963	4,399	2,963	2,963
Number of schools	208	205	205	208	205	205

Note: Standard errors of measurement in parentheses. All interval variables (including the dependent variable) are standardized. Confidence level—*90%; **95%; ***99%.

Figure 2. **Characteristics of low- and high-SEC schools, %**Figure 3. **Academic achievement of students attending high- vs. low-SEC schools**

2.2. Comparing the effect of one year of attending a low- vs. high-SEC school by propensity score matching

To compare the independent contribution of school SEC to academic achievement, a matched sample was formed from the bottom 40% and the top 40% of the distribution of schools by the percentage of students with at least one parent with degree. The database contained 85 low-SEC schools and 83 high-SEC schools (Appendix 1). The percentage of students with educated parents in these two groups was on average 23 and 74%, respectively. Apart from the socioeconomic status of students, schools with different SEC in Russia also differ in location and type (percentage of gymnasiums and regular schools offering gymnasium classes) (Figure 2).

There are clear disparities in academic achievement between low- and high-SEC schools (Figure 3), the gaps in PISA scores between students in different types of schools being wider than those in TIMSS performance. On the whole, this supports the hypothesis that PISA correlates stronger than TIMSS with student SES. Anyhow, the difference in scores is significant for both assessments.

Figure 4. **Mean PISA-2012 mathematics scores of students from low- and high-SEC schools before and after sample matching**

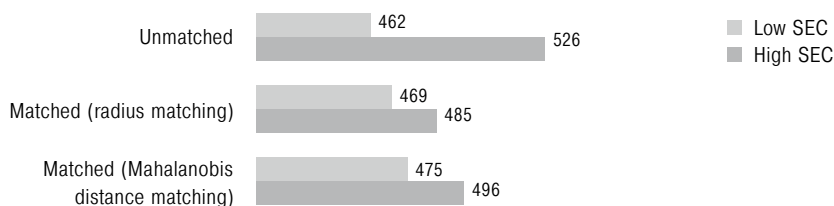
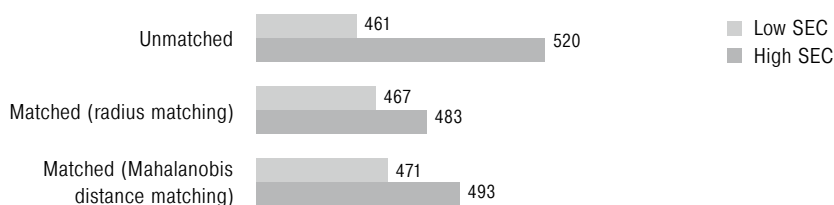


Figure 5. **Mean PISA-2012 science scores of students from low- and high-SEC schools before and after sample matching**



The PSM method was applied to answer the main research question. The final sample was composed of ninth-graders with similar characteristics enrolled in different types of schools. Depending on the exact method, selection resulted in matched pairs for 2,587 and 2,810 students in mathematics and for 2,851 and 2,586 students in science. In each case, there were no significant differences in the individual characteristics of students from different types of schools (Appendices 2, 3, 4, and 5).

In the matched samples, whichever method was used, the gap in PISA-2012 mathematics performance (Figure 4) at the end of the 9th grade between students from low- and high-SEC schools is reduced dramatically. Still, the difference remains statistically significant ($t = -3.09$ and $p < 0.01$; $t = -4.41$ and $p < 0.01$). For students with similar observable characteristics, one year of attending a low-SEC school results in an average decrease in mathematics performance by 0.23 SD, or 19 score points.

Similar results were obtained for academic achievement in science (Figure 5). In both subjects, attending a low-SEC school as a ninth-grader has a negative impact on academic performance regardless of student characteristics ($t = -2.87$ and $p < 0.01$; $t = -4.19$ and $p < 0.01$). PISA-2012 science scores obtained by students in low-SEC schools were 0.25 SD, or 19 score points, lower than the scores of students who spent their 9th grade in high-SEC schools.

3. Limitations This study has a few important limitations, primarily concerning the data and the method.

First, analysis of compositional effects requires quite a wide range of data. Ideally, assessment of prior attainment would imply using an indicator of student performance at the very baseline or before being enrolled in a particular school. When the longitudinal study started in 2011, students were already enrolled in the 8th grade. Their TIMSS scores in mathematics were largely explained by the educational institution itself and could not be considered as a pure indicator of student ability, which depended on individual characteristics only. Furthermore, TIMSS and PISA differ in content. Strictly speaking, their results cannot be used as a single indicator measured at different times. The present study makes an assumption that there are similarities between the two tests and that their scores may be used as comparable indicators of student achievement to a certain extent. Finally, assessment of school composition in this study is restricted to one cohort of students. More reliable within-school analyses will require data on the socioeconomic status of every single student enrolled. These limitations narrow the interpretation down to assessing the effect of only one year of attending schools of different types on the academic success of only one cohort of students.

Second, PSM is a quasi-experimental method, applied only as an attempt to bring the conditions closer to the gold standard for causal inference. Only measurable student and school characteristics can be used for sample matching. It is not impossible that there were no disparities in unobservable characteristics between the students of high- and low-SEC schools in the matched sample. Therefore, inferences were made about the compositional effect that was at least unrelated to the analyzed student and school characteristics, which are key factors of academic achievement.

Third, this study lacks analysis on the reading subject or Russian language, which prevents any inferences about the universal effect of school SEC on academic achievement. Assessment of the impact on other subjects could possibly add insight to the findings of this paper.

- 4. Conclusion**
- School socioeconomic composition is one of the most powerful factors of academic achievement, compared to other individual and school characteristics.
 - Low school SEC makes an independent negative contribution (up to 0.25 SD) to mathematics and science achievement.
 - Earlier studies that did not use quasi-experimental designs tend to overestimate the impact of SEC by at least one third.
 - SEC-related disparities in academic achievement cannot be fully explained by school location.

Analysis results show that school SEC is an independent factor contributing to inequality of educational outcomes in Russia. The influence of school SEC on academic achievement in mathematics and science is stronger than that of any other school or individual characteristic. Even previous-year achievement is related weaker to performance, regression analysis shows.

Quasi-experiments also confirm the significant effect of school composition. Children of the same gender and age with similar levels of performance and socioeconomic status, attending schools of comparable size, differ in their progress by the end of the 9th grade if they get into schools of different SEC. In a year, a student attending a low-SEC school will perform on average a quarter of SD lower in PISA than a student attending a high-SEC school. That is, Russian students with comparable levels of ability differ in their opportunity to succeed, which is determined by a school parameter over which they have no control. The effect differs little across the subjects, which may indicate the universality of school SEC impact on academic achievement in general.

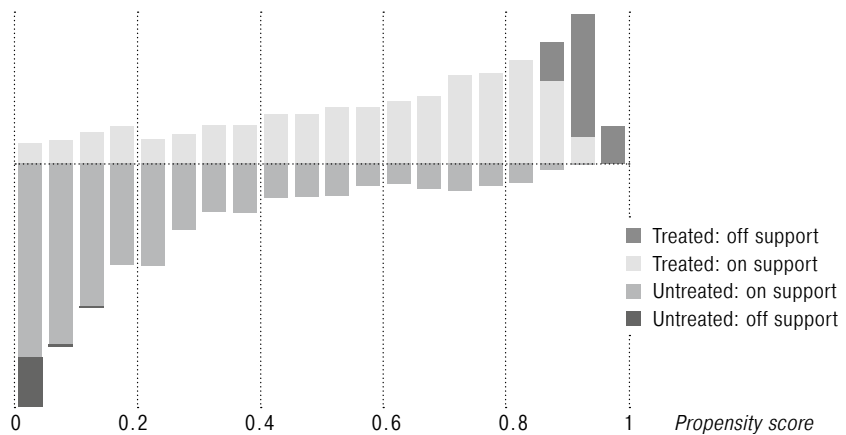
The effect measured in multilevel regression analysis is nearly three times higher than the one obtained by a quasi-experiment. However, it is significant in both cases. Even though earlier studies in the field that did not use quasi-experimental designs tend to overestimate the role of the compositional effect quite considerably, they still make valid inferences about the contribution of this indicator unrelated to individual student characteristics. Meanwhile, where the compositional effect derives from remains unclear. Presumably, the causes may be rooted in the content and organization of learning, as well as school resources, teacher characteristics, teaching practices, and peer effects [Danhier 2016; Demanet, Houtte 2011; Opdenakker, Damme 2001; Perry 2012; Hanushek et al. 2003; Palardy 2014].

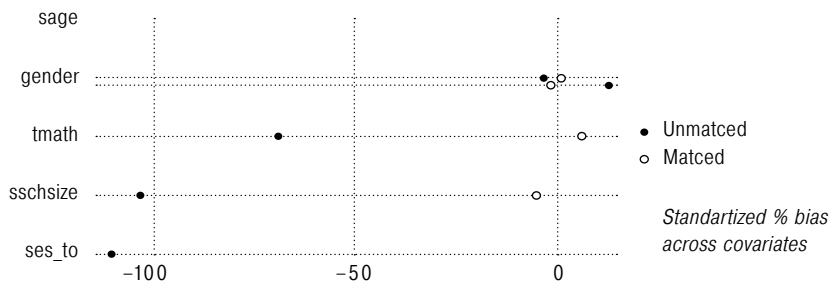
In the recent years, Russia has been retaining a medium level of school socioeconomic segregation [Kosaretsky, Froumin 2019]. Concentration of disadvantaged students in the same schools may set off the negative effects of low school SEC. This may affect institutions that have never been a concern before: socioeconomic composition can be low in well-resourced schools and schools located in cities or good neighborhoods. Selective support of such schools requires further investigation into the genesis of the compositional effect and a detailed analysis of learning environment components that contribute to the reproduction of inequality through school socioeconomic composition.

Appendix A1. Descriptive Statistics

	All schools			Low SEC			High SEC		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Student characteristics									
Gender	4,893	49%	50%	1,561	48%	50%	2,313	50%	50%
Ethnicity	4,886	83%	37%	1,559	82%	38%	2,309	83%	38%
Age	4,893	14.74	0.47	1,561	14.77	0.51	2,313	14.70	0.44
SES	4,372	0.53	0.50	1,356	0.25	0.43	2,128	0.74	0.44
TIMSS mathematics	4,893	538.98	78.28	1,561	517.09	69.19	2,313	569.29	77.90
TIMSS science	4,893	542.46	72.78	1,561	525.02	67.63	2,313	566.82	72.49
PISA mathematics	4,399	492.22	81.54	1,431	459.11	72.51	2,068	523.65	78.27
PISA science	4,399	488.97	78.02	1,431	458.04	71.03	2,068	516.97	76.33
School characteristics									
School size	207	628.37	375.55	83	437.47	317.32	82	816.93	357.35
City	210	48%	50%	85	26%	44%	83	70%	46%
Town	210	20%	40%	85	14%	35%	83	20%	41%
Rural settlement	210	32%	47%	85	60%	49%	83	10%	30%
School type	148	33%	47%	57	12%	33%	60	60%	49%
Ethnic composition	210	83%	24%	85	81%	29%	83	82%	21%
SEC	210	48%	25%	85	23%	11%	83	74%	14%
SEC SD	210	43%	12%	85	40%	13%	83	41%	12%

A2. PSM results for PISA-2012 scores in mathematics (radius matching: caliper=0.004)

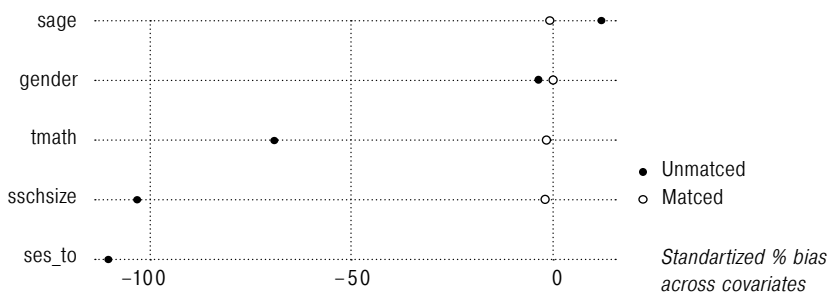




Variable	Matched/ unmatched	Mean: treatment group	Mean: control group	<i>t</i>	<i>p</i> > <i>t</i>
Gender	Unmatched	0.49753	0.5146	-0.93	0.354
	Matched	0.50842	0.50446	0.18	0.859
Age	Unmatched	0.01845	-0.10417	3.38	0.001
	Matched	-0.01836	-0.00078	-0.39	0.694
SES	Unmatched	0.24959	0.73128	-29.79	0.000
	Matched	0.3003	0.28543	0.73	0.463
TIMSS-2011	Unmatched	-0.29077	0.36175	-18.84	0.000
	Matched	-0.14502	-0.19828	1.28	0.200
School size	Unmatched	-0.52933	0.41776	-27.82	0.000
	Matched	-0.35715	-0.30585	-1.46	0.144

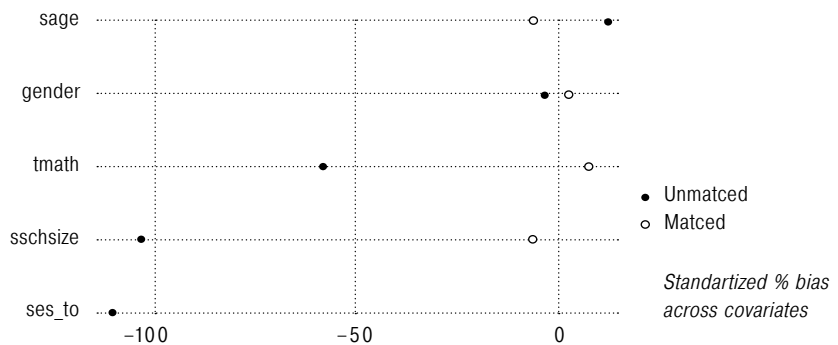
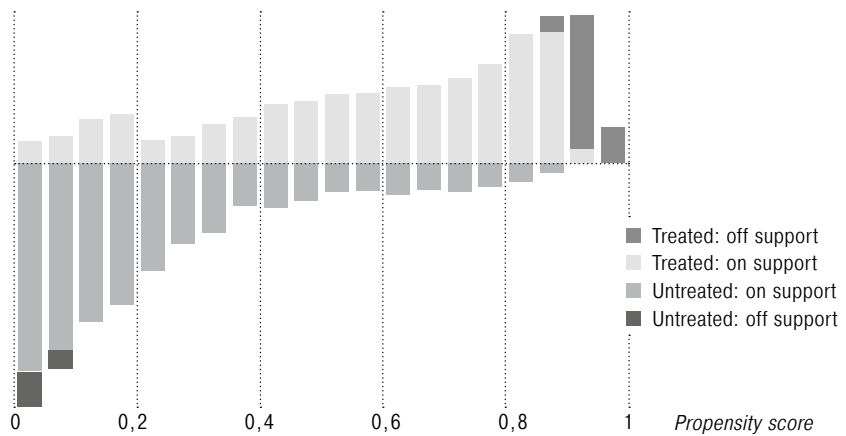
A3. PSM results for PISA-2012 scores in mathematics
(Mahalanobis distance matching, caliper = 0.2)

	Off support	On support	Total
Comparison group	0	1,883	1,883
Treatment group	510	704	1,214
Total	510	2,587	3,097



Variable	Matched/ unmatched	Mean: treatment group	Mean: control group	<i>t</i>	$p > t $
Gender	Unmatched	0.49753	0.5146	-0.93	0.354
	Matched	0.50568	0.50568	-0.00	1.000
Age	Unmatched	0.01845	-0.10417	3.38	0.001
	Matched	0.02943	0.03147	-0.05	0.961
SES	Unmatched	0.24959	0.73128	-29.79	0.000
	Matched	0.3125	0.3125	0.00	1.000
TIMSS-2011	Unmatched	-0.29077	0.36175	-18.84	0.000
	Matched	-0.03267	-0.0178	-0.36	0.722
School size	Unmatched	-0.52933	0.41776	-27.82	0.000
	Matched	-0.28537	-0.27092	-0.36	0.716

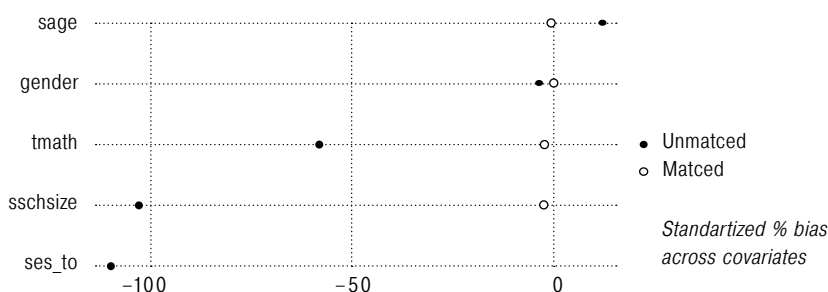
A4. PSM results for PISA-2012 scores in science
(radius matching: caliper = 0.005)



Variable	Matched/ unmatched	Mean: treatment group	Mean: control group	<i>t</i>	<i>p</i> > <i>t</i>
Gender	Unmatched	0.49753	0.5146	-0.93	0.354
	Matched	0.50213	0.50213	0.00	1.000
Age	Unmatched	0.01845	-0.10417	3.38	0.001
	Matched	0.04677	0.05901	-0.29	0.769
SES	Unmatched	0.24959	0.73128	-29.79	0.000
	Matched	0.30156	0.30156	-0.00	1.000
TIMSS-2011	Unmatched	-0.23932	0.32676	-15.97	0.000
	Matched	-0.02749	-0.00544	-0.50	0.620
School size	Unmatched	-0.52933	0.41776	-27.82	0.000
	Matched	-0.27637	-0.25258	-0.59	0.554

A5. PSM results for PISA-2012 scores in science
(Mahalanobis distance matching, caliper = 0.2)

	Off support	On support	Total
Comparison group	0	1,883	1,883
Treatment group	511	703	1,214
Total	511	2,586	3,097



Variable	Matched/ unmatched	Mean: treatment group	Mean: control group	<i>t</i>	<i>p</i> > <i>t</i>
Gender	Unmatched	0,49753	0,5146	-0,93	0,354
	Matched	0,50213	0,50213	0,00	1,000
Age	Unmatched	0,01845	-0,10417	3,38	0,001
	Matched	0,04677	0,05901	-0,29	0,769
SES	Unmatched	0,24959	0,73128	-29,79	0,000
	Matched	0,30156	0,30156	-0,00	1,000
TIMSS-2011	Unmatched	-0,23932	0,32676	-15,97	0,000
	Matched	-0,02749	-0,00544	-0,50	0,620
School size	Unmatched	-0,52933	0,41776	-27,82	0,000
	Matched	-0,27637	-0,25258	-0,59	0,554

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