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CONTEXTUALIZING ACADEMIC PERFORMANCE IN RUSSIAN SCHOOLS: SCHOOL CHARACTERISTICS, THE COMPOSITION OF STUDENT BODY AND LOCAL DEPRIVATION[5]

This study focuses on how social contexts promote disparities in academic performance between Russian high schools. In particular, we investigate how a school's average Unified State Examination (USE) scores in Russian and mathematics relate to the social composition of its student body, its material and human resources, and local deprivation. We develop a two-level hierarchical regression model to analyze data from school profiles collected in two Russian regions (Yaroslavskaya Oblast' and Moskovskaya Oblast') during the 2011-12 academic year. Both social characteristics of the student body and the school's material and human resources were associated with academic performance. However, after controlling for the characteristics of pupils and schools, our study did not discover any significant independent effects of the local context. In conclusion, we discuss the implications of these findings with regard to developing contextualized measures of academic performance in Russia, the limitations of current research and suggest several possibilities for its empirical development.

JEL codes: I21, I24

Keywords: school context, school resources, local deprivation, academic performance, educational inequality

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1. Introduction

Evaluating school performance in an objective and transparent manner is one of the most pressing issues in assessing the quality and management of education in Russia. One approach to this is to simply look at the results of standardized tests, such as the Unified State Examination (USE). However, this does not account for the fact that schools operate under different social conditions. Over the past several years this has been recognized in many educational systems across the world, where it has become common that the assessment of school performance accounts for external factors that affect student results and over which schools themselves have little or no control. Education policymakers understand that an assessment of school quality is impossible without considering who is being taught and under what conditions. The relationship between the educational achievements of students and the social and economic characteristics of their families has become a universally recognized fact, confirmed by numerous international studies.

The external (or contextual) factors which are usually considered when assessing schools and making administrative decisions (including determining the amount of funding and teacher salaries, and implementing targeted support programs) are most often the socioeconomic characteristics of students. Considering socioeconomic factors helps identify educational institutions where the student body is composed of poorer families so that they receive the additional support required to sustain quality education. There is another positive effect from accounting for contextual factors: identifying schools which display a better capacity for improving the results of students from disadvantaged families can help select the best practices for improving the situation at other schools.

Unfortunately, such contextualization practices are almost completely overlooked in Russia's education system. The aim of this paper is to explicate why and how this may be important for the sake of improving education in Russian schools.

We use data from a survey of schools conducted in two Russian regions to investigate how the average USE results at the school level are related to the socioeconomic composition of the student body, school material and human resources, and the level of local deprivation.

Section 2 presents the general conceptual framework of our study and relates it to the relevant literature. Section 3 presents our data and discusses the scope and capacity of current Russian statistics with respect to accounting for the local context. Section 4 describes the statistical models we use in this study. Section 5 presents and discusses the results of our statistical analysis. Section 6 concludes and discusses the limitations of the present analysis.

2. The literature review and the conceptual model

Social inequalities in education and in particular the effect of the local context on educational outcomes have long been studied in sociology and the economics of education. Ever since the publication of the Coleman Report [Coleman 1966] researchers have drawn attention to the fact that

the socioeconomic standing of parents and the social composition of the student body in general have a significant impact on the academic achievement of children.

The literature in this field is voluminous [for reviews, see White 1982; Sirin 2005; Breen, Jonsson 2005]. Generally, it suggests that students from families with a higher socio-economic status (however measured) have certain advantages in the educational outcomes, whether it is the probability of the transition to the next educational level, or academic performance. In economics and sociology there are multiple theories that explain the association between socio-economic background and academic outcomes from different perspectives [Becker 1993; Breen, Goldthorpe 1997; Erikson, Jonsson 1996; Coleman 1988; Bourdieu, Passeron 1980]. All of them suggest that children from socially advantageous families benefit in education mainly because of higher material and cultural parental investments. Recent research in behavioral genetics suggests that part of the association between social background and educational results may be accounted for by genetic inheritance [Bowles, Gintis, Groves 2008].

It is not our aim here to discuss these theories in detail. However, what should be mentioned is the fact that social inequality in educational outcomes must be taken into account when assessing the efficiency of the elements of educational systems. Hence, accounting for socioeconomic differences in evaluating school efficiency has become a tradition in many developed countries [see Measuring Improvements… 2008 pp.135-137, for a list of contextual school data recorded in some OECD countries]. The typical characteristics of families (or the aggregate social characteristics of the student body) accounted for in their national evaluation systems usually include the level of parents' education and family income. In some countries these are substituted by data on various forms of social support received directly by students or their families (e.g. the eligibility status in the National School Lunch program in US [Improving the Measurement of Socioeconomic Status… 2012]). The status of unemployment among parents is another way of approximating family welfare (e.g., in Norway). Accounting for minority ethnicity, migrant status and/or competence in the native language among students is another tradition in evaluating school performance and research in inequality of educational attainment [e.g. Borjas, 1995].

In this paper, we incorporate this long-established relationship between the social composition of the student body and educational achievements in schools as one of the building blocks in our conceptual framework presented in Figure 1 (*link 4*).There may be an alternative explanation to this relationship, which is why in our diagram this type of connection is shown as reciprocal: higher academic achievement in certain schools may be perceived as a sign of a better school, thus families to compete with each other in order to send their children there. Schools give preference to families that already have high social and cultural status, as this enables them to secure better results with relatively little effort. This may be quite problematic for the purposes of evaluating school efficiency, since it reinforces the self-selection bias [e.g. Bifulco 2002], which is hard to address in the absence of the individual-level (and preferably longitudinal) data on the social origins and the academic achievement of students. In other words, we must admit that without such data it would be hard to know whether better school performance is caused by favorable social context or it merely acts as an attractor to families with higher social standing.

Figure 1. The hypothesized impact of various sets of factors on academic performance in schools

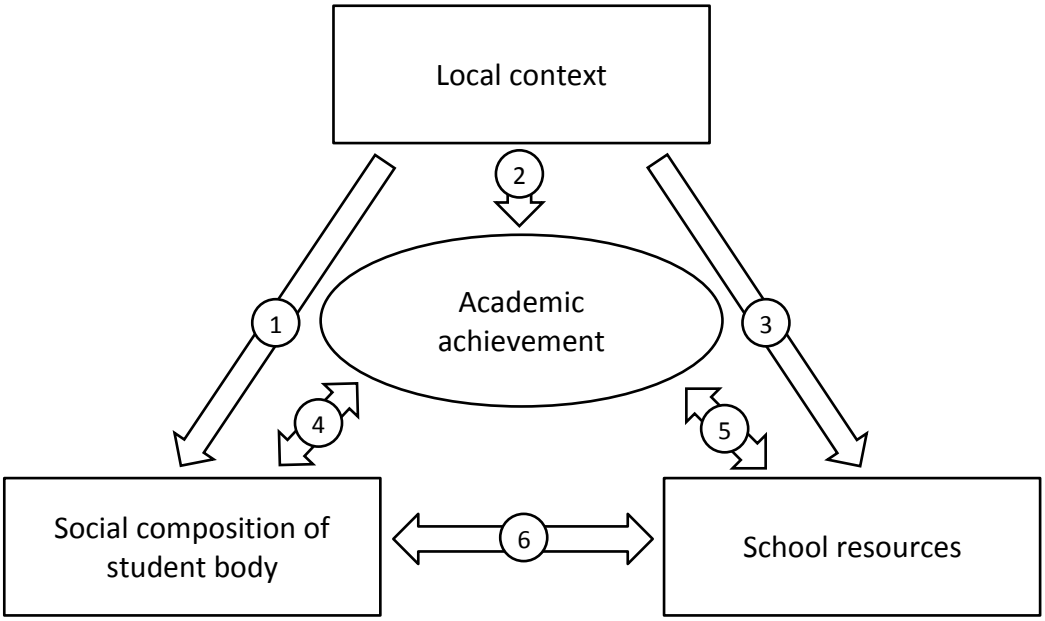

Fig. 1. The hypothesized impact of various sets of factors on academic performance in schools

Another relationship in our conceptual model (*link 5*) draws on the literature that evaluates how the performance of schools is affected by the resources they possess, e.g. educational facilities, financial support, quality of teachers and school programs. This may look trivial since common sense suggests that it has a direct impact on educational opportunities provided to the children. However, the research shows that after accounting for all conceivable contextual factors (i.e. ones over which schools have little direct control), the relationship between the availability of resources and the academic achievement of students has been reported as weak and statistically unconvincing [e.g. Hanushek 1989; Woessmann 2005]. And although some recent work which draw on better data and more advanced statistical techniques confirm such a relationship, it was found to be still fairly limited [e.g. Hedges, Laine, Greenwald 1994; Rivkin, Hanushek, Kain 2005; Rockoff 2004]. Nevertheless, the key to evaluating the true effectiveness of educational institutions – i.e. defining its optimal financial and organizational arrangements – is located within this set of factors, which is why they must not be ignored.

Yet again, the statistical association between school resources and average academic performance may be explained by the effect of resources on performance, but also the other way round as better schools may, for example, attract teachers of better quality or enjoy larger financial support from the state.

Another component of the conceptual model is represented by relationship between school resources and the characteristics of the student body (*link 6*). When selecting schools for their children, families pay attention to the kind of teachers who work at the school, the school principal, and how effectively the school manages its budget and/or additional money invested by parents. The choice of school might be significantly impacted by the socioeconomic and cultural characteristics of the family. That being said, the families themselves and the resources they possess

can also sometimes be considered as part of the school's assets (hence the reciprocal direction of cause and effect). They can actively participate in making key decisions concerning the improvement of the educational process, invest their resources in schools, and even serve as a marker of social status for other households which make decisions about which schools to send their children to. The main institutional mechanisms that ensure this relationship are parent committees or parent meetings at which money is collected to cover various school needs, and through which families can collectively communicate suggestions to school staff which might affect the quality of education.

Finally, we come to what we believe is the element of novelty in the context of existing research on Russia's case – the impact of the *local context* on the functioning of educational institutions. In other words, rather than just analyzing the schools themselves, we also consider them in the context of socioeconomic conditions of the territory in which they are located. As is shown in Figure 1, there are three main channels through which the local context might be related to academic performance in schools. First of all, the territory in which a school is located may be regarded as a direct provider of its resources (*link 3*) – e.g. it provides human resources and finances. This is one of the main reasons behind the fact that urban schools are generally considered to be more advantageous than rural schools: as a rule, urban schools receive more generous funding, and it is easier for them to search and find better qualified teachers. Beyond that a school's location may also affect the social composition of its student body (*link 1*): as a rule, urban citizens are better educated and enjoy greater welfare than people from rural areas. This causes a respective bias in the composition of students between urban and rural schools, and affects academic performance.

But the associations of the local context with academic performance through the student body and resource availability only represent the trivial mechanisms by which local deprivation might affect the performance of educational institutions. It gets far more interesting to consider the less obvious contextual relationships which are connected to the "neighborhood effects" (*link 2*). One of the first researchers to observe how neighborhood deprivation might lead to perpetuating the disadvantages of its inhabitants was Wilson [1987]. This study showed how the presence and diffusion of particular role models, social norms and limited expectations in the local community produces a vicious cycle which prevents people from financially and socially disadvantaged families from improving their life chances. In Wilson's view, the deindustrialization of urban areas which accompanied the transition to a post-industrial society in America has caused many successful blue and white-collar workers to permanently migrate from urban centers (as a result of the reduction in the number of suitable jobs). What happened was that this outward migration also took away the benchmarks of successful life management, which could have served as a reference model for those who could not leave. The result was further social degradation of the downtowns, an even larger increase in unemployment and, consequently, the emergence of permanently disadvantaged areas where poverty became the source of even greater poverty. One of the main conclusions from this study is that sustainable reproduction and distribution of success-oriented role models must be supported by real-life experience.

This way of reasoning was further developed by Jencks and Mayer [1990], who also extended it to explain the persistence of educational inequality. The relevance of neighborhood effects to education problems stems from the fact that neighborhoods represent relatively bound areas where young people spend most of their time attending schools and socializing with peers. In other words,

intense interaction with the social environment entails consequences in the form of assimilating behavior models and social norms. By having generalized much empirical research on this subject, Jencks and Mayer concluded that children from low-income families tend to benefit from living in "good" districts, i.e. those with a higher concentration of richer and more successful families, as these districts produce positive contextual effects. These effects manifest themselves through the dissemination and adoption of behavioral norms and ideas about possible life trajectories for which young people strive, which are explicitly (under pressure from the community) or implicitly (in the form of expectations) imposed on them by living in that environment. Researchers distinguish between the "epidemic" effect (personal replication of various stereotypes and norms, including stigmatized ones) among peers and the "collective socialization" effect, when adult role models serve as benchmarks for the younger generation [e.g. Crane 1991; Evans, Oates, Schwab 1992].

The current evidence of how neighborhoods affect educational outcomes of children is also vast[7]. A paper by British sociologists, who studied the performance of schools in Scotland, shows that the level of local deprivation has a sustained negative impact on student achievement, even after taking into account the independent influence of individual abilities, family characteristics and the quality of the schools [Garner, Raudenbush, 1991]. A measure of local deprivation was captured by a synthetic index, which incorporated information about the overall level of unemployment, the level of unemployment among young people, the share of single-parent households, the share of families consisting entirely of retired people, the share of multi-child families, the share of families living in conditions that do not meet housing standards, and the share of disabled people or those suffering from chronic disease. Similar conclusions about neighborhood effects and their impact on a wider range of aspects in adolescent development (from intellectual development in childhood to the chance of successful school completion) were reached by a group of American researchers [Brooks-Gunn et al, 1993], who approximated the local context via the shares of local population with certain income levels.

Jensen and Harris [2003] in their study of education expectations make a peculiar remark about the appropriateness of different measures of local context and the ways in which neighborhoods are identified. Precisely they showed that neighborhood effects get significantly more pronounced, when a dependent variable and its independent predictors have a similar nature: e.g. if student expectations is the dependent variable, the most pronounced predictor for neighborhood influence would be the educational structure of local population, rather than its income structure or unemployment rate. The authors also claim that it is crucial to distinguish between the location of the school and the location of the household residence, since they do not always correlate and can thus reflect different contexts of socialization and social reproduction.

The relevance of local context in accounting for factors which affect academic performance has also been confirmed in a number of other studies [Overman, Heath 2000; Owens 2010; Sykes, Kuyper 2009]. All of the above implies that local context should be regarded as an additional factor, which directly influences the functioning of educational institutions, and it thus has to be accounted for in models that contextualize academic performance along with more traditional indicators.

[7] The local context (or neighborhood-effects) has an impact on a wide range of social phenomena, and is obviously not limited to the problem of education inequality. These effects have also been closely investigated with regard to such issues as crime, deviant behavior (alcoholism, drug addiction, etc.), health inequality, teenage pregnancy, etc. For the most comprehensive review of relevant studies see [Sampson, Morenoff, Gannon-Rowley 2002].

Social inequalities in the Russian educational system have been studied before [Gerber, Hout 1995; Gerber 2000]. More recent attempts to confirm the impact of social background on the academic achievement of Russian schoolchildren have been carried out by Prakhov & Yudkevich [2012] and Pinskaya, Kosaretsky & Frumin [2011]. We also know that in Russia there is an extreme inequality between educational institutions with respect to the social composition of their student body and resources (both human and material), which often correlate, producing even greater disparities in learning opportunities [e.g. Konstantinovsky 1999; Konstantinovsky et al 2006]. Some studies have also looked at the educational inequalities in Russia in the local context [Alexandrov et al. 2012; Sobkin, Pisarsky 1998]. However, Alexandrov et al. [2012] do not focus on academic performance as much as on the educational paths of students, and the local context is investigated as a system of circumstances which determine the most likely scenario for their implementation. Sobkin and Pisarsky [1998], on the other hand, deal with the regional context only, without going down to the more immediate context of municipalities.

This paper contributes to the field by investigating simultaneous effects of social background, school resources and local context on the academic performance of schoolchildren by drawing on data from two Russian regions.

3. Data

The survey that we use in our research was conducted at the school level in two regions, Moskovskaya Oblast' and Yaroslavskaya Oblast'. It was, in the first place, the willingness of the regional administrative bodies to assist in collecting the data. The regions display pronounced differences between schools and municipalities. The data collected include extensive information about the social composition of the student body, 17 indicators and a number of important school characteristics The full list of those indicators is available upon request, although the ones which were used in this particular analysis can be found in Appendix, which also contains basic descriptive statistics for both regions.

Our sample only includes schools which provide complete secondary education, as we rely on average USE scores to evaluate the performance of educational institutions. The particular feature of the USE is that it is taken by the students who enter and complete the non-compulsory stage of secondary education after the 11^{th} grade. USE is preceded by State Final Certification exam (SFC), which is taken by all students upon the completion of the 9th grade (compulsory secondary education). But, unfortunately, we could not use SFC scores to enrich our analysis as the data in which they were provided in social profiles were incomparable between Yaroslavskaya and Moskovskaya Oblast' (because of differences in measurement units and a large number of missing data)

The sample of schools in both regions which provided the social profiles and data on average USE scores covers 1029 institutions for the scores in math and 1033 for the scores in Russian. This accounts for 69% of the total number of schools in Moskovskaya Oblast' (785 completed social profiles out of 1132) and 94% in Yaroslavskaya Oblast' (248 profiles out of 263).

Standardized tests are just one possible means of measuring academic achievement. The efficiency of educational institutions should be evaluated in much broader terms, rather than just by assessing students' ability to pass their final exam. As mentioned above, schools provide more than just knowledge and basic training for children. Their "effects" also include social adaptation of individuals, and developing important skills and competencies, which cannot be directly measured through tests and examinations. A complete notion of school efficiency must account for these outputs as well. However, despite their many limitations, USE results have the advantage of relative availability, comparability and quantification, not to mention that they are institutionally bound with practices which govern university admissions having a deterministic effect on life chances of children.

The data in our sample has a hierarchical *two-level* structure, since we, *first*, look at schools as separate entities, and then consider them in the context of their location which represent the *second level* of analysis.[8] The total number of settlements[9] in the sample of our study is 309, of which 228 are located in Moskovskaya Oblast' and 81 in Yaroslavskaya Oblast'. A little over two thirds of these are rural settlements, which are particularly over-represented in Yaroslavskaya Oblast' (over 80%, or 68 settlements) compared to a much greater urbanization in Moskovskaya Oblast' (around 50%, or 118 settlements).

Until recently, researchers did not have access to statistical data at the level of municipal settlements. The Federal State Statistics Service has only been publishing detailed statistics at the regional level (for instance, the "Regions of Russia" collection). It is unsurprising that there has been virtually no solid research on intraregional variation in contemporary Russia. Perhaps the only exception is the work carried out in the Samara region by Ayvazyan et al. [2006]. Ayvazyan, who has published extensively on measuring the quality of life in Russia, developed a methodology that could be used at both the regional and municipal level. However, the larger share of statistical information required to do the local measurements had to be exclusively provided by the regional statistical office, rather than collected from an open source. As such, despite a number of elegant methodological solutions to create a meaningful index, Ayvazyan's work cannot be used for a systematic and reproducible assessment of local deprivation.

However in 2011 the Federal State Statistics Service opened access to its on-line database containing statistical information from municipal profiles. At present, this database is being completed with new information, a significant portion of which is already available to the users. The data cover various aspects of life at municipal level. In particular it allows researchers to assess 1) the state of housing and communal services; 2) the population's involvement in the system of social welfare; 3) the provision of health services and education; 4) the state of cultural and leisure infrastructure; and 5) the overall socioeconomic situation.

In total, the database includes over 900 statistical indicators for municipalities. However on closer inspection it became clear that the database is still quite fragmented and disorderly, and it certainly is not user-friendly especially when it gets to extracting larger packages of data on each settlement. Because of these limitations, we were forced to skip a number of indicators, such as the density of

[8] This is currently the lowest available level for extracting statistical data. In many other countries, researchers are able to work with data for individual regions within settlements.
[9] The number of settlements with schools.

city communal network, total local budget expenditures, and the number of children registered for preschool.

The Federal Statistics Service provides municipal data for the period 2006-11, although in many cases they were present only for certain years. Where possible, we used the most recent data (2011, as the school data was collected in 2011-12). However, in other cases we had to use the data for earlier years to provide at least some approximation of the selected variables for the maximum range of local areas. And yet we had to drop many indicators because of their incompleteness. Below is the final list of variables related to local areas, which were selected for our analysis:

1. *Total population* (the size of settlement, an approximation of its urbanization)
2. *The area of deteriorated housing as a share of total housing stock* (an approximation of local housing conditions)
3. *The share of families receiving state social support to pay for housing and communal services* (an approximation of local household deprivation)
4. *The number of healthcare personnel per 1,000 people* (an approximation of access to local medical services)
5. *Street area provided with lighting as a share of total street area* (an approximation of the state and security of local urban facilities)
6. *Average monthly nominal wage in profit and non-profit organizations* (an approximation of the state of local economy and household earnings)

This data was available for more than 80% of the 309 settlements in two selected regions (228 in Moskovskaya Oblast' and 81 in Yaroslavskaya Oblast').

4. The models

Given the hierarchical structure of our data, the most appropriate way of modeling the relationships between variables located at different levels of analysis is hierarchical linear modeling (HLM) [see Rumberger, Palardy 2004; Gelman, Hill 2007].

Accordingly this model also consists of two levels. The first-level (or school-level) model can be generalized as follows:

$$Y_{ij} = \beta_{0j} + B_{nj} \times (STUDENT\ BODY\ CHARACTERISTICS)_{ij} +$$

$$+ B_{mj} \times (SCHOOL\ CHARACTERISTICS)_{ij} + \varepsilon_{ij}$$

where Y_{ij} is the average USE score in the *i*-th school in the *j*-th settlement; β_{0j} is an average USE value for each *j*-th settlement independent of school and its student body characteristics; B_{nj} is a vector of *n* parameters which reflect the relationship between relevant characteristics of the student body and the average USE results in *j*-th settlement (where *n* corresponds to the number of student body characteristics included in the model); B_{mj} is also a similar vector of *m* parameters, which measure school characteristics; an ε_{ij} is a random error (or random effect), i.e. the residual variance in USE results which cannot be explained by the factors included in the model.

The second-level (or settlement-level) model can be expressed as follows:

$$\beta_{0j} = \gamma_{00} + C_{s0} \times (SETTLEMENT\ CHARACTERISTICS)_j + \mu_{0j}$$

and

$$\beta_{zj} = \gamma_{z0} + C_{sz} \times (SETTLEMENT\ CHARACTERISTICS)_j + \mu_{zj}$$

$$\text{for } z = 1, 2, \ldots, n+m$$

where β_{0j} and β_{zj} are parameters from the first-level model, γ_{00} is a fixed average USE value independent of settlement, school and student body characteristics; C_{s0} is a vector of parameters which reflect the fixed relationship between USE results and the corresponding characteristics of settlements; γ_{z0} is a vector of fixed effects, which correspond to relationship between average USE results and the *z*-th variable in the list of school and student body characteristics; C_{sz} is a set of vectors which reflect interaction effects, i.e. different elasticities of USE results with respect to corresponding school-level characteristics (*z*) that may depend on some of the observed settlement characteristics; μ_{0j} is a residual which reflects the random variance of average USE results in schools of *j*-th settlement after statistically controlling for all other factors; μ_{zj} is a residual which allows for the random variance of the relationship between USE results and school characteristics among different settlements.

The evaluation of the model parameters is carried out simultaneously on both levels. In general, it allows us to 1) evaluate the direct relationship between average USE results and various characteristics of the student body, schools and settlements (vectors C_{s0} and γ_{z0} for all $z = 1, 2, \ldots, n+m$); 2) evaluate elasticity of USE results to various school characteristics depending on the characteristics of the settlement (a vector of so called "interaction" effects C_{sz}); and 3) determine residual variance of average USE scores between schools and settlements (ε_{ij} , μ_{0j}, and μ_{zj}).

Since we could only take a limited number of indicators describing the local context from Federal State Statistics data, we recreated some of its possible characteristics by drawing on available data from school social profiles. This was a simple procedure of averaging some of the school-level indicators for each settlement. For instance, where we could not get access to local crime statistics, we took the average share of children who have a record at local Juvenile Affairs Commissions among all schools in a given settlement as a proxy for juvenile crime and the prevalence of delinquent behavior.

Averaging the indicators, however, is associated with certain difficulties, especially when we consider including them in our regression models. Particularly, it may lead to strong multicollinearity, since the settlement-averaged variables and their school-level prototypes would most likely correlate. Therefore, in respective models we did the mean-centering of school-level variables to avoid such problems and to account for it when interpreting the estimation results. This procedure is quite common for distinguishing contextual and individual effects, and has been has been used in other research as well [e.g see Raudenbush, Bryk 2002, p.33; Rumberger, Palardy 2004, pp. 243-245].

5. Results and discussion

We start with some descriptive statistics. Table 1 provides basic characteristics for the distribution of schools' average USE results in Russian and math in 2011 for schools located in Moscovskaya Oblast' and Yaroslavskaya Oblast'.

The average USE scores both for Russian and math look almost identical between the two regions. However, within both regions there can be found significant differentiation of schools by distribution of average USE scores. The difference between the maximum and the minimum average USE scores reaches about 50 points (which is more than a half of the maximum value). Significant differentiation is also displayed by the difference between the top and bottom quartiles, and the coefficient of variation. But what we are primarily concerned with is whether these differences can be attributed to certain contextual factors. To answer this question we draw on results of the multivariate analysis discussed below.

Table 2 provides estimation results for base models. At this point no predictors are included in the models so that it is possible to evaluate the overall, within-group and between-group variances in average USE scores. Within-group variance refers to the variance related to inter-school differences within settlements. Between-group variance is the variance related to inter-school differences between settlements. Both are a part of the overall variance.

From Table 2 we see that the overall variance is relatively high, which tells us that academic performance in our sample of schools varies to a significant extent. However, as we show later, this uncertainty decreases as we gradually add predictors into this model. And yet we can already see that the contribution of the local context into the variance of USE results among schools is fairly modest, around 10% of the overall variance. This means that the sources of this great disparity in academic performance are most likely hidden in schools, rather than the local areas in which they are located. In order to explain why this might seem counter-intuitive, we would like to mention that settlements in our sample could vary from small (~500 citizens) rural villages to cities like Yaroslavl (~600,000 citizens).

Tab.1. The distribution of schools' average USE scores in Moskovskaya Oblast' and Yaroslavskaya Oblast' in 2011

	USE in Russian		USE in math	
	Moskovskaya	**Yaroslavskaya**	**Moskovskaya**	**Yaroslavskaya**
Mean value	44.9	44.3	62.6	62
Standard deviation	7.4	8.4	7.4	7.3
Coefficient of variation (standard deviation / average value)	0.16	0.19	0.12	0.12
Minimum value	21	24.4	30	38.7
Q1 (lower quartile – bottom 25%)	40.7	39.4	58	58
Median value	45.5	44.8	63	62.5
Q3 (upper quartile – top 25%)	49.4	50.6	67.9	66.8
Maximum value	77	71.3	87.4	86.8
n (number of schools)	785	246	783	248

Tab. 2. Regression estimates for the models without predictors (base models)

Model parameters	**USE in math**		**USE in Russian**	
	Model 0m		**Model 0r**	
	Fixed effects	**Random effects**	**Fixed effects**	**Random effects**
Model constant (a fixed average USE score unaccounted for other factors)	44.6*** (0.3)	-	61.8*** (0.3)	-
RESIDUAL WITHIN-GROUP VARIANCE	-	53.4 (2.6)	-	49.7 (2.5)
RESIDUAL BETWEEN-GROUP VARIANCE	-	4.4 (1.7)	-	4.9 (1.9)

Note: The figures in tables are 1) coefficient estimates for "fixed effects";
2) variance values for "random effects";
3) standard deviation for each value is provided in brackets
* significant at the 90% level; ** at the 95% level; *** at the 99% level

The social composition of student body and the average USE scores

In the next stage of our analysis we consider how the variance of average academic performance in schools corresponds to the variance of a number of social characteristics which describe the composition of their student body. The results of the regression model are presented in Table 3.

The information presented in the following tables need to be interpreted as follows. Each table contains outputs for different models labeled "m" and "r", where "m" corresponds to scores in math as dependent variable, and "r" corresponds to scores in Russian.

In Models 1m and 1r the strength of the relationship between school characteristics and the average USE scores is assumed to be fixed across all settlements. The only exception is the random variance of the constant, which is the fixed average USE score unaccounted for all other factors in respective models. The coefficients in the "fixed effects" column should be interpreted as ordinary regression coefficients. In Table 3 all independent variables are measured on a scale of 0 to 1, which means that, for instance, in Model 1a a 10% increase in the share of single-parent families corresponds to a decrease of 1.1 points in the average USE scores.

Unlike the first set of models, Models 2m and 2r also include random effects, i.e. possible variations of coefficients between different settlements (vectors labeled with the letter "C" in the equations provided in the previous section). The effects are measured in estimated variances. In the second set of models we drop all the variables which display no statistical significance in the first set of estimations.

The following set of predictors have a positive and statistically significant relationship with the average USE scores in schools: 1) the *share of children from families with both parents having a higher education*, and 2) the *share of students from families with decent housing*. This supports the well documented relationship between children's academic performance and the socioeconomic status of their parents (see the review of the literature and a description of our general conceptual framework in section 2). These two indicators are the most accurate proxies for schools' socioeconomic context, since all other characteristics which are in one way or another associated with this concept (e.g. families with unemployed, other proxies for housing conditions) have no statistical relationship with schools' average academic performance. However, we have to admit that the magnitude of effects for both indicators cannot be considered large. For instance, a 10% difference in the share of children from families with both parents having a higher education correspond to a difference of mere 0.9-1.1 points in the average USE scores. This effect is nearly identical for scores in Russian and in math. For the second indicator, its magnitude is even smaller.

Predictors which indicate negative and statistically significant relationship with schools' academic performance include: 1) the share of students from single-parent families, 2) the share of students

with Russian as a non-native language, and 3) the share of students having a disciplinary record (at school or in Juvenile Affairs Commissions). The first indicator is also a good approximation for socioeconomic context: we know that single-parent families often fall into certain risk categories as they are limited to only one source of income and the cost of unemployment for such families is particularly high. In addition, it might have particular implications for the academic performance of children because of a quite likely lack of attention from such parents, who often have little spare time to devote to their children and their problems.

The fact that the presence of children from migrant families in school is negatively correlated with average USE score is worth discussing in light of the results of Alexandrov, Baranova & Ivanyushina, [2012]. Their analysis of data collected in the region of Saint Petersburg led them to conclude that the ethnicity had almost no relationship with academic performance after controlling for all relevant characteristics. In our study, schools with a larger proportion of children from migrant families tend to have a lower average USE score, and, as can be seen further in Table 7, this effect persists even after enhancing the model with a number of other school characteristics. But our analysis is being carried out on a sample of schools, rather than individual students.

So it is possible that the effect we observe happens due to selection, i.e. it might be that migrants are forced (or selectively admitted) to attend the less successful schools. However, we do not discard the hypothesis about the particular relevance of cultural and language barriers which might make it difficult for migrant students to master the Russian school curriculum. This problem does exist, supported by evidence from teachers who have experience working with students from migrant families [ibid, p. 196].

Finally, the share of students with disciplinary records signifies a highly unfavorable and problematic situation with the student body in schools. Although such information was not available in the school social profiles, we would assume that in some cases these are dedicated types of schools, which specialize in educating children with delinquent behavior. In some of the schools the share of such children could reach a third of their total student body, which in all cases is associated with extremely low academic results.

Tab. 3. Regression estimates for relationships between average USE scores in schools and their student body characteristics

Model parameters	**USE in math**			**USE in Russian**		
	Model 1m	**Model 2m**		**Model 1r**	**Model 2r**	
	Fixed effects	**Fixed effects**	**Random effects**	**Fixed effects**	**Fixed effects**	**Random effects**
Model constant (a fixed average USE score unaccounted for other factors)	43.3*** (1.4)	44.3*** (1.0)	-	60.2*** (1.3)	61.4*** (1.5)	-
The share of students from multi-child families	-0.7 (5.1)	-	-	0.3 (4.7)	-	-

The share of students from single-parent families	-11.4*** (2.5)	-10.0*** (2.3)	0.0 (0.0)	-9.6*** (2.3)	-8.9*** (2.2)	12.3 (36.5)
The share of students from foster families	-15.2 (9.3)	-	-	-10.2 (8.5)	-	-
The share of students from families with one parent in employment	2.4 (1.8)	-	-	2.3 (1.6)	-	-
The share of students from families with both parents unemployed	7.2 (8.4)	-	-	9.5 (7.7)	-	-
The share of students from single-parent families where the only parent is unemployed	-1.1 (5.2)	-	-	5.9 (4.8)	-	-
The share of students from families with both parents (or single parent) disabled	-1.9 (14.3)	-	-	-20.4 (13.2)	-	-
The share of students from families with both parents having a higher education	9.7*** (1.3)	9.4*** (1.3)	3.6 (7.0)	10.6*** (1.2)	9.9*** (1.2)	5.2 (7.8)
The share of students from families with at least one of the parents having a higher education	1.8 (1.7)	-	-	4.2*** (1.6)	4.2** (1.6)	16.1 (19.2)
The share of students from families considered at social risk	5.7 (6.2)	-	-	14.5** (5.7)	5.0 (9.6)	743.7 (987.7)
The share of students from families with decent housing	3.8** (1.5)	3.8*** (1.0)	2.3 (6.2)	3.1** (1.4)	2.4** (1.2)	2.6 (6.1)
The share of students from families with low-quality housing	2.1 (2.4)	-	-	0.7 (2.2)	-	-
The share of students from families living in private houses	-1.6 (1.8)	-	-	-3.6** (1.7)	-4.2*** (1.6)	13.2 (14.1)
The share of students with Russian as a non-native	-9.8***	-8.6***	0.0 (0.0)	-10.9***	-10.7***	0.0 (0.0)

language	(3.3)	(3.2)		(3.0)	(3.0)	
The share of students from foster families	28.1 (22.1)	-	-	54.0*** (9.2)	54.5** (23.0)	2220.2 (2843.3)
The share of students on school record	-19.1* (10.3)	-30.4** (13.0)	2295.9 (1252.2)	-29.7*** (9.2)	-29.4*** (10.6)	386.2 (507.1)
The share of students on record in the Juvenile Affairs Commission	-70.0*** (13.6)	-78.3*** (16.4)	540.6 (1105.4)	-63.3*** (12.5)	-86.5*** (16.0)	1578.4 (1305.4)
RESIDUAL WITHIN-GROUP VARIANCE	37.7 (2.0)	-	35.5 (2.0)	32.0 (1.7)	-	29.3 (1.9)
RESIDUAL BETWEEN-GROUP VARIANCE	4.9 (1.8)	-	3.2 (3.8)	4.4 (1.7)	-	0.4 (3.4)

Note: The figures in tables are 1) coefficient estimates for "fixed effects";
2) variance values for "random effects";
3) standard deviation for each value is provided in brackets
* significant at the 90% level; ** at the 95% level; *** at the 99% level

The list of student body characteristics which have statistically insignificant relationship with academic performance, includes such indicators as the share of students from multi-child families, the percentage of children from families at social risk, which were included in our school social profiles. This are two possible explanations: 1) particularly small and insignificant variances in these indicators among schools, which limits the opportunity to estimate their statistical effects (see the descriptive statistics in Appendix 1); and the fact that these indicators are already accounted for by other characteristics of the student body which have a significant impact on academic performance. Looking at individual data for each student would be helpful to make a more accurate analysis, but at this point we are limited to working with aggregate data for schools.

By expanding our basic Models (0m and 0r) to include the socioeconomic characteristics of the student body, the residual between-group variance of the average USE scores in schools has been reduced by approximately 34% for tests in math and 41% for tests in Russian. This shows that this group of factors as a whole has a relatively strong impact on academic performance.

We would also like to highlight the part of the Table 3, which displays "random effects". These effects, as explained earlier, reflect the actual variance of the corresponding coefficients between the groups of observations (settlements in our case). The greater the values of these variances, the more differences in coefficients are observed between settlements. Again these differences are considered "random" in the sense that they cannot be related to any of the settlement characteristics observed and included in the model (at this point there are none).

The school characteristics and the average USE results

We now analyze the relationship between the distribution of the average USE scores and several school characteristics[10]. The results of this analysis are presented in Table 4.

One of the first findings to note is that there exists a rather large and statistically significant disparity in academic performance between typical schools and those that offer advanced educational programs. Even after controlling for several other school characteristics (including the very likely differences in human and material resources between such schools) the average USE scores in lyceums and gymnasiums (i.e. university-preparatory schools) are higher by 3.5 (in math) to 5.1 (in Russian) points compared with the much larger share of typical schools.

Another important and quite expected finding is that there is a strong association between average USE results and the school size measured in the number of students: the larger the school, the higher the average USE scores in both Russian and math. This effect holds even if we control for other school characteristics which might be associated with school size, including the composition of its student body (see the final results in Table 7 below). It seems as if school size encapsulates some of the unobserved context in which educational institutions function and which is positively related to the academic performance of their students. One possible explanation is that larger schools benefit from scale: it helps them attract more funds and hire better-qualified teachers, which, in turn, impacts the quality of training and consequently examination results. However, in the context of the ongoing debates about whether to optimize school districts and to enlarge them, in our sample of rural schools the effect of school size on academic performance is not significant.

Our approximation of teacher workload (measured by the ratio of students per teacher) also has a statistically significant, but weak effect on academic performance after controlling for the total number of students in school along with other variables. This is quite reasonable: if we take two schools with the same number of students, where the first one has more teachers than the second, we would expect the first one to provide a higher amount of learning opportunities, since the teachers would be able to pay more attention to students.

[10] The initial number of variables to account for schools' resources and their organizational characterizes was a little larger compared to the one included here, but we had to drop some indicators due to large amounts of missing data. These indicators included, for instance, the average age of teachers, the share of second-category teachers, the share of teachers with university degrees, library stock, and some other characteristics related to the quality of education institutions.

Tab. 4. Regression estimates for relationships between average USE scores in schools and school characteristics

Model parameters	USE in math			USE in Russian		
	Model 3m	Model 4m		Model 3r	Model 4r	
	Fixed effects	Fixed effects	Random effects	Fixed effects	Fixed effects	Random effects
Model constant (a fixed average USE score unaccounted for other factors)	37.6*** (1.8)	38.4*** (1.2)	-	55.5*** (1.7)	55.0*** (1.2)	-
Lyceum or gymnasium (i.e. a university-preparatory school)	3.9*** (0.6)	3.5*** (0.6)	0.0 (0.0)	5.1*** (0.6)	4.7*** (0.6)	0.0 (0.0)
Magnet schools	1.8** (0.8)	1.5* (0.8)	3.6 (3.6)	2.3*** (0.7)	1.9** (0.8)	3.3 (2.6)
Evening schools	-5.9*** (1.5)	-5.8*** (1.4)	0.0 (0.0)	-9.1*** (1.3)	-9.4*** (1.2)	0.0 (0.0)
Number of students	0.009*** (0.0)	0.009*** (0.0)	0.0 (0.0)	0.008*** (0.0)	0.008*** (0.0)	0.0 (0.0)
Students per teacher ratio	-0.2** (0.1)	-0.1** (0.001)	0.0 (0.0)	-0.1** (0.05)	-0.1** (0.05)	0.0 (0.0)
Principal with a degree in management	-0.03 (0.4)	-	-	-0.3 (0.4)	-	-
The school needs urgent repairs	2.1 (2.3)	-	-	-1.1 (2.1)	-	-
The school needs partial repairs	-0.8* (0.5)	-0.5 (0.5)	0.0 (0.0)	-0.01 (0.4)	-	-
The share of first-category teachers	0.6 (1.7)	-	-	2.7* (1.6)	3.2** (1.5)	0.0 (0.0)
The share of teachers with highest qualifications	6.8*** (1.5)	6.5*** (1.3)	0.0 (0.0)	5.9*** (1.4)	5.4*** (1.3)	0.0 (0.0)

The share of teachers with a university degree in pedagogy	2.3 (1.8)	-	-	1.0 (1.6)	-	-
The share of retirement-age teachers	-2.7** (1.3)	-2.2* (1.3)	0.0 (0.0)	-1.8 (1.2)	-	-
Computers per student ratio	11.4*** (3.0)	17.8*** (4.6)	371.6 (121.9)	4.6* (2.8)	8.4* (4.2)	388.9 (112.6)
RESIDUAL WITHIN-GROUP VARIANCE	36.8 (1.9)	-	34.0 (1.8)	30.9 (1.7)	-	28.4 (1.5)
RESIDUAL BETWEEN-GROUP VARIANCE	2.9 (1.4)	-	0.6 (1.0)	3.2 (1.7)	-	0.0 (0.0)

Note: The figures in tables are 1) coefficient estimates for "fixed effects";
2) variance values for "random effects";
3) standard deviation for each value is provided in brackets
* significant at the 90% level; ** at the 95% level; *** at the 99% level

The quality of the teaching staff is also closely correlated with the average USE results. The share of teachers with the highest qualifications has a statistically significant positive effect on test scores for both Russian and math. On average, each 10% increase in the share of teachers with highest qualifications is associated with an increase of the average USE score by 0.6-0.7 points. In addition, even after controlling for this indicator, the share of first-category teachers also positively (although less significantly) affects the scores in Russian; while the proportion of retirement-age teachers appears to have a weak negative association with scores in math. The rest of the indicators, which are related to teacher qualifications – the share of second-category teachers and the share of teachers with a university degree in pedagogy – seem to have a negligible effect on academic performance after controlling for what may seem as their best general proxy, teachers with highest qualifications. The insignificance of principal's management degree may most likely reflect the fact that this formal status has little substance with respect to the real competence and work experience in the relevant field.

The logistical, technical and material aspects of the academic process, which was measured by the state of school facilities, does not seem to be a decisive factor in school academic performance. The only persistent effect was observed with respect to computerizing of school classes. This effect is only appropriate for USE scores in math, which has a certain logic to it as the mastering of information technologies for which computer classes are particularly essential requires mathematics.

In general, school characteristics alone reduce between-group variance in average USE scores by around 36% in math and 43% in Russian. The amount of variance explained by school characteristics is practically equal to the amount of variance explained by the socioeconomic composition of the student body. Below we show that these effects hold even after being estimated simultaneously and after accounting for the differences in the local context.

Tab. 5. Regression models estimates for relationships between average USE scores and settlements characteristics

Model parameters	USE in math				USE in Russian			
	Fixed effects		Random effects		Fixed effects		Random effects	
	the constant	the variable coefficient	Residual within-group variance	Residual between-group variance	the constant	the variable coefficient	Residual within-group variance	Residual between-group variance
Model 5m, r **Variable:** 1 – urban school; 0 – rural school	43.1*** (0.8)	2.4*** (0.9)	52.5 (3.1)	4.4 (2.0)	59.3*** (0.8)	3.9*** (0.9)	50.4 (3.0)	3.9 (0.9)
Model 5m, r **Variable:** Log total population	36.1*** (2.9)	2.0*** (0.6)	52.2 (3.1)	4.6 (2.0)	49.8*** (2.6)	2.8*** (0.6)	50.2 (3.0)	2.5 (1.5)
Model 5m, r **Variable:** The area of deteriorated housing as a share of total housing stock	45.2*** (0.5)	-8.2 (8.2)	52.9 (3.2)	4.8 (2.2)	62.5*** (0.5)	-7.0 (8.0)	51.0 (3.1)	4.3 (2.2)
Model 5m, r **Variable:** The share of families receiving state social support to pay for housing and communal services	45.9*** (0.8)	-9.0 (7.0)	52.9 (3.2)	4.7 (2.1)	63.1*** (0.8)	-8.2 (6.9)	51.0 (3.1)	4.1 (2.2)
Model 5m, r **Variable:** The number of healthcare personnel per 1,000 people	44.8*** (0.9)	0.02 (0.1)	52.8 (3.2)	5.0 (2.2)	62.1*** (0.9)	0.01 (0.1)	50.1 (3.1)	4.5 (2.3)
Model 5m, r **Variable:** Street area	42.9*** (1.1)	2.6**	52.5	5.0	59.2*** (1.0)	4.1*** (1.3)	50.4	3.9

provided with lighting as a share of total street area		(1.3)	(3.2)	(2.1)			(3.0)	(1.9)
Model 5m, r **Variable:** Average monthly nominal wage in profit and non-profit organizations (roubles)	42.5*** (1.2)	0.0001 ** (0.0)	52.7 (3.2)	4.5 (2.1)	59.3*** (1.2)	0.0001 *** (0.0)	50.9 (3.1)	3.6 (2.0)

Note: The figures in tables are 1) coefficient estimates for "fixed effects";
2) variance values for "random effects";
3) standard deviation for each value is provided in brackets
* significant at the 90% level; ** at the 95% level; *** at the 99% level

The local context and the average USE results

Finally, we attempt to analyze the possible relationship between academic performance in schools and certain characteristics of the local context. To do this we first provide estimation results for a set of models, each including one independent variable at a time (see Table 5). We did not consider the simultaneous effects for the whole set of settlement-level variables, since some of them exhibited strong mutual correlation and were a potential source of multicollinearity. We also wanted to establish which of these characteristics are associated with average academic performance in schools.

Table 6 shows that there exists a disparity between urban and rural schools of 2.4 points in USE scores in math and 3.9 points in Russian. This difference is also captured by the more subtle measure of settlement size calculated as its log total population: i.e. the larger and more urbanized settlement, the higher the academic performance for the average school located in it. The explanatory power of both of these models is nearly identical, which is reflected in the fairly equal amount of residual variance. There is no fundamental difference in which indicator to use in order to account for the scale and status of the settlement when interpreting the related differences in the academic performance of schools.

Strikingly, the rest of the characteristics have no statistical relationship with the average USE results, the only exceptions being the street area provided with lighting as a share of total street area and the average monthly nominal wage. However, it can be assumed that these characteristics reflect less of an independent effect in the sense that they are already accounted for in the size and respectively the level of urbanization of the settlement. To confirm that this is the case, we have estimated a separate set of models where these predictors are assumed to exert a simultaneous effect on the average USE scores in local schools (see Table 6). As shown, the only statistically significant effect is already captured by the size of the settlement, with other indicators providing a negligible reduction in residual variance.

Tab. 6. Regression estimates for simultaneous relationships between average USE scores in schools and certain settlement characteristics

Model parameters	**USE in math**		**USE in Russian**	
	Model 12m		**Model 12r**	
	Fixed effects	**Random effects**	**Fixed effects**	**Random effects**
Model constant (a fixed average USE score unaccounted for other factors)	36.4*** (2.9)	-	50.2*** (2.7)	-
Log total population	1.6** (0.8)	-	2.3*** (0.7)	-
Street area provided with lighting as a share of total street area	0.7 (1.5)	-	1.3 (1.4)	-
Average monthly nominal wage in profit and non-profit organizations (roubles)	0.0 (0.0)	-	0.0 (0.0)	-
RESIDUAL WITHIN-GROUP VARIANCE	-	50.5 (2.5)	-	50.2 (3.0)
RESIDUAL BETWEEN-GROUP VARIANCE	-	4.2 (1.6)	-	2.7 (1.6)

Note: The figures in tables are 1) coefficient estimates for "fixed effects";
2) variance values for "random effects";
3) standard deviation for each value is provided in brackets
* significant at the 90% level; ** at the 95% level; *** at the 99% level

The final model

Until now we have been trying to establish the relationships between academic performance in schools and the separate groups of factors (those attributed to the composition of the student body, the schools themselves and the local context). In the final section of our analysis we will combine these factors into one model in order to confirm whether these relationships hold, when considered simultaneously (see Table 7).

Our estimations suggest that practically all relationships retain their significant effects on academic performance of schools, although there are two exceptions: the share of students on the school disciplinary record and the size of settlement.

In the first case it can be hypothesized that the practice of putting students with behavioral issues on record may vary from institution to institution. We believe, that this factor becomes negligible because it largely overlaps with a much stronger indicator (i.e. the share of students on record in

Juvenile Affairs Commissions) and is compensated for by other contextual and organizational characteristics of schools which are included in the models.

Table. 7. Regression estimates for relationships between average USE scores in schools and the three groups of factors

Model parameters	**USE in mathematics**			**USE in Russian**		
	Model 13m	**Model 14m**		**Model 13r**	**Model 14r**	
	Fixed effects	**Fixed effects**	**Random effects**	**Fixed effects**	**Fixed effects**	**Random effects**
Model constant (a fixed average USE score unaccounted for other factors)	37.3*** (2.4)	36.5*** (1.5)	-	56.4*** (2.2)	56.8*** (1.1)	-
1 – Yaroslavskaya Oblast'; 0 – Moskovskaya Oblast'	4.4*** (0.8)	4.1*** (0.7)	-	3.6*** (0.7)	3.5*** (0.7)	-
Student body characteristics						
Share of students from single-parent families	-8.7*** (2.3)	-8.4*** (2.2)	9.2 (18.3)	-7.3*** (2.1)	-7.9*** (2.0)	0.0 (0.0)
The share of students from families with both parents having a higher education	5.6*** (1.3)	5.5*** (1.3)	0.0 (0.0)	5.7*** (1.2)	5.8*** (1.2)	0.8 (5.8)
The share of students from families with decent housing	3.9*** (1.0)	3.9*** (1.0)	0.0 (0.0)	3.3*** (1.0)	3.4*** (0.9)	0.5 (3.0)
The share of students with Russian as a non-native language	-5.2* (3.1)	-4.8 (3.0)	0.0 (0.0)	-6.7** (2.8)	-7.0** (2.8)	0.0 (0.0)
Share of students on the school record	-5.7 (10.2)	-	-	-13.7 (9.0)	-	-
Share of students on record in the Juvenile Affairs Commission	-47.4*** (13.9)	-59.9*** (11.9)	469.8 (1065.9)	-28.8** (12.7)	-47.0*** (12.9)	587.1 (955.0)

School characteristics						
Lyceum or gymnasium (i.e. a university-preparatory school)	2.5*** (0.6)	2.3*** (0.6)	0.0 (0.0)	3.8*** (0.6)	3.8*** (0.6)	0.0 (0.0)
Magnet school	1.3* (0.8)	1.3* (0.7)	0.0 (0.0)	1.6** (0.7)	1.6** (0.7)	0.0 (0.0)
Evening school	-1.3 (1.7)	-	-	-5.3*** (1.5)	-5.7*** (1.6)	0.4 (9.7)
Number of students	0.006*** (0.0)	0.007*** (0.0)	0.0 (0.0)	0.005*** (0.0)	0.005*** (0.0)	0.0 (0.0)
Students per teacher ratio	-0.10* (0.06)	-0.09 (0.06)	0.005 (0.004)	-0.07 (0.06)	-0.07 (0.05)	0.0 (0.0)
The share of teachers with highest qualifications	6.0*** (1.4)	6.1*** (1.3)	0.0 (0.0)	4.3*** (1.2)	4.2*** (1.2)	0.0 (0.0)
Computers per student ratio	9.7*** (2.9)	15.6*** (4.3)	249.3 (103.7)	2.8 (2.7)	-	-
Characteristics of the local context						
Log total population	0.1 (0.5)	-	-	-0.0 (0.5)	-	-
RESIDUAL WITHIN-GROUP VARIANCE	32.8 (1.7)	-	31.3 (1.7)	27.6 (1.5)	-	27.2 (1.6)
RESIDUAL BETWEEN-GROUP VARIANCE	4.3 (1.4)	-	0.0 (0.0)	4.0 (1.6)	-	3.7 (2.1)

Note: The figures in tables are 1) coefficient estimates for "fixed effects";
2) variance values for "random effects";
3) standard deviation for each value is provided in brackets
* significant at the 90% level; ** at the 95% level; *** at the 99% level

A similar logic applies to the size of the settlement. We noted earlier that 1) only a small amount of residual variance in average USE scores can actually be attributed to the differences in settlements and 2) that the size of these settlements, which has displayed some relationship with academic performance in schools when included in the basic model, does not significantly improve the amount of explained variance. After controlling for a number of immediate school characteristics the indirect effect of the local context measured in the size of settlement disappears, which is most likely explained by the fact that the difference in average USE scores between urban and rural

schools stems almost entirely from the differences in school characteristics and student body composition. Territories appear to have no independent contextual influence on school academic performance, at least when measured in terms of the size of settlements.

Tab. 8. Regression estimates for relationships between average USE scores in schools and aggregated contextual characteristics

Model parameters	**USE in math**			**USE in Russian**		
	Model 15m: more than two schools (N=754)	**Model 16m:** more than three schools (N=694)	**Model 17m:** more than four schools (N=630)	**Model 15r:** more than two schools (N=757)	**Model 16r:** more than three schools (N=697)	**Model 17r:** more than four schools (N=631)
Model constant (a fixed average USE score unaccounted for other factors)	41.9*** (1.9)	41.4*** (2.1)	40.7*** (2.3)	58.9*** (1.7)	57.7*** (1.9)	56.8*** (1.9)
1 – Yaroslavskaya Oblast'; 0 – Moskovskaya Oblast'	3.0*** (1.1)	3.6*** (1.3)	4.9*** (1.4)	2.2** (0.1)	3.6*** (1.1)	3.3*** (1.1)
Student body characteristics						
Share of students from single-parent families	-9.0*** (2.5)	-8.3*** (2.6)	-9.3*** (2.7)	-5.7** (2.3)	-6.0*** (1.1)	-5.9*** (2.4)
The share of students from families with both parents having a higher education ****	6.4*** (1.5)	6.5*** (1.5)	6.4*** (1.5)	5.9*** (1.4)	6.1*** (1.4)	6.2*** (1.4)
The share of students from families with decent housing****	4.5*** (1.3)	3.9*** (1.3)	3.6*** (1.3)	4.0*** (1.1)	3.7*** (1.2)	3.7*** (1.2)
The share of students with Russian as a non-native language ****	-4.3 (5.3)	-5.7 (5.3)	4.4 (5.3)	-7.0 (4.9)	-7.2 (4.9)	-6.9 (4.8)
Share of students on record in the Juvenile	-56.8*** (11.6)	-57.9*** (11.8)	-59.2*** (12.2)	-58.1*** (10.4)	-54.1*** (10.6)	-54.3*** (10.1)

Affairs Commission ****						
School characteristics						
Lyceum or gymnasium (i.e. a university-preparatory school)	2.4*** (0.7)	2.3*** (0.7)	2.6*** (0.7)	3.2*** (0.6)	3.1*** (0.6)	3.4*** (0.6)
Magnet school	1.3 (0.8)	1.4* (0.8)	1.6* (0.9)	1.5** (0.7)	1.7** (0.8)	1.7** (0.8)
Number of contingent	0.006*** (0.0)	0.006*** (0.0)	0.006*** (0.0)	0.006*** (0.0)	0.006*** (0.0)	0.006*** (0.0)
Students per teacher ratio	-0.2*** (0.1)	-0.2*** (0.1)	-0.2** (0.1)	-0.2*** (0.1)	-0.2*** (0.1)	-0.2*** (0.1)
The share of teachers with highest qualifications****	6.6*** (1.8)	7.5*** (1.9)	7.7*** (1.9)	8.3*** (1.7)	9.1*** (1.7)	8.8*** (1.7)
Characteristics of the local context						
The share of students from families with both parents having a higher education *****	3.8 (4.0)	7.7 (4.7)	6.9 (5.3)	8.4** (3.5)	13.4*** (4.2)	10.7** (4.4)
The share of students from families with decent housing*****	2.9 (2.4)	1.8 (2.7)	2.2 (2.8)	2.3 (2.1)	2.4 (2.4)	3.3 (2.4)
The share of students with Russian as a non-native language*****	-16.6 (12.7)	-12.9 (16.8)	-13.8 (17.9)	-21.2* (11.1)	-21.3 (14.8)	-9.9 (14.9)
Share of students on record in the Juvenile Affairs Commission *****	-48.7* (28.8)	-27.8 (31.4)	-57.2 (36.0)	-55.1** (25.2)	-33.5 (27.6)	-22.4 (30.3)
The share of teachers with highest qualifications *****	5.9* (3.1)	5.1 (3.6)	7.3* (3.8)	2.9 (2.7)	1.3 (3.1)	2.9 (3.1)
RESIDUAL WITHIN-GROUP VARIANCE	33.3 (1.9)	32.4 (1.9)	31.5 (1.9)	28.11 (1.6)	27.3 (1.6)	26.1 (1.6)

RESIDUAL BETWEEN-GROUP VARIANCE	3.9 (1.5)	4.2 (1.6)	3.9 (1.5)	2.5 (1.4)	2.9 (1.4)	2.0 (1.2)

Note: The figures in tables are 1) coefficient estimates for "fixed effects";
2) variance values for "random effects";
3) standard deviation for each value is provided in brackets
* significant at the 90% level; ** at the 95% level; *** at the 99% level

**** the value is centered relative to the average value for the settlement

***** the average value for the settlement

To test this conclusion further we have also evaluated a set of models, where local contextual effects are approximated via aggregated information from school social profiles (see the last part of section 5, where the obtaining of such variables is discussed). This, however, imposes certain limits on our model specifications. Some smaller rural settlements in our sample feature only one school, which renders the averaging procedure and respective coefficient in the model senseless. For that reason, we estimated our models only for those settlements which feature more than three schools. Table 8 provides the results of this estimation for three different samples.

From Table 8 we can generally observe that the statistical relationship between the settlement-level variables and academic performance is quite negligible. The only exception, which shows some robustness in spite of reducing the sample, is the aggregated share of families with both parents having a higher education in the models with USE scores in Russian.

Tab. 9. The differences in average school characteristics between Moskovskaya Oblast' and Yaroslavskaya Oblast'

	Moskovskaya Oblast'	**Yaroslavskaya Oblast'**
The share of normal secondary schools	66%	75%
The share of lyceums or gymnasiums (i.e. university-preparatory schools)	20%	4%
The share of magnet schools	10%	5%
The average share of teachers with highest qualifications	0.40 (0.18)	0.23 (0.14)
The average share of students from single-parent families	0.24 (0.09)	0.28 (0.09)
The average share of students from families with both parents having a	0.28 (0.20)	0.14 (0.15)

higher education		
The average share of students from families with at least one of the parents having a higher education	0.25 (0.14)	0.17 (0.13)
The average share of students from families with decent housing	0.74 (0.20)	0.64 (0.32)
The average share of students on school record	0.02 (0.03)	0.03 (0.04)
The average share of students on record in the Juvenile Affairs Commission	0.01 (0.02)	0.01 (0.03)

Note: mean values are followed by standard deviation in brackets

However, with other predictors being neither significant, nor robust, it cannot be concluded that this effect is actually sustainable. In section 2 we provided some reasoning about how the social structure of the population living in a certain territory may have particular synergetic effect stemming from geographical concentration of cultural and human capital. However, it is hard to say why this effect so explicitly manifests itself particularly with respect to language competence. It might be that this is particularly sensitive to the social context as they are more closely related to the notion of cultural capital than mathematical skills. And there is actually indirect evidence suggesting that this might be true, since USE scores in Russian are also better explained by social context characteristics (41% of explained variance), than the scores in math (34% of explained variance). However, without additional research and the more accurate data on the structure of the population, the state of local infrastructure and other information on local socioeconomic context it is too early to make any far reaching conclusions.

To round up this part we conclude that so far our results suggest no compelling evidence that the local context has a profound effect on academic performance in Russian schools.

Finally, we would like to comment on the statistical significance of the dummy-variable, which marks the difference in average academic performance between average schools in Yaroslavskaya Oblast' and Moskovskaya Oblast' (see Tables 7 and 8). In opening our discussion we noted that intraregional distributions of average USE scores look very similar. It could also follow from this finding that schools in Yaroslavskaya Oblast' are just as efficient as schools in Moskovskaya Oblast' (or vice versa). However, this assertion only holds true if we accept that the schools in both regions operate under similar conditions. And this is simply not true as the social and economic situation between these regions is different, just as there are significant differences between the schools themselves (see Table 9).

Table 9 contains clear evidence that the schools in Moskovskaya Oblast' on average enjoy a better social context and a better resource provision than the schools in Yaroslavksya Oblast'. But if we

control for this difference in circumstances (as we do in our models in Table 7, for instance), we can see that the schools in Yaroslavskaya Oblast', in fact, tend to outscore the schools in Moskovskaya Oblast' by around 4 points in math and 3.4 points in Russian on average. Thus, if we do not account for these differences and make comparisons between schools based exclusively on their USE scores, we may get a false impression about their actual performance.

6. Conclusions and future considerations

The primary objective of our analysis was to establish whether the existing disparity in academic performance of Russian schools might be associated with the differences in the social context, which these schools confront both at the level of institutions and at the level of the local areas in which they are located. In the first part of our paper we discussed various social mechanisms by which social disadvantage may hinder the educational results exhibited by schools. A substantial part of this review was dedicated to the discussion of the so called "neighborhood effects", which are manifested in the resources available to institutions and certain attitudes, role models and behavior patterns that may provide substantial advantages or disadvantages to households and schools in carrying out their respective functions. These effects have been well documented in the literature; however, we were unable to find any substantial attempts to verify these theories in the Russian context.

Although, we have shown that social characteristics of the student body do affect academic performance in a predictable way, as do the factors which are related to schools' organizational and material resources, we were unable to discover any substantial effects of the local context. What this means is that there is more or less equal probability that students from schools featuring identical characteristics would exhibit same academic performance independent of the size of their settlements and the rate of local deprivation. At first sight, this might appear as an optimistic finding for Russian education policy makers (especially against the situation observed in some developed Western countries), since the local context does not seem to create additional challenges for schools beyond the student body. And yet it should not be substituted for the fact that there are no differences between schools located in the less deprived and more deprived areas. These differences do exist, but they are first and foremost contained within the schools themselves.

Our findings also have a certain applied value. They clearly demonstrate the need to account for the social context in schools in order to provide a more adequate evaluation of school performance. This might be especially valuable for families who make decisions about which school to send their children to, as well as for policy makers who make decisions about assigning resources to educational institutions. Contextualized measures of academic performance have been widely used in many developed countries for this purpose, and Russian policy makers should look for certain ways to adapt their experience if they choose to follow the same path of improving educational opportunities for their children. The results of our research are a modest proof that there is nothing technically or ethically impossible in providing such measures.

Finally, a few words about the limitations of our analysis and future considerations.

First, our results are limited to two Russian regions from which the sample of schools was collected. Although we found significant differences between Yaroslavskaya and Moscovskaya Oblast', we suppose that expanding our sample, at least by adding Moscow's municipal districts, would allow us to double-check some of the findings and perhaps shed more light on the significance of the local context. Including the districts of Moscow would enable us to consider a significantly higher differentiation in local deprivation and socioeconomic conditions.

Second, our analysis was carried out on aggregated data for schools, which actually makes it impossible to distinguish between individual (e.g. family) and contextual (e.g. school environment) effects with regard to academic performance of students. Moreover, our information about academic performance in schools is based purely on average USE scores, and we do not know anything about the actual distribution of USE scores within schools. This could be solved by adding individual level of analysis into our models, but such data was unavailable to us when we carried out our research. However new possibilities have opened up with the publishing of data from a panel of school students in Yaroslavskaya Oblast'.

Third, we had a very limited number of local area indicators to account for the differences in the local context and socioeconomic conditions. It would make sense to continue with this analysis by drawing on more data, which would also characterize demographic (mortality or life expectancy, morbidity, birth rates, etc.), social (crime rates, suicide rates, etc.) and economic indicators (unemployment rate, educational and occupational structure of population). Some of this data should also be available soon, after the publishing of the Russian Census of 2010.

Lastly, there was asynchrony between the student body measurements and USE scores. This asynchrony is due to the fact that USE scores are a characteristic of the last cohort of students, while school contextual characteristics refer to all of the cohorts. Because of this our estimations for the effects of family characteristics on academic performance in schools might be underestimated. Again involving individual student-level data could solve this.

We certainly wish that these limitations would be overcome in the future, as they are vital for developing more accurate and calibrated tools for assessment of school performance.

References

Book: Alexandrov, D, Tenisheva, K, Savelieva, S, Kochkin, E 2012, Educational Pathways and Trajectories of Rural Students. Sociology of Education and Science Laboratory Working Papers SESL, WP 001.

Journal article: Bifulco, R 2002, Addressing Self-Selection Bias in Quasi-Experimental Evaluations of Whole-School Reform: A Comparison of Methods, Evaluation Review, vol. 26.

Journal article: Borjas, G 1995, Ethnicity, Neighborhoods and Human-Capital Externalities // American Economic Review, vol. 85, no. 3.

Book: Bourdieu, P 1983, Forms of Capital, Richardson J.G. (Ed.) Handbook of Theory and Research for the Sociology of Education, Greenwood Press.

Book: Bourdieu, P, Passeron, J-C 1980, Reproduction in Education, Society and Culture, Sage.

Book: Bowles, S, Gintis, H, Groves, MO 2008 (Eds.). Unequal Chances: Family Background and Economic Success, Princeton University Press.

Journal article: Breen, R, Goldthorpe, JH 1997, Explaining Educational Differentials: Towards a Formal Rational Action Theory // Rationality and Society, vol. 9, No. 3.

Journal article: Breen, R, Jonsson, JO 2005, Inequality of Opportunity in Comparative Perspective: Recent Research on Educational Attainment and Social Mobility, Annual Review of Sociology, vol. 31, no. 1.

Journal article: Brooks-Gunn, J, Duncan, GJ, Klebanov, PK, Sealand, N 1993, Do Neighborhoods Influence Child and Adolescent Development?, American Journal of Sociology, vol. 99, no. 2.

Book: Coleman, JS 1966, Equality of Educational Opportunity (COLEMAN) Study (EEOS), Ann Arbor, MI.

Journal article: Coleman, JS 1988, Social Capital in the Creation of Human Capital, American Journal of Sociology, vol. 94.

Journal article: Crane, J 1991, The Epidemic Theory of Ghettos and Neighborhood Effects on Dropping Out and Teenage Childbearing, American Journal of Sociology, vol. 96, no. 5.

Book: Erikson, R, Jonsson, JO 1996, (Eds.) Can Education Be Equalized? Boulder, CO, Westview.

Journal article: Evans, WN, Oates, WE, Schwab, RM 1992, Measuring Peer Group Effects: A Study of Teenage Behavior, Journal of Political Economy, vol. 100, no. 5.

Journal article: Garner, CL, Raudenbush, SW 1991, Neighborhood Effects on Educational Attainment: A Multilevel Analysis, Sociology of Education, vol. 64, no. 4.

Book: Gelman, A, Hill, J 2007, Data Analysis Using Regression and Multilevel/Hierarchical Models. Cambridge: Cambridge University Press,

Journal article: Gerber, T, Hout, M 1995, Educational Stratification in Russia During the Soviet Period, American Journal of Sociology, vol. 101, no.3.

Journal article: Gerber, T 2000, Educational Stratification in Contemporary Russia: Stability and Change in the Face of Economic and Institutional Crisis, Sociology of Education, vol. 73, no. 3.

Journal article: Hanushek, EA 1989, The Impact of Differential Expenditures on School Performance, Educational Researcher, vol. 18, no. 4.

Journal article: Hedges, LV, Laine, RD, Greenwald, R 1994, Does Money Matter? A Meta-Analysis of Studies of the Effects of Differential School Inputs on Student Outcomes, Educational Researcher, vol. 23, no. 3.

Book: 2012, Improving the Measurement of Socioeconomic Status for the National Assessment of Educational Progress: a Theoretical Foundation. Recommendations to the National Center for Education Statistics.

Book: Jencks, C, Mayer, SE 1990, The Social Consequences of Growing Up in a Poor Neighborhood / Lynn L.E., McGeary M.G.H. (Eds.) Inner-city Poverty in the United States, National Academy Press.

Journal article: Jensen, B, Harris, MN 2003, Neighbourhood Measures: Quantifying the Effects of Neighbourhood Externalities, Economic Record, vol. 84, no. 264.

Report: 2008, Measuring Improvements in Learning Outcomes: Best Practices to Assess the Value-Added of Schools, OECD.

Journal article: Overman, HG, Heath, A 2000, The Influence of Neighbourhood Effects on Education Decisions in a Nationally Funded Education System: the Case of Australia. CEP Working Paper no. 924, Centre for Economic Performance, London School of Economics and Political Science.

Journal article: Owens, A 2010, Neighborhoods and Schools as Competing and Reinforcing Contexts for Educational Attainment, Sociology of Education, vol. 83, no. 4.

Report: 2010, PISA 2009 Results. Overcoming Social Background: Equity in Learning Opportunities and Outcomes (Volume II), OECD.

Book: Raudenbush, SW, Bryk, AS 2002, Hierarchical Linear Models: Applications and Data Analysis Methods, 2nd Edition, Sage.

Journal article: Ray, A, McCormack, T, Evans, H. 2009, Value Added in English Schools, Education Finance and Policy, vol. 4, no.4.

Journal article: Rivkin, SG, Hanushek, EA, Kain, JF 2005, Teachers, Schools, and Academic Achievement, Econometrica, vol. 73, no. 2.

Journal article: Rockoff, JE 2004, The Impact of Individual Teachers on Student Achievement: Evidence from Panel Data, American Economic Review, vol. 94, no. 2.

Book: Rumberger, RW, Palardy, GJ 2004, Multilevel Models for School Effectiveness Research, Kaplan D. (Ed.) Handbook of Quantitative Methodology for the Social Sciences. Thousand Oaks, CA, Sage.

Journal article: Sampson, RJ, Morenoff, JD, Gannon-Rowley, T 2002, Assessing 'Neighbohood Effects': Social Processes and New Directions in Research, Annual Review of Sociology, vol. 28, no. 1.

Journal article: Sirin, SR 2005, Socioeconomic Status and Academic Achievement: A Meta-Analytic Review of Research, Review of Educational Research, vol. 75, no. 3.

Journal article: Sykes, B, Kuyper, H 2009, Neightbourhood Effects on Youth Educational Achievement in the Netherlands: Can Effects Be Identified and Do They Vary by Student Background Characteristics?, Environment and Planning, vol. 41, no. 10.

Journal article: White, K 1982, The Relation Between Socioeconomic Status and Academic Achievement, Psychological Bulletin, vol. 91.

Book: Wilson, WJ 1987, The Truly Disadvantaged: The Inner City, the Underclass, and Public Policy, Illinois, University of Chicago Press.

Journal article: Woessmann, L 2005, Educational Production in Europe, Economic Policy, vol. 20, no. 43.

Book: Ayvazyan, SA 2012, Analysis of the quality of life of the population (an econometric approach). M., Nauka.

Journal article: Ayvazyan, SA, Isakin, MA 2006, Integral indicators of the quality of life of the regional population as a criteria for the effectiveness of socioeconomic policy conducted by regional authorities, Applied econometrics, no. 1.

Journal article: Ayvazyan, CA, Stepanov,VS, Kozlova, MI 2006, Measuring synthetic categories of the quality of life of the regional population and identifying key areas for improving socioeconomic policy (Samara Region and its municipalities) // Applied econometrics, no. 2.

Journal article: Alexandrov, DA, Baranova, VV, Ivanyushina, V.A. 2012, Children and parents – migrants in cooperation with Russian schools, Questions of education, no. 1.

Report: Alexeev, AI, Zubarevich, NV, Kuznetsov, OV 1998, Regional differences and human development. A presentation on developing human potential in the RF. M, Human rights.

Book: Konstantinovsky, DL 1999, Dynamics of inequality. Russian youth in a changing society: orientation and paths in the sphere of education (from the 1960s to 2000), M., Editorial URSS.

Book: Konstantinovsky, DL, Vakhshtayn, VS, Kurakin, DY, Roshchina, YM 2006, Access to quality education: opportunities and limitations, Monograph, Logos.

Book: Lapin, NI, Belyaeva, LA 2010, Program and typical tools "A social portrait of Russia's regions" (modification – 2010). M. Russian Academy of Sciences Institute of Philosophy.

Journal article: Leyzerovich,E 2007, Typology of localities in Russia (Russian economic micro-regions: network and typology), Social reality, no. 7.

Journal article: Pinskaya, MA, Kosaretsky, SG, Frumin, ID 2011, Schools that work effectively in difficult social contexts, Questions of education, no. 4.

Journal article: Prakhov, IA, Yudkevich, MM 2012, The influence of household income on USE results and choice of university, Problems of education, no. 1.

Book: Sobkin VS, Pisarsky, PS 1998, Types of regional education in the Russian Federation. Works of social education, M., Russian Academy of Education Center for Sociological Education, M., Center for Sociology of Education RAO.

Appendix.

Basic descriptive statistics for schools' social profile indicators

Variables	**Moskovskaya Oblast'**		**Yaroslavskaya Oblast'**	
	Value	**N**	**Value**	**N**
Academic performance indicators				
The mean of the average USE score in math	44.9 (7.4)	785	44.3 (8.4)	246
The mean of the average USE score in Russian	62.6 (7.4)	783	62.0 (7.3)	248
Student body characteristics				
The average share of students from multi-child families	0.07 (0.03)	785	0.11 (0.08)	232
The average share of students from single-parent families	0.24 (0.09)	785	0.28 (0.09)	233
The average share of students from foster families	0.01 (0.01)	785	0.02 (0.05)	233
The average share of students from families with one parent in employment	0.28 (0.13)	785	0.31 (0.12)	232
The average share of students from families with both parents unemployed	0.01 (0.01)	785	0.02 (0.05)	230
The average share of students from single-parent families where the only parent is unemployed	0.02 (0.04)	785	0.02 (0.03)	230
The average share of students from families with both parents (or single parent) disabled	0.01 (0.01)	785	0.01 (0.02)	232
The average share of students from families with both parents having a higher education	0.28 (0.20)	782	0.14 (0.15)	231

The average share of students from families with at least one of the parents having a higher education	0.25 (0.14)	783	0.17 (0.13)	232
The average share of students from families considered at social risk	0.01 (0.02)	785	0.03 (0.07)	231
The average share of students from families with decent housing	0.74 (0.20)	764	0.64 (0.32)	232
The average share of students from families with low-quality housing	0.05 (0.08)	785	0.11 (0.15)	232
The average share of students from families living in private houses	0.11 (0.13)	785	0.24 (0.28)	232
The average share of students with Russian as a non-native language	0.03 (0.06)	785	0.03 (0.08)	232
The average share of students from foster families	0.00 (0.00)	785	0.01 (0.02)	233
The average share of students on school record	0.02 (0.03)	785	0.03 (0.04)	233
The average share of students on record in the Juvenile Affairs Commission	0.01 (0.02)	785	0.01 (0.03)	233
Note: 1) mean values are followed by standard deviation values provided in brackets; 2) "N" stands for the valid number of schools (i.e. those which displayed the corresponding figure in their social profiles)				

Variables	Moskovskaya Oblast'		Yaroslavskaya Oblast'	
	Value	N	Value	N
School characteristics				
The share of normal secondary schools	66%	783	75%	248
The share of lyceums or gymnasiums (i.e. university-preparatory schools)	20%	783	4%	248
The share of magnet schools	10%	783	5%	248
The share of evening schools	3%	783	-	248
The average number of students	561 (313)	785	418 (310)	233
The average students per teacher ratio	17.0 (4.7)	785	12.3 (5.4)	211
The share of principals with a degree in management	49%	785	28%	213
The share of schools requiring urgent repairs	0%	785	3%	213
The share of schools requiring partial repairs	29%	785	10%	214
The average share of first-category teachers	0.27 (0.12)	785	0.41 (0.16)	213
The average share of teachers with highest qualifications	0.40 (0.18)	785	0.23 (0.14)	213
The average share of teachers with a university degree in pedagogy	0.85 (0.12)	785	0.86 (0.11)	213
The average share of retirement-age teachers	0.42 (0.16)	785	0.24 (0.14)	213
The average computers per student ratio	0.09 (0.06)	785	0.13 (0.11)	211
Characteristics of the local context				
The share of school located in urban areas	75%	785	48%	213

Average total population (thousand people)	79 (64)	756	219 (263)	240
The mean value of the area of deteriorated housing as a share of total housing stock	0.03 (0.04)	663	0.03 (0.03)	230
The mean of the share of families receiving state social support to pay for housing and communal services	0.11 (0.05)	573	0.08 (0.04)	203
The mean of the number of healthcare personnel per 1,000 people	7.9 (7.1)	678	7.9 (3.6)	240
The average value of the street area provided with lighting as a share of total street area	0.80 (0.76)	757	0.73 (0.36)	239
The average monthly nominal wage in profit and non-profit organizations (roubles)	23619 (6091)	719	15004 (4446)	240
Note: 1) mean values are followed by standard deviation values provided in brackets; 2) "N" stands for the valid number of schools (i.e. those which displayed the corresponding figure in their social profiles)				

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