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EDUCATIONAL EQUITY IN MOLDOVAN COMPULSORY SCHOOLS

Factors behind Outcome Differences in PISA 2015

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Master's thesis:	30 credits
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Abstract

This thesis contributes to educational equity research in Moldova based on the large-scale educational assessment data from PISA 2015. Applying two-level modeling technique, the differences in the effect of student personal background and schools' compensatory power on PISA achievement were examined simultaneously between different subgroups of students and schools. The Input-Process-Output conceptual model that has been applied extensively in the Educational Effectiveness Research, was used as the theoretical framework in the current study and was operationalized with the achievement and contextual data available in Moldova PISA 2015. The study found that none of the variables covered by PISA 2015 in Moldova (such as student SES, school SES, preschool attendance, medium of instruction, etc.) could be defined as a strong predictor of academic performance of Moldovan students. The context of school location, on the other hand, is the strongest school-level factor, which was found to be positively associated with increased inequity in cognitive results of Moldovan students, particularly in metropolitan and urban schools and in science objects. The results on school level show that Moldovan teachers generally apply an egalitarian approach to their students, providing the same amount of support, guidance, and feedback to all students disregarding their socio-economic differences. Similarly, the school-level models point to an even distribution of more- and less-qualified teachers across the schools. Studying in anyone of two media of instruction offered in Moldova appears to be not related to students' academic performance. This result can be interpreted as the compensatory power of Romanian-medium-school teaching style against the inequity in cultural background of Moldovan students.

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Aim: To examine within-country differences in the effect of school-level factors and schools' compensatory power through directly comparing the estimated coefficients on individual- and between-school levels.

Theory: Input-Process-Output (IPO) conceptual and analytical model in the rubric of educational outcomes and predictive factors of Educational Effectiveness Research

Method: Two-level models with random-slope were estimated at student- and school levels using Mplus application as a statistical tool.

Results: None of the variables covered by PISA 2015 in Moldova may be defined as a strong predictor of cognitive performance of Moldovan students. The context of school location is the strongest school-level factor, positively associated with increased inequity in cognitive results of Moldovan students. Equal distribution of more- and less-qualified teachers across the schools. Compensatory power of Romanian-medium-school teaching style against the inequity in students' cultural background.

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My own commitment to educational equity started two decades ago, from volunteering for disabled children and their families with non-profit Association for Persons with Mental Handicap “Humanitas.” I want to thank Dr. Aurelia Racu—the then Chair of Special Psychological Pedagogy Department in State Pedagogical University in Moldova and a passionate co-organizer of “Humanitas.” Inspired by 1990 Jomtien World Conference on Education for All, Dr. Racu showed me and several generations of young special teachers a different perspective on the world of inequalities; she leaded us to educational inclusion in Moldova and encouraged me for further studies abroad. Thanks to her, the question of obtaining a master’s degree in educational research and applying for PhD was never “if” but “when” for me.

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During two academic years of my IMER studies in the University of Gothenburg, I had an opportunity to get acquainted with a whole variety of topics in education from philosophy of education and policy concerns, through qualitative research methods, and to applied statistics. I am very fortunate to meet IMER’s ambitious tutors Dr. Ernst Thoutenhoofd, Dr. Girma Berhanu, and Dr. Kajsa Yang Hansen and to learn from them a great deal about research in education. A big thank you to them for facilitating my journey into the world of academia.

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Table of Contents

List of Tables and Figures

Introduction

Global educational academia largely agrees that socio-economic status (SES) in modern society still chiefly determines educational outcomes as well as subsequent occupational and economic outcomes, and in that, socio-economic differences in educational outcomes are very often used as indication of the degree of educational equity (Coleman … York, 1966). Educational equity is a common goal of educational systems worldwide to impart skills needed to reach maximum potential in the social and economic life of students, regardless of their socio-economic status. Attention has long been given to the mechanism through which socio-economic status (SES) of children's family influences their academic outcomes (e.g., Coleman et al., 1966). The Input-Process-Output (IPO) model explicitly theorizes a multi-input-multi-output production process and subjects to behaviors that can be identified at student-, classroom-, school- and community level. IPO theoretical model is hierarchical in nature: it searches for the causal links of different factors simultaneously within and across different levels of a school system and is widely used in the school effectiveness and school improvement studies. Since, the main purpose of the current study is to examine the educational equity in Moldova and to try to identify different aspects of student background, peer group, and school characteristics that may affect academic performance. The IPO model is, therefore, applied as the theoretical framework, and a multilevel analytical approach is chosen to facilitate the testing of the theoretical model statistically with PISA 2015 data.

Educational Inequity and PISA Studies

The issue of inequity in educational opportunities—when SES influences students' opportunities to receive education and develop their skills—came into Western academia's considerable attention in 1960s, during the crisis in sociology of social mobility revealed by the empirical analyses of Bendix and Lipset (1959). They prompted Boudon's model of distribution of social opportunities, which implies that decreasing inequity in educational opportunities is not necessarily followed, accompanied, or preceded by a reduction in inequity of social opportunities (Boudon, 1974).

A decade or two ago, economic dependence on successful schooling had been finally generalized, that made educational equity more important than ever in academic discourse (Teese, 2007). Furthermore, although higher-income states have been heavily investing in education, their efforts to improve social equity in schooling merely via widespread schooling for all proved insufficient: structural barriers that hinder equity in educational access and outcomes have to be revealed and eliminated (OECD, 2016b, p.265). Thus, Program for International Student Assessment (PISA), implemented by the Organization for Economic Co-operation and Development (OECD), has revealed the actuality of educational inequity in modern multicultural urban communities through thoroughly investigating both the result of students' competences and their motivation, effort, and background characteristics (e.g., OECD, 2005; OECD Library, 2017). In 17 years of its existence, PISA has become increasingly influential worldwide. For instance, Denmark and Germany made major reviews of their educational systems in accordance with PISA results exclusively (Sammons, 2010, p. 51).

PISA 2015 was focused on two means to reach educational equity: inclusion and fairness (OECD, 2016b, p. 203). Inclusion is defined as ensuring that all students attain basic core competencies. In this context, education systems where a large proportion of 15-year-olds remain outside the educational institution and/or have not acquired the basic skills needed to fully participate in society are not considered to be sufficiently inclusive. Fairness refers to the degree of independence of pupils' educational performance from their background circumstances. A "meritocratic" notion of fairness agrees that students do vary by personal characteristics, but asserts that differences in educational opportunities and academic results should not originate from social background (Cleary, 1968). In the given report, the concepts of academic results and academic achievement are conceptualised as student's performance in PISA and are described as student cognitive performance and outcomes: to avoid straightforward assumption that PISA scores represent the exact true abilities of tested students in the core subjects assessed. It is important to warn about a similar term that has been planned to be included in PISA 2018 as a Global Competency Assessment, but is not being discussed in the present thesis.

By the latest results of PISA, with a collective effort of all stakeholders, "the level of equity in an education system can change in the span of a decade" (OECD, 2017b). Thus, in the majority of 13 countries with improved average reading performance since 2000 till 2012, the gains occurred due to a dramatic decrease in numbers of their lowest-performing students. Most importantly, in several of those countries the link between SES and the performance scores loosened between 2000 and 2009 (OECD, 2010b, pp. 77-79). Impressive results of Brazil, Bulgaria, Chile, Denmark, Germany, Montenegro, Slovenia, Thailand and the United States in 2015 further corroborate the abovementioned statement: their students' SES became a weaker predictor of the scores whereas average performance remained unchanged (OECD, 2016b, p. 234).

PISA captures socio-economic discrepancies via an aggregated Index of Economic, Social, and Cultural Status (ESCS), which was developed for the first assessment in 2000 and has been constantly improved from then (OECD, 2016b, p. 205). The ESCS index consolidates students' self-reported information on their parents' educational level, parents' occupation, and whether or not they have certain possessions in their home (such as durable goods and educational and cultural resources). PISA surveys persistently examine the association between scores on ESCS and performance in three academic realms of mathematics, reading, and science as a measure of educational equity in all PISA-participating counties.

Thus, in 2012, on average, a difference of one standard deviation in the ESCS index was associated with a difference of over one-third of a standard deviation in students' math scores (39 PISA points) and ESCS explained as much as 15% of the overall within-country variation in student outcome in mathematics (OECD, 2013b). As the Table 1 shows, only three years later, in PISA 2015, the average ESCS index across OECD countries explained 13.0% of the variation in mathematics result (OECD, 2016b, p. 216). Moreover, in 10 out of 24 countries that performed in science above the OECD average, the strength of the ESCS-achievement link is weaker than the OECD average (OECD, 2016b, p. 218). These numbers indicate beginning of a new era of increasing equity in education.

Moldovan Context

As the Report of Moldovan Ministry of Education shows (MoE, 2016, p. 62), my native country Moldova is rightly concerned with the level of equity in her schools too. Moldova is a small country, which lacks the natural resources. It is predominantly rural and has little industry (Popescu, 2012). It is the poorest country in Europe, with a PPP per capita half that of Europe's second poorest, Albania (Mungiu-Pippidi & Munteanu, 2009). Thirty percent of the Moldovan GDP are the remittances from international labor migration, which is disproportionally large-scaled and "rapidly feminized" with more than 25% of the economically active population working abroad (Popescu, 2012). The impact of migration of parents are children "left behind" (Vanore, Mazzucato, & Siegel, 2014).

Majority of Moldovan citizens identify themselves as Moldovans or Romanians and speaks Romanian as a native language; they also educate their children via Romanian or Moldovan tongue (which are two names for the same language). Roughly 20 percent of the population of Moldova belongs to national minorities of Russians, Ukrainians, Gagauz, and Bulgarians. They speak their native languages as a first language of communication and study in Russian (Moldova Demographics, 2018).

The Ministry of Education of the Republic Moldova also states that the results of high-school examinations in three consequent years 2012-2014 demonstrated that pre-university education slips quickly to a point of crisis which is insufficient to allow candidates to be more successful than 60% of GPA. Modern youth, admitted to Moldovan undergraduate programs, are insufficiently literate in core disciplines: mathematics, Romanian language, foreign language, history, and social science. Consequently, university programs fail to produce the graduates of an adequate skills and knowledge (MoE, 2015).

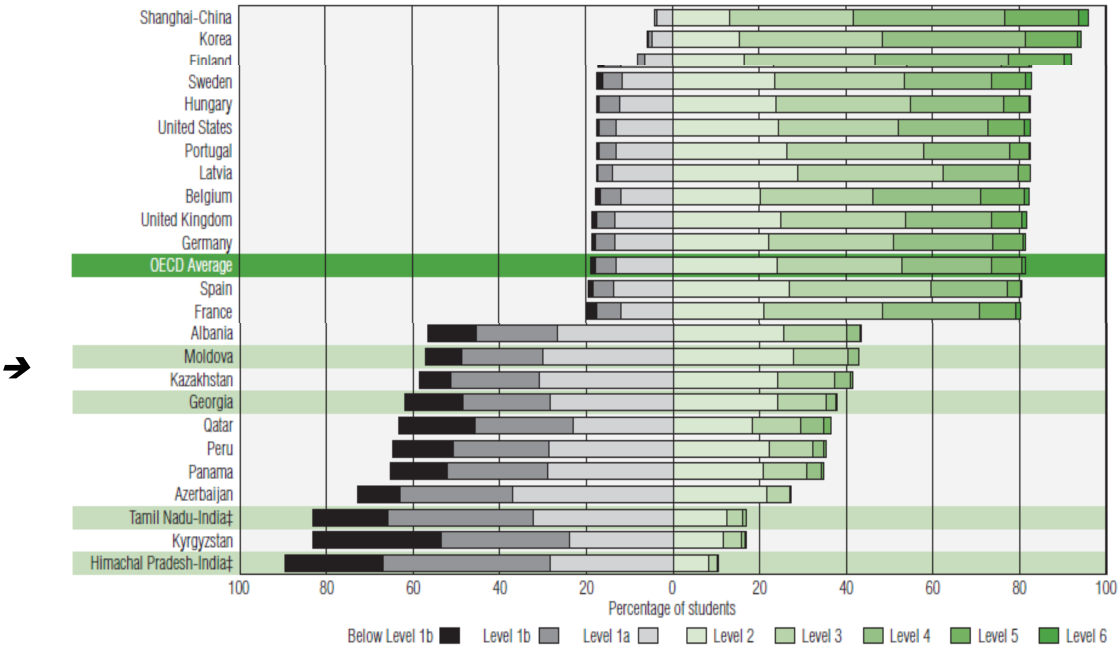
A shortage of qualified secondary-school teachers has been addressed by the Ministry of Education in the 2020 Education Strategy, which emphasized “educating, supporting, and motivating teachers for ensuring quality education.” But the problem seems to begin from the educational level of school teachers per se: their social and economic status makes the profession unattractive and of little value. Teachers’ salaries are of a low level even by Moldovan standards. Hence, teachers are perceived as socially vulnerable; young people's choice for this profession is steadily declining, resulting in less-qualified Bachelor-of-Education students every successive year (MoE, 2015, pp. 6-7).

Thus, there is no incentive system, neither governmental support, nor state policy to support school teachers. An average monthly salary of a school faculty—according to the legislative and normative acts in force—is 2640 MDL (the local currency) in comparison to 4240 MDL for industrial jobs, 6882 MDL for public utilities workers, 7538 MDL for work in finance and insurance, or 8312 MDL for information-technology specialists. A Master-of-Education graduate receives 2200 MDL if employed as a school-teacher, a school psychologist earns 2000 MDL, and a school librarian -- 1140 lei (an equivalent of 100 euro). Salaries of Moldovan school teachers are 20-times smaller than earnings of teachers from OECD countries that showed high results in PISA (MoE, 2015, pp. 7-8).

PISA 2009 Plus

In 2010, Moldova first time participated in PISA: in its 2009+ project, organized for 10 additional participants—countries who were unable to participate within the PISA 2009 project timeframe and were allowed a reduced and delayed timeline (Walker, 2011). Although the results showed the relationship between socio-economic status and reading performance just slightly weaker than the OECD average (Walker, 2011, p. xvii), they also revealed the urgency to strengthen the quality of education: Moldova’s 15-year-olds scored the lowest in Europe.

Figure 1 demonstrates that around 60 percent of Moldovan students lack the basic levels of proficiency in reading and math literacy (being below proficiency level 2), which are necessary to participate effectively and productively in the society. Level 1a— which is considered to be below the baseline level of reading proficiency, was the modal proficiency level in Moldova or for 30.1% of participants. The proportions of 15-year-old students estimated to be performing at level 1b and below level 1b were also substantial—18.8%. More than 8.0% respectively (Walker, 2011, pp. 14-15). Finally, the proportions of Moldovan students estimated to be in middle proficiency levels (2, 3, and 4) on the scientific literacy scale was 52.4%, while 20% of students were estimated to be performing below level 1 (Walker, 2011, p. 56).



Note: figure ordered by proportion of students in Level 2 and above.

Figure 1. Extract of the percentages of students at each proficiency level of reading literacy in PISA 2009. Adopted from Walker, 2011, p. 12

Gender Differences in PISA 2009+

PISA has consistently shown that boys outperform girls in mathematics, but in the Republic of Moldova in all three areas the girls score better than boys (MoE, 2017). In PISA 2009+, Moldovan data show a statistically significant difference of 14 score points in scientific literacy in favor of girls; girls also out-perform boys in reading literacy about 45 points. No significant difference is being found in Mathematics between boys and girls (Walker, 2011, pp. 19 and 89). It is worth mentioning that Moldova is one of three countries (along with Armenia and Philippines) that in TIMSS (Trends in Mathematics and Science Study) 2003 showed gender differences in mathematics in favor of girls for the first time in IEA history (Ma, 2007, p. 34).

Education Reform Project

To consolidate and extend reforms in education, in January, 2013, the World Bank Board of Executive Directors approved a US$40 million credit to the Republic of Moldova for the Education Reform Project. From 2013, with support of the World Bank, European Union, Open Society Foundations, and Austrian Government, the Republic of Moldova embarked on a number of educational reform programs (MoE 2015; World Bank, 2017a). Primarily focused on preparing students for the future global economy, this investment in Moldovan educational system also aimed such long-term goals as to induce economic growth, enhance productivity, contribute to personal and social development, and reduce social inequity. One of its short-term ambitious goals, however, was to assure much greater competitiveness in terms of

PISA rankings, while at the same time not diminishing and even improving the uniformity in student achievement—providing equal opportunities for all, giving every student the same chances to succeed, and creating the right conditions for all students regardless of socio-economic background, gender, or ethnicity.

PISA 2015 Results

Following years of investment in the education sector, Moldova has made a major leap in student performance ranking among the top 3-6 positions for increases in the average score for each tested discipline: in science, the increase was 9 points; 17 points in reading, and 13 points in mathematics (MoE, 2017). The progress in reading represented almost one year of schooling (Casap, 2017). Moldova also recorded an increase in the share of students with the highest levels of PISA competence in reading and at the same time a decrease in the share of students who fail to reach the basic level of competence. The latter contributes to improving educational equity as does the fact that a share of students able to demonstrate at least basic proficiency in all three subject areas also improved significantly in comparison with the results of PISA 2009 (World Bank, 2016).

According to the World Bank Report (2016), Moldova is the second among the five low middle income countries that participated in PISA 2015. The performance of Moldovan students considerably improved in all three disciplines, and "the change in science performance per three-year period between 2006 or later and 2015 shows one of the strongest increases among PISA-participating countries" (Education GPS, 2018).

Equity Indicators

In terms of equity and its indicators of inclusion and fairness (Table 1), Moldovan students' ESCS accounts for 12% of the variance in science scores, that is non-significantly different from the OECD average of 12.9% (OECD, 2018, p. 8); between-school difference in science is one of the smallest among PISA-participants; both girls and boys in Moldova have made progress in mathematics compared to PISA 2009, and the gender gap in science decreased considerably: from 14 points in PISA 2009 to 7 points in PISA 2015 (Education GPS, 2018). On the other side, far more boys than girls perform below minimal reading proficiency level (Walker, 2011, p. 69); in all three areas, girls scored better than boys; and the gender difference in reading is one of the largest among PISA-participants with girls out-performing boys (Education GPS, 2018). Moreover, the percentage of resilient students in Moldova is only 13% while the OECD average is 29% (OECD, 2016b, p. 207).

A strong equity factor of pre-school attendance is maintained in Moldova via compulsory pre-primary education law: the enrolment levels have expanded rapidly up to 80% and above after 1999 and have sustained (UNESCO, 2015, pp. 61, 222). The obligatory age is of 5 years old, and student-teacher ratio is 10 (p. 197).

Table 1. Comparison between Moldova and OECD average in the equity Indicators of Inclusion and Fairness in Education in PISA 2015

Indicators	Moldova Average	OECD Average
Proportion of between-school variance in Moldovan students' performance accounted for by ESCS (PISA 2009)	13.5	23.6
Percentage of variation in science performance explained by students' ESCS (PISA 2015)	12	12.9
Percentage of variation in math performance explained by students' ESCS (PISA 2015)	N/D	13
Percentage of between-school variation explained by school contextual factors in reading output	77%	76% - 98%
Score-point difference in reading associated with one-unit increase on the ESCS index at the individual level (PISA 2015)	30	N/D
Score-point difference in reading associated with one-unit increase on the ESCS index at the school level (PISA 2015)	15	N/D
Score-point difference in science associated with one-unit increase on the ESCS index (PISA 2015, student level)	33	38
Percentage of resilient students (PISA 2015)	13.4	29.2
Gender difference in science performance (PISA 2015)	7 points higher for girls	3.5 points higher for boys
Gender difference in math performance (PISA 2015)	Non-significant difference	8 points higher for boys
Gender difference in reading performance (PISA 2015)	52 points higher for girls	27 points higher for girls
Educational coverage of the national 15-year-old population (PISA 2015)	0.93	0.89

N/D = No data available

Moreover, despite impressive advances in performance in PISA 2015, Moldova needs to continue reducing the achievement gaps between subpopulations of students. According to World Bank (2016), science performance gap between the top and bottom income groups is equivalent to almost three years of schooling and between urban- and rural-area students is equivalent to almost 1.5 years of schooling. Seemingly satisfying numbers in equity in Table 1, compared with the OECD average, should be treated with caution, as they may turn delusive taking into account Moldova's extremely low share of students in the top two deciles of ESCS, 6.9 % or 64th rank out of 69 countries (Education GPS, 2018). Thus, "moderate equity" may present equally poor population with equally low knowledge and skills.

Research Purpose

The research was focused on the observed differences in Moldovan students' scores from PISA 2015 data to assess the extent to which socio-economic background, medium of instruction (MoI), teaching style, and urban or rural context of the school location are sources of educational inequity in the Republic of Moldova.

PISA measures the extent to which 15-year-old students (i.e. at the age of approaching the end of compulsory education) have acquired key knowledge and skills that are crucial to become fully functional in modern societies. PISA's regular assessments focus on the core school subjects of science, reading and mathematics. Research findings indicate that studies based on PISA results had led to advances in educational research "simultaneously pointing to the need for caution when using this research to inform educational policy" (Hopfenbeck et al., 2017).

The point of departure of the present thesis is a two-level analysis of PISA 2015 data on students' cognitive performance (Moldovan data) rather than the statistical method applied. Hence, the relationship between students' knowledge levels and teaching and learning context—such factors as student SES, medium of instruction, and teaching approach—were examined. Differences in outcomes between students attending different schools were emphasized, and PISA's construct of social, economic and cultural status (ESCS) were used to examine the complex relationships between school-level variables and academic outcomes.

Research Questions

The research topic of the thesis is a two-level analysis of PISA 2015 data on Moldovan students' cognitive performance identifying the factors behind differences in performance of fifteen-year-olds. To answer the general question of the study "Does Moldovan formal education reproduces social inequality or foster socio-economic opportunity?" the following research questions (RQ) were addressed:

RQ1: Is ESCS a strongest predictor of Moldovan student's performance?

RQ2: How is the regional school location, or urban versus rural context, is linked to the equity in Moldovan secondary education?

RQ3: How is the language of schooling linked to the equity in Moldovan secondary education?

RQ4: Are Russian-medium and Romanian schools of Moldova equitable?

RQ5: Has teaching style a compensatory power on ESCS-performance relationship in Moldovan schools?

RQ6: Do different schools have different degree of educational equity, measured by the variation of the effect of SES on performance?

Research Relevance

In order to increase educational equity in a country, the strength of the strong relation between student SES and academic outcomes needs to be reduced. To do so, school characteristics that reduce SES-achievement ties have to be identified (Gustafsson, Nilsen, Yang Hansen, 2016). According to OECD, "as policy makers have limited direct impact on teaching and learning processes, information on school-level factors that help to improve schools, and thus indirectly improve student learning, have high priority" (OECD, 2016a, p. 104).The results of the given research are supposed to inform all Moldovan stakeholders, who are still little aware of the potential of data for promoting school improvement (Civic.md, 2016). With extensive educational reforms being on the way (Casap, 2017), PISA 2015 brought unprecedented amount of data available for analysis and further development of a number of proposals on educational policy and practice, as O. Tsicu, a member of the Expert Council for Education, acting within the framework of the Educational Project of the Soros Foundation in Moldova, told in May, 2017 (IPN).

However, Moldovan science is in a declining state in all respects: funding, new staff entry, and renovation of scientific equipment (Dumitrasco, 2014). So far, there are only two documented PISA-based analyses on Moldovan data—standard assessments from OECD for PISA 2009 (Walker, 2011) and PISA 2015 (Education GPS, 2018). The Ministry of Education and the National Agency for Curriculum and Evaluation also publicly presented the detailed report (MoE, 2016) on the results of the Republic of Moldova's participation in PISA 2015, but the report is a mere extract from OECD findings. My investigation, therefore, may turn into a sufficient contribution to Moldovan educational reforms, inclusive growth, and into reduction of social and regional inequity in Moldova.

There are two more gaps that the given study will address: a) absence of quantitative research written in English on educational inequity in post-Soviet states, and b) strikingly understudied within-country analyses of educational efficiency and equity—especially in comparison with the number of between-country studies. Thus, Agasisti and Cordero-Ferrera (2013, p. 1080) noted, "there is still low attention to the within-countries analyses of educational efficiency and equity, especially when concerning international (European) comparisons" (Agasisti & Cordero-Ferrera, 2013). Having done my own systematic literature review search for the given study, I agree that cross-country comparisons are a rear exercise in PISA-based research.

Finally, thriving technology has been providing more and more opportunities for capturing and studying cognition, skills, and attitudes. PISA data, stored in publicly accessible files, are a mighty source of information on student performance and a variety of factors it is rooted in. Overall, human society has been changing dramatically, becoming more and more open, technology-oriented, and heterogeneous. To keep constantly evolving learning environments functional, we must make education equal as soon as possible. With collected help of studies via advanced statistical methods—including the given one—the issue of educational inequity is likely to be tackled in majority of the countries within two-three decades, similarly to the topic of illiteracy, which persists today only in the least-income countries (OECD, 2016b, p. 265).

Ethical Considerations

Ethical considerations of a research are principles that dictate how a researcher should act so as his/her research is not to be harmful to others. Researcher's behavior therefore is increasingly constrained by the codes of ethical conduct which require investigators to act in ways that do as little harm as possible to the people they study. The main ethical problem of large-scale assessments like PISA is dealing with the privacy and confidentiality of the received data because a great deal of personal information obtained is sensitive, for instance family wealth and academic performance.

PISA data has already been protected by the National Research Coordinator in each participating country. Privacy considerations have been applied to all components of the assessment, by design and by default, following General Data Protection Regulation recommendations or national legislations (OECD, 2018, p. 9). Schools and students are assigned unique ID numbers, and no individuals neither institutions can possibly be identified from the data files publicized at PISA homepage. All variables and coded samples of the survey are freely available for secondary analysis, and ethical consent is not required.

Outline

The thesis consists of six chapters. The first chapter of introduction states the scientific problem of educational inequity and its contextual background in the republic of Moldova. It also positions the questions aimed to be answered by the research. The second chapter presents the theoretical and conceptual framework of the study. In the third chapter, the methodology and research techniques for the analysis are outlined. The fourth chapter describes the analyses of all statistical models of the study and their results. The answers for research questions are suggested in the fifth chapter, and the recommendations for the future research are provided in the last chapter.

Theoretical and Conceptual Framework

Many studies on the issue of educational equity assert that socio-economic gap in students' academic and other outcomes continues to be a challenge to educational equity (Noël & de Broucker, 2001). Yet, other studies argue that schooling in capitalist societies maintains class inequalities by directing students into distinct class-based educational (and consequently occupational) paths (e.g., Bowles & Gintis, 2001). Still others present formal education as a central mechanism that sustains intergenerational transmission of social, economic, and cultural resources and benefits as well as disadvantages (Bourdieu, 1986, 1987, 1997). As a result, a range of theories have been rivalling each other in an attempt to conceptualize and tackle educational inequity: from Functionalist, Conflict, and Interactionist Theories through School-centered Explanations (Between-school- vs Within-school Differences) to Social Reproduction theories and further (Marks, 2013).

So-called multilevel theories have been developed following the advances made in modeling and computing technology. The operationalization involves a number of theoretical assumptions and specification problems for auxiliary theories (Klein & Kozlowski, 2000). They emphasize three core concepts: 1) the levels of variability in human society, including individual- and environmental level variabilities (hereafter, defined as individual- and school level respectively); 2) the interplay between a person and his/her social environment is dynamic; 3) variability across individuals within the same environment interplays with variability within the same individual across environments (e.g., Chan, 1998). Similarly, from 1970s, in School Effectiveness Research (EER), educational researchers have been theorizing that taking group structure into account would enhance the dependencies between individual observations (Kreft & de Leeuw, 1998, p. 6). The main concern of EER area is the identification those factors in teaching, curriculum, and learning environments that directly or indirectly explain variations in students' outcomes (among others, see e.g., Kyriakides & Creemers, 2017).

Theoretical Stands on Educational Equity

Quality and equity— the two global dimensions of school effectiveness—have been at the heart of educational research (Strand, 2010). The model of distribution of social opportunities introduced by Boudon (1974), explains that every person's educational opportunities largely depend on two groups of factors: 1) the SES influences per se on the skills and expectations that he or she learns from family (primary effects, expressed through uneven academic performance of students with differing social origins), and 2) the way that social class affects the educational choices made by students and their parents (the secondary effects, that operate over and above academic performance). Despite equal performance, the secondary effect conditions children from socially advantaged families to choose further education much more often than children from less advantaged families would do so, and particularly in academic tracks. Finally, according to the model, it is theoretical distinction between primary and secondary effects that explains why higher equity in educational achievement and lessened schooling inequities would not necessarily weaken the strong relation between one person's social origin and his/her SES as an adult (Bulle, 2008).

The concept of educational equity, which indicates how schools compensate for input characteristics (e.g. SES, gender and ethnicity), has been developed starting from Bourdieu's Theory of Cultural Capital. According to Barone, Bourdieu's theory is "the most well-known and widely accepted sociological explanation of the primary effects" (Barone, 2005, p.173). The theory outlines a complex system in which parents transmit cultural capital to children; children, in turn, exploit their acquired cultural capital in the educational system, and, as a result, families that possess richer cultural capital get an advantage that helps them reproduce their privileged socio-economic status (Bourdieu, 1989).

Theoretical framework of Berne and Stiefel in the 1980s distinguished between:

a) Horizontal equity: equality of treatment for those who start from the same point;

b) Vertical equity: educational differentiation to bring everyone to the same level of competence;

c) Equal educational opportunity (EEO): compensatory measures regarding the lack of resources or the existence of disadvantageous situations that prevent the possibility of the same results being achieved (Castellia, Ragazzia, & Crescentini, 2012).

Dynamic Model of Educational Effectiveness and Improvement (Creemers & Kyriakides, 2012) studies equity and within-school variation in terms of consistency, stability, and differential effectiveness. This model of EER explores approaches to conceptualize and measure the equity gap, among other things. Its major research questions concern "the 'who' (which student groups), the 'what' (which outcomes, both cognitive and socio-emotional) and the 'when' (trends over time of school trajectories)" while measuring effectiveness and improvement as well as planning the interventions to promote equity (Sammons, 2017, p. 3).

Dynamic Model of Cultural Reproduction (Jæger & Breen, 2016) is drawn on Pierre Bourdieu's theory of cultural reproduction (1997) as a formal model of the pathways through which cultural capital enhances children's educational and socio-economic opportunities. The model clarifies conceptually and empirically why inequities in educational and socio-economic outcomes persist over generations with Bourdieu's theory as the basis: parents transmit cultural capital to their children, and children convert it into educational success.

Input-Process-Output (IPO) Model as a Conceptual Framework

OECD mastered a highly elaborated context framework with primary theoretical conception based on the Input-Process-Output model, which consists of the sensibility of environment, the integration of resource, and the implementation of goals in terms of educational effectiveness (OECD, 2013a; Townsend, 2007, p. 396). Table 2 shows a recent version of Input-Process-Output model, where the input, process, and outcome factors are observed and structured on student-, classroom-, school-, and system levels, as elements of a Two-dimensional Taxonomy of predictive factors and educational outcomes (Cresswell, Schwantner, & Waters, 2015, p. 72).

Table 2. Two-dimensional Taxonomy of Educational Outcomes and Predictive Factors

	Input	Processes	Outcomes
Students	Gender, grade level, socio-economic status Educational career, grades Immigration background, family environment and support ICT experience, attitudes, skills Openness, problem-solving styles	Attendance/truancy Outside-class activities - e.g. participation in after-school programmes Motivation, engagement Learning and thinking strategies, test taking strategies Learning time (including homework and private tuition)	Mathematical performance Mathematics-related attitudes, beliefs and motivation General school-related attitudes and behaviour, e.g. commitment, truancy Learning motivation, educational expectations
Classrooms	Class size, socio-economic background and ethnic composition Teacher education/training, expertise	Quality of instruction: structure, support, challenge Opportunity to learn: implemented curriculum, assigned tasks, mathematics-related activities Instructional time, grouping, assessment and feedback	Aggregated student variables
Schools	Socio-economic background and ethnic composition Affluence of the community School funding, public vs. private School size Parental involvement	Achievement orientation, shared norms, leadership, teacher morale and co-operation, professional development Admission and recruitment policies, tracking, course offerings/school curriculum, evaluation Teacher-student relations, supportive environment	Aggregated student variables Promotion/retention and graduation rates Attendance
Countries (Systems)	Economic wealth, social (in)equality Diversity policies	School funding, tracking and allocation, policies for professional teacher development, support for special needs and language minority students, hiring and certification policies Accountability and evaluation policies, locus of decision making	Aggregated student variables Average graduation level

Source: OECD. (2013). PISA 2012 Assessment and Analytical Framework: Mathematics, Reading, Science, Problem Solving and Financial Literacy. Paris: PISA, OECD Publishing, p. 175.

The IPO conceptual and analytical model presents educational processes as a link between educational inputs and outcomes (Table 2). To specify, schools process contextually and climatically pupils with different backgrounds—personal and family characteristics as well as various cognitive and affective conditions—into different sets of learning outcomes (Ma, Yuan, & Luo, 2016, p. 514). IPO was developed in the early 1990s as a result of a shift from “input-output” to “input-process-output” structure of EER studies attempting to define the reasons for schools affecting students’ results differently (Reynolds … Stringfield, 2014). Today, IPO is at the basis of existing educational effectiveness models and theories (Scheerens, 2015).

In accordance with multilevel theories and theoretical stands on educational equity, IPO positions all inputs, processes, and outcomes on different levels of analysis (Table 2). School-level factors are determined by formal or informal school-policy decisions and are set as constant values for all participants studying in the same school. They explain a considerable proportion of the difference between individual schools (the between-school variance) in academic performance, much of which is associated with socio-economic and demographic factors (Marzano, 2003). This suggests that an individual school's policy, accountability, educational resources, and learning environment are influenced by the social and demographic intake of the school. Schools accommodating students from higher socio-economic backgrounds tend to be more autonomous on their curricula, make more use of assessment, foster better student-teacher relationships, and use more educational resources; no wonder that students attending those schools show better educational outcomes (Walker, 2011, p. xviii).

However, School Effectiveness Research in the last 35 years demonstrates that effective schools can compensate a profound impact of the background on student achievement (Marzano, 2003). IPO model, in a specific, quantitative way, outlines the relationships between individuals and the contexts in which they are embedded, and provides deeper insights into the ways the factors of both individual- and school levels explain the outcomes of a test. For instance, without accurately incorporating personal-background variables into statistical models, a researcher would bias his or her analysis in ways that underestimate the role of school-level factors and overestimate the effect of individual- or student-level characteristics (ethnicity, gender, etc., see e.g., Hox et al., 2017). Such error would induce faulty findings regarding the importance of school-level determinants, thus resulting in misleading educational reforms. IPO abridges the theory-to-methods translational gap and helps to conceptualize the settings. That, in turn, helps to understand the level (i.e. the individual- or school level) at which an intervention will be most effective and, thus, promotes theory- and research-driven educational policies (Ma et al, 2008). Eclectic approach or, in other words, borrowing from more established theories was implemented to define variables in models and to interpret the results (Snow, 1973).

Hence, IPO conceptual model provides a well-defined analytical framework for multilevel modeling to manipulate hierarchical and nested data (students within schools): the two-dimensional taxonomy is its grating (or rather strands, to make it more dynamic), which consists of several general theories such as Dynamic Model of Cultural Reproduction, drawn on Pierre Bourdieu's theory of cultural reproduction (Jæger & Breen, 2016) and Dynamic Model of Educational Effectiveness and Improvement (Antoniou & Kyriakides, 2011). In the meshes, the knowledge base of educational effectiveness research is plaited in: being based on equity problematics, these findings are more narrow and specific to particular constructs or content areas, explaining the associations between variables in an integrated theoretical way.

The critique on IPO model is mainly on its exclusive engagement with perceptual indices and ignoring direct observations of behaviors. Subjective nature of personal perceptions and self-reported measures that are used for IPO studies (including the present report) is not always in agreement with validity criteria and is the main concern of the opponents of IPO (Sammons, Reynolds, & Teddlie, 2002, p. 60).

Literature Review of Research on Equity Problematics

Knowledge as a problematic involves its understanding not as a fixed body of information, but rather as being constructed (Holstein & Keene, 2013, p. 633). G. H. von Wright's concepts of *explanandum* and *explanans* (1971) provide a bridge between IOP model and a network of theories, where variables of interest are connected with explanandum being a concept or a phenomenon questioned and explanans being an explanation provided by research.

In equity problematics, explanandum and explanans are closely intertwined and defining each other, thus identifying inequity in education among different taxonomic groups outlined by SES, gender, ethnicity, or another characteristic. Hence, equity problematic is largely defined by a combination of academic results and grouping the students in taxonomies (Lindblad et al., 2015, p. 64). To construct a network of theories for particular variables, I carried out a systematic literature review of EER studies.

According to OECD (2012), a student attending a "more affluent" school, where majority of students come from a high SES, is likely to experience a more favorable learning environment, peer influence, better teaching quality and resources than a student of a "more disadvantaged" school. As a result, attainment is affected accordingly. Different mechanisms seem to work at individual- and school levels. Equity refers to "fairness [that] implies that personal or socio-economic circumstances, such as gender, ethnic origin or family background are not obstacles to educational success" (OECD, 2012, p. 15). PISA results have drawn attention to educational inequity associated with SES, gender, and migrant status, demonstrating that disadvantaged groups are likely to score lower (OECD, 2014b). Some countries are more successful in breaking the disadvantaged trap. The countries that participate in every assessment cycle are able to monitor over time the developments of equity in their educational systems and to compare them with other systems. The consistency of all stages—from data collection through analysis, to interpretation— warrants comparability.

PISA provides data that help evaluate education systems with respect to these different criteria for equity. Thus, one of the important messages of OECD PISA reports is that high-performing countries tend to allocate resources more equitably across "more disadvantaged" and "more affluent" schools (OECD, 2014a). The current study is an attempt to contemplate the results of PISA data analyses in framework of

IPO conceptual and analytical model and to examine whether Moldova is heading towards such distribution of the resources.

Literacies in PISA Studies

PISA defines science literacy as what 15-year-old students should know, value, and be able to do to be "prepared for life in modern society" (OECD, 2013c). Mathematical literacy is defined as an individual's faculty to formulate, employ, and interpret mathematics in different circumstances. It allows an individual to recognize the role that mathematics play in the world and to make well-founded judgments and decisions (OECD, 2013a). Finally, OECD defines reading literacy as the ability to understand and use those written language forms required by society and/or valued by the individual, to construct meaning from a variety of texts, to read for learning, participating in communities of readers, and for enjoyment (Campbell, Kelly, Mullis, Martin, & Sainsbury, 2001, p.3). Mathematical, reading, and science literacies are educational outcomes of the IPO model (Table 2). Depending on the purpose of a research, they may be set either at individual level or as a school average at school level.

Socio-economic Status

According to IPO, the SES (or ESCS for that matter) is an input in the model and might be measured at different levels depending on the research question (Table 2). SES is a broad concept that incorporates many different characteristics of a student, his or her school, and the local educational system and refers to student's family's position in a hierarchy according to access to wealth, power, and social status (Gustafsson et al., 2016, p. 1). In PISA, student's socio-economic background is expressed by the index of economic, social, and cultural status (ESCS), which is calculated from the highest level of student's parents' occupation, their highest level of education, and an index of home possessions, including cultural possessions, educational resources, and other items in the home. The ESCS index is internationally comparable and reflects many important differences across students' families. Students are socio-economically advantaged if they are in the highest 25 percentiles of the ESCS score in their country and are socio-economically disadvantaged if they are in the lowest 25 percentiles of ESCS.

SES–Academic-outcome Association at Individual Level

Across OECD member-countries, 14.8% of variation in students' performance can be explained by disparities in students' SES. The stronger this relationship is, the less likely are students from disadvantaged families to achieve high levels of performance (OECD, 2013b, p. 34). Educational research has a 50-year record that those students are also less likely to study specialized math and science subjects (Considine & Zappala, 2002). On the other side, several studies found only modest or no differential effects of student SES on academic outcome (Strand, 2010; Marks, 2013).

Home socio-economic status appeared to be strongly related to students' mathematics outcomes on average across OECD countries (Brese & Mirazchiyski, 2008) with SES accounting for 13.0% of the variation in mathematics outcome, 12.9% of the variation in performance in science, and 11.9% of the variation in reading achievement (OECD, 2016b, p. 216).

Cultural status, although being a part of ESCS, individually predicts a large share of the reading achievement of a student (Yang & Gustafsson, 2004) in full accordance with Bourdieu's concepts (1997). Cultural background also plays a greater role in reading development than in development of mathematical or science-related skills. Educational level of parents and student's early reading activities affect the reading achievement of a student, while parents' early reading activities with their children mediate a large part of the effect on reading achievement by the number of books at home (Myrberg & Rosén, 2009).

SES–Academic-outcome Association at School Level

School SES or student-body SES is a school-level characteristic of how school SES is composed. The variable is calculated as an averaged measure of all students' SES within a school (Ma et al., 2016, p. 512), and, in IPO model, is considered as an input factor at the school level (Table 2).

In relation to IPO model, the school-level predictors are categorized from two perspectives: context and climate (Ma et al, 2008). School-context predictors are classified as input factors, while the following school-climate variables are considered the processes (OECD, 2013a, p. 174).

a) Context predictors characterize the physical background (e.g. school urban or rural location and resources), the student body (e.g. enrolment size and school-average SES), and teachers (e.g. teaching approach and teacher education levels). For all country-participants of PISA 2009 and PISA 2009 +, the contextual factors account for between 76% and 98% of the between-school variance in reading outcome. Moldova, however, is on the lower end of this distribution, only 76% of between-school variance in reading outcome explained by contextual school-level factors (Walker, 2011).

b) Climate variables—also named as evaluative variables— characterize the learning environment (e.g. instructional organization and disciplinary climate).

More than half of a century, educational researchers have been discussing uneven results on SES-achievement correlation at different levels of assessment after J. S. Coleman and his team stated that school-level inputs were only weakly associated with student outcomes (Coleman et al., 1966). Thus, at the individual level, the both cultural and social capital always manifest themselves as two of the most important predictors of reading literacy outcome (Alivernini, 2013). Similarly, there is a bulk of studies that confirm the second key observation of Coleman: school-level predictors play a much weaker role in predicting learning outcomes in reading and mathematics than individual-level predictors do (Rolfsman, Wiberg, & Laukaityte, 2013). More than that, sometimes, individual-level characteristics may fully explain the whole variation of students' outcomes and even school differences (Sulkunen & Nissinen, 2013).

However, a growing number of studies suggest that schools do make a tangible contribution to student outcome (Wößmann, 2003; Hattie, 2009); particularly, via such changes as class sizes reduction, teacher quality increment, and peers' success (Rivkin, Hanushek, & Kain, 2005). Likewise, most of the school-level variables are likely to be linked to mathematics performance (OECD, 2013a, p. 188).

To summarize the highlights on SES input of IPO model:

- Differential school effects are the overall impact of a school on its "average" student (Reynolds et al., 2014). But the same school might affect its students differently: the same teachers, syllabus, school climate, and approaches may be more efficient for one group of students than for another group.
- Either a school is over- or underperforming, the differences persist across subjects, grades, and years (Leigh & Thompson, 2008).
- Most importantly, research consistently shows a strong direct correlation between socio-economic status of student's family and his or her educational success disregarding whether the analyses are made on student- or school-level data (Graetz, 1995, pp. 28, 32-35). In most countries, the correlation is about 0.20 - 0.40 at the individual level (Sirin, 2005); and it is even higher with data aggregated to the school level (Gustafsson et al., 2016, p. 1).

Curvilinear Relations

There is a range of studies investigating differential school effects for student groups that are variant in prior achievement, gender, ethnic origin, and SES (Scheerens & Bosker, 1997). Thus, research, based on Dynamic Model of Educational Effectiveness and Improvement (Creemers & Kyriakides, 2012), assumes curvilinear relations and interaction effects on student achievement and shows that school effects are oftentimes a function of variables that were used to set the groups. Factors do not necessarily equally impact different groups of students, schools, and education systems; and the level of the factor plays a substantial role in size of that variance (Kyriakides, 2008). For example, teaching approach may interact with or, in other words, vary in its effectiveness across individual-level background characteristics and school-level contexts. Thus, students from disadvantaged families are more likely to be influenced by teacher's feedback (Trouilloud, Sarrazin, Bressoux, & Bois, 2006). A good example of curvilinear relation may make the relationship between student achievement and the frequency of classroom evaluations: the initial positive effect (as more assessments students get as better the results are) would reduce at higher levels, that is "teaching to the test" when too many evaluations take all time of class-periods, and it becomes impossible to convey new concepts to students adequately.

Disciplinary Climate

Disciplinary climate contingent to teacher's effective classroom-management skills is a school-level process predictor of the IPO model (Table 2). From Edmonds' (1979) historical findings of five "correlates" to more recent studies, research shows that efficient learning is largely supported by a positive and respectful class environment, which is focused on student performance and is relatively free of disruption (Marzano, 2007). Orderly environment is also a moderator between students' interests and their academic outcomes (Lipowsky, … Reusser, 2009). Finally, a strong positive curvilinear association was revealed between cognitive activation strategies and mathematics outcomes with school-level factor of disciplinary climate and student SES as moderators: while the link tends to be stronger in schools with an orderly climate that facilitated learning for students from advantaged families, for disadvantaged students the association is even stronger, but it turns into negative for high levels of teacher-directed instruction (Baumert, … Tsai, 2009). As opposed to that, there is no association between student-oriented instruction approach with mathematics outcomes (Caro, Lenkeit, & Kyriakides, 2015, p. 3). Furthermore, when educational resources are taken into account, a climate predictor of ordinary classroom explains far greater variance in performance than contextual predictors do (Fini, R., 2007, p. 174).

Teacher's approach and feedback is another school-level process predictor of the IPO model (Table 2). Many studies consider teachers as an important, or even the most important, factor in improving students' outcomes (Aaronson, Barrow, & Sander, 2007). Teachers' use of effective instructional approaches may promote resilience and positive effects on motivational-affective outcomes. For instance, providing feedback and support could help to improve students' motivation and confidence and, by extension, student resilience (Seidel & Shavelson, 2007). Many studies consider teacher's feedback as one of the most important factors for learning outcomes (Hattie & Timperley, 2007) because effective judgments inform students on what they need to learn and where to go next, allowing them to correctly assess their own skills.

A Dynamic Model of Cultural Reproduction describes how student's cultural capital is converted into educational performance with teachers' perceptions of student's capabilities as a mediator, when family's cultural background results into greater teacher's attention and support, and, consequently, better student's outcomes. A student with richer cultural capital is perceived as more capable and even gifted, leading to biased evaluations by teachers and higher grades. Moreover, such students are treated more positively by teachers, which would lead to a better learning context and even better educational performance. Well-off parents' investment in child's cultural capital helps others assess child's cultural capital, which, in turn enhances the image of the child, teacher's inputs in him or her, child's academic results and future socio-economic success (Jæger & Breen, 2016).

A complex relationship of mutual mediations appears among those three variables as low SES serves as a mediator between teacher's supportive behavior and students' performance: disadvantage students' outcomes improve significantly when teacher generates a warm and supportive climate (Reynolds, et al., 2014, p. 26). OECD resilience report also has emphasized the importance of school climate (2018).

Inquiry-based teaching practices & teacher-led inquiry activities are process predictors of the IPO model (Table 2). Research shows that inquiry-based teaching plays an important role in science education and is positively associated with students' outcomes in science, particularly when it is directed by teacher (Furtak, Seidel, Iverson, & Briggs, 2012). Inquiry-based instruction also enhances attitudes towards science and transferable critical thinking skills (Hattie, 2009).

Gender

Gender is considered a strong individual-level input predictor. However, when aggregating it at school-level, researchers come to contradictory conclusions: while some studies found that schools are equally effective for boys and girls (Thomas, 2001), others reveal differences in gender gaps among schools (Strand, 2010).

At individual level, findings across the globe are more consistent. Gender is the only criterion in educational research where scientists agree on some amount of biological predisposition of girls to reading literacies (Buckingham, 1999, p. 5; Horne, 2000; UNESCO, 2015). Additionally, boys suffer societal educational disadvantage in comparison to girls in all disciplines, and particularly so in reading literacy (Buckingham, 2000). Differential teaching approaches, curricula, and assessment, for example, less structured approaches to teaching grammar to boys, and, finally, SES factors are greatly associated with the gender gaps across all socio-economic levels (Teese, Davies, Charlton, & Polesel, 1995).

But research on PISA data shows that while girls have still been much more involved in reading and perform significantly higher in reading tasks supposedly due to social bias (Gustafsson, Yang Hansen, & Rosen, 2013), on average, nevertheless, the gender gap in reading in favor of girls has narrowed by 12 points between 2009 and 2015 across OECD countries (OECD, 2016b).

PISA findings also suggest that student's engagement in reading mitigates the score differences both across the genders and between students from different levels of SES (OECD, 2010a). Overall, changes in the gender gap in learning outcomes might be used as a measure of progress towards gender parity (UNESCO, 2015, p. 35). For example, there is evidence of the shrinking of the gap separating girls from out-performing boys in mathematics and science (Sanchez & Wiley, 2010), and of the fluctuations of the gap in favor of girls in reading and language, which was steadily increasing around the millennium (Buckingham, 2000), but has been decreasing for a decade or so.

Geographical Location of a School

Geographical location of a school oftentimes mirrors the level of affluence of the local community as well as many other input predictors at the school-level of the IPO model (Table 2). Students from non-metropolitan areas are more likely to perform lower in terms of academic outcome and retention rates than students from metropolitan areas (Cheers, 1990). Even if educational facilities in regional schools were at a sufficient level, their students remain disadvantaged by a range of other factors: lower family budget, the availability of transport, restricted and limited subject choice, and limited recreational facilities to name but a few (Considine & Zappala, 2002, p. 95). Moreover, the quality of the educational resources in regional schools of many countries is still a far cry from what metropolitan schools offer (HREOC, 2000, p. 12).

Pre-primary Attendance

Pre-primary attendance is a part of educational career, set as a student-level input predictor of the IPO model (Table 2). As student performance is strongly associated with his or her personal background, pre-school learning in the formative years before formal schooling is likely to play its role in student's academic success (Blau & Currie, 2006). However, pre-primary attendance is likely to impact equality of educational opportunity for disadvantage students only if the majority of a country's children attend pre-primary institutions (Hanushek, & Woessmann, 2014, p. 170). As by 2017, in a majority of OECD countries, education begins for most children well before elementary school: 78% of three-year-olds are enrolled in early-childhood education facilities. In OECD countries that are members of the European Union, 80% of three-year-olds are enrolled (OECD, 2017a, p. 262). Pre-school education is recognized as an equity factor because it appears promoting school readiness and better adjustment to school and is conceptualized as an efficient means of raising school performance of all children, and especially of those who experience a lack of parental support (Anders, … von Maurice, 2012).

Instrumental Motivation and Science Self-efficacy

Instrumental motivation and science self-efficacy are affective (or personality) variables of PISA and are process predictors at the individual level of the IPO model (Table 2). A number of meta-analyses studying the influence of personality on achievement showed the relationship between academic performance and a range of personality variables (such as anxiety, dogmatism, extraversion, etc.) close to zero. However, self-efficacy, self-concept, and motivational characteristics appear largely correlated with student achievement (Hattie, 2009). Self-efficacy beliefs are also associated with stronger interests in science careers and with a greater likelihood of selecting science majors. (Schoon, 2001).

Self-efficacy is observed to serve as a moderator between low SES levels and science-related career of an economically disadvantaged student (OECD, 2011, p. 46). Low-SES students who are self-confident to handle tasks effectively and address the challenges are significantly more likely to succeed in science than disadvantaged students with low levels of self-efficacy. On average, across OECD countries, of all students' attitudes and behaviors variables studied by PISA, self-efficacy has the strongest association with resilience (idem).

Environmental Awareness and Environmental Beliefs

Environmental awareness is considered a core to the construct of scientific literacy PISA 2015 (OECD, 2016a, p. 37). A positive attitude to science and a concern for the environment and an environmentally sustainable living are considered as characteristics of a scientifically literate individual. Hence, PISA considers the extent of being interested in science and recognizes its value and implications as an important measure of the outcome of compulsory education. In 52 of the country-participants (including all OECD member-countries) in PISA 2006, students with a higher interest in science performed better in science (OECD, 2007, p.143). PISA 2006 showed that students with higher ESCS reported higher levels of environmental awareness and that this construct is linked with students' performance in science (OECD, 2007). Therefore, PISA 2015 included Environmental Awareness and two measures of environmental beliefs that were developed for PISA 2006.

Equity and School-level SES

The direction and strength of the association of school-average SES with the within-school relation between student's SES and achievement was revealed as a better measure of equity at system level than other measures such as ICC of SES, academic achievement across schools, between-school regression of performance on SES, or the standard deviation of a test-score (Gustafsson et al., 2016, p. 12). Non-tracked, comprehensive educational systems generally show stronger relationship between cognitive performance and SES on the individual level (within school). The educational systems with organizational differentiation (as in many developing countries), on the contrary, have steeper relations between socio-economic status and academic performance on the school level (between schools). Such systems are defined as anti-compensatory educational systems (Burger, 2016). The anti-compensatory educational systems have lower within-school slopes than compensatory educational systems. Compensatory systems manage to break the vicious circle between low SES and poor achievement via healthier school climates, high priority for academic success, high quality of instruction, and eliminating adverse peer effects.

Methodology

Relatively young field of statistical modeling has won the preferences of modern methodologists in educational research and contributed disproportionally to the fact that more than 75% of educational research had been done by quantitative methodology by 2010, and statistical modeling is overwhelmingly represented in educational research on PISA data (Zhang & Wang, 2017, p. 440). Such popularity of statistical modeling for work with PISA data (as well as with all other large-scale assessments) is justified by the fact that advanced statistics enable the researchers to go beyond basic descriptive and intermediate methods, developing well-thought-out, context-specific research models reflecting the actual change, gain, or loss on some variables and simultaneously permitting to test for significance of those alterations.

Sampling and Data Collection

The study used Moldovan data from PISA 2015, an internationally agreed two-hour testing which has been administered in a triennial cycle since 2000. The assessment of interest was the sixth testing of over half-a-million students, representing 28 million 15-year-olds in 35 OECD member-countries and 37 partner-countries and regions including 5325 students from 227 Moldovan educational institutions, namely gymnasiums, high schools, vocational schools and colleges (MoE, 2017).

Table 3. Sample Characteristics

Sample & Sub-samples	N of Schools (N of Russian-MoI Schools)	N of Students (% from Total)	% of Girls	% of Russian-MoI Students
Total Sample	227 (61)	5325 (100%)	49.5%	20%
Metro Sub-sample	41 (18)	1171 (22%)	52.7%	30.3%
Urban Sub-sample	39 (18)	1082 (20.3%)	51.2%	31%
Rural Sub-sample	147 (25)	3072 (57.7%)	47.6%	12.3%

As a preparation for the main testing in 2015, a pilot testing was conducted in April 2014 in Moldova, collecting responses of 1440 pupils from 38 schools. The actual assessment was conducted in October 2015, preceded by a two-stage stratified sampling design with schools selected at the first stage (the probability of selection is proportional to size). At the second stage, a random sample of 35 fifteen-year-olds was chosen from every school (if applicable) for participation (OECD, 2014b). PISA 2015 Moldovan data were collected from 5325 students of 227 schools in all contextual areas of the country (Table 3): 41 schools in metropolitan areas, 39 schools in urban areas, and 147 schools in rural areas. This distribution truly represent the distribution of secondary schools across the country with three metro-cities, 55 towns, and 1478 villages (Characteristics - Population, 2014). Similarly, the 40-to-60 ratio of urban to rural parts of the sample is very close to 45-to-55 ratio of Moldovan population (Moldova Demographics, 2018). Gender and language distributions of the sample are also representative of the target population—fifteen-year-old school students—80 % of which are native speakers of Romanian language (Moldova Demographics, 2018; The Population, 2017). Two media of instruction (MoI) have been used in Moldova: Romanian and Russian. Accordingly, 20% of PISA 2015 sample in Moldova are Russian-MoI-taught students. Twenty schools out of 227 that were sampled teach in both MoIs; and out of remained 207 schools, 41 are Russian-medium. Unequal distribution of Russian-taught students across the urban and rural contexts reflects the actual situation in Moldova with non-Romanian native speakers (Russians, Ukrainians, Gagauz, Roma, and Bulgarians) living disproportionally in urban areas (Moldova – Russians, 2018).

The average cluster size was 20-23 respondents per school (depending on model). The total number of students within schools varies from 1 to 35. Every selected student was administered a background questionnaire and a subset of cognitive items, majority of which were on scientific literacy (a major domain in PISA 2015), while others – on reading- and mathematical literacy (the minor domains in PISA 2015).

Matrix Sampling

A sophisticated scheme of presenting the items in subject-tests (in math-, reading-, and science literacies) was used to minimize testing burden on participants without compromising accurate proficiency estimates of population. Every student answered a part of an extensive pool of questions, and cross-sectional estimates of achievement were calculated from that data (OECD, 2009, p. 43). Several non-overlapping booklet designs (sets of questions) with 10 to 15 items per block ensured a sufficient exposure of the sample to items (idem, p. 89). Since, the participants only took a small subset of test items and the non-overlapping part of the test items were regarded as the missing values. The performance level is thus estimated with measurement error (von Davier, Gonzalez & Mislevy, 2009). In order to account for the measurement errors, a set of ***Plausible Values*** (PVs, Appendix 7) is computed for each student with a multiple imputation technique (Mislevy, 1991) and a generalized partial credit model, taking into account all the available information of responses in test items and background variables (Yamamoto & Kulick, 2000). Hence, the estimates of student performance are obtained on the whole assessment, although each student responded to a subset of the assessment items pool. Plausible values should not be treated as individual test scores, but as a measure of population performance.

Dataset and Variables

PISA features a wealth of personal background information reported by participating students. In accordance with IPO's Two-dimensional Taxonomy of Predictive Factors (Table 2), a large section of the student questionnaire is allocated for contextual factors that are linked to cognitive and non-cognitive outcomes. They are used by PISA to define the indicators. The factors are classified as being either input factors—which are mostly related to the social and personal background of students—or process factors, which are mostly related to the teaching-learning context (Table 4). These data are an excellent resource for those who research in the school contexts and correlates of learning (OECD, 2013a, p. 177).

The data set of the given study contains 19 variables as shown in Tables 4 and 6. Since the IPO model's hierarchical structure was assumed for the predictors of student performance, the independent variables of the given study (non-shadowed in Table 4) were classified into two groups:

- individual-level factors: student ESCS, gender, early learning opportunities (pre-school attendance), age of starting the schooling, instrumental motivation, sense of belonging to school, environmental awareness, and epistemological beliefs;
- school-level factors: school socio-economic composition (or school-averaged student ESCS), five variables of teaching style as perceived by students (e.g. the extent to which class time is spent in independent activities, such as working in workbooks, versus small group activity, and whole-class teacher-centered instruction), language of schooling, and school urban/rural location.

Cognitive outcomes or the results of students' performance in three cognitive areas (shadowed in Table 4) were classified as the outputs and dependent variables of the study; each is represented by ten plausible values for every student (Appendix 7). All three variables were analyzed in relation to the baseline level of science proficiency—"the level of achievement on the PISA scale at which students begin to demonstrate the science competencies that will enable them to participate effectively and productively in life situations related to science and technology" (OECD, 2016b, p.72).

The student data consist of all individual- and school-level variables. The school values are constant for students within the same schools: the language of schooling and metro/urban/rural context of the school are presented in PISA data, while other school-level variables are defined by averaging the means of the corresponding individual-level variables (Table 4).

Table 4. Variables of the Study

Levels of IPO Model	Levels of Two-level Modeling			
	Student (Individual) Level		School Level	
	Predictor	Variable Name	Predictor	Variable Name
Input	Gender	Gender	Metro/Urban/Rural Context	Context
	ESCS	ESCS	Student-body ESCS*	***SchESCS***
	Pre-school attendance	PreschEd		
	Age of starting the schooling	SchStart		
	Environmental awareness	EnvAware		
Processes			Language of schooling (MoI)	LangSch
	Teaching-style	TeachSty	Teaching-style*	TeachSty
	Disciplinary climate	DisciplS		
	Teachers' Support	TeachSup		
	Inquiry-based teaching	InquiryB		
	Teacher-directed instruction	TDInstr		
	Perceived Feedback	PerFeedb		
	Instrumental motivation	InsMotiv		
	Enjoyment of science	ScienJoy		
	Science Self-efficacy	SSelfEff		
	Sense of Belonging to School	ScBelong		
	Epistemological Beliefs	EpistemB		
Output	Affective non-cognitive			
	Instrumental motivation	InsMotiv		
	Enjoyment of science	ScienJoy		
	Science Self-efficacy	SSelfEff		
	Sense of Belonging to School	ScBelong		
	Epistemological Beliefs	EpistemB		
	Environmental awareness	EnvAware		
	Dependent Variables of the study			
	Total Performance	***PerformT***	Total School Performance	***SPerformT***
	Mathematics Result	MathRes	School Math Result	***SMathRes***
	Reading Result	ReadRes	School Reading Result	***SReadRes***
	Science Result	ScieRes	School Science Result	***SScieRes***

The variables generated by SPSS and Mplus are bold and in italics.
Underlined variables are doubled as Input- and Output variables or as Process- and Output variables, as suggested by the existing research.
*School-averaged

Descriptive statistics of the variables of the study are presented in Table 5, and Table 6 shows the corresponding students' performance means produced by the present study and by OECD.

Table 5. Comparative View of Students' Performance Means Produced by the Study and by OECD

Means	Math	Reading	Science	ESCS
Moldovan individual average (one-level Model 1)	**419.9**	**417.19**	**427.84**	-0.67
Moldovan PISA 2015 individual average (by OECD)	420	416	428	
PISA 2015 individual average in OECD countries (by OECD)	490	493	493	0
Moldovan between-school average (two-level Model 3)	415.7	411.8	424.1	-0.76

Bold numbers are common in the tables 5 and 6

ESCS index is composed of several factors of socio-economic status at the individual level including general status factors and more specific factors of cultural resources at home, allowing to test the gross effect of its various components (i.e., occupational status and education level of parents, family wealth, and family's possessions of cultural and educational resources). According to existing research, all factors incorporated in ESCS relate to three scores of student's academic achievement: in math, reading, and science, although to a different extent. Student's Environmental awareness and Epistemological Beliefs are two items where the direction of causality is strongly in question. PISA 2015 incorporated two trend questions from PISA 2006 on students' awareness of environmental matters (OECD, 2017c, p. 309).

The variables of segregated versus mixed-sex schools, upper- and lower-secondary programs, and private- versus public schools were excluded from the given study due to their negligent variance in Moldovan education. Firstly, in Moldova, more than 99% of 15-year-old students attend mixed-sex schools. Secondly, only 7.7% of all participants of PISA 2015 were in the upper-secondary programs. Lastly, there are few private schools in Moldova—around 20 institutions for the whole country from primary to higher secondary levels.

That fact was reflected in Education GPS (2018), which ranked Moldova the seventh highest by the percentage of students attending government or public schools (98.5 %). PISA 2009+ results also point to school-governance variable as a constant factor: “In Moldova the differences in school governance between schools contribute virtually nothing to predicting differences in reading performance between schools” (Walker, 2011, p. 82).The proportion of between-school variance in Moldovan students’ performance accounted for by ESCS derived by PISA from student responses was also rather law in comparison to other countries-participants—13.5% (idem, p. 77; Figures 2 and 3).

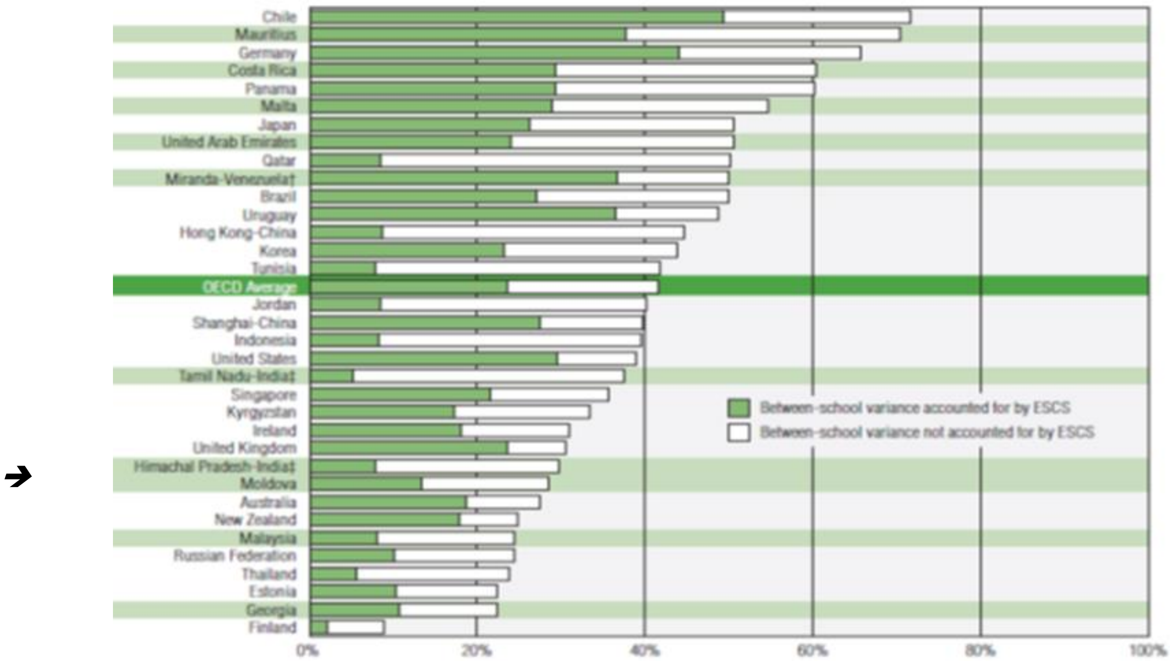


Figure 2. Proportion of total variance in reading that is between-school variance in PISA 2009

Country or economy	Proportion of between-school variance in performance accounted for by ESCS (%)
Tamil Nadu-India‡	5.2
Malaysia	8.0
Himachal Pradesh-India‡	7.8
Georgia	10.6
Moldova	13.5
OECD Average	23.6
United Arab Emirates	23.9
Malta	28.9
Costa Rica	29.3
Miranda-Venezuela†	36.6
Mauritius	37.8

Figure 3. Proportion of total variance in reading that is between-school variance in PISA 2009+

Table 6. Estimated Sample Means (extracted from one-level Models 1 and 1G)

Variables	Total Sample (St. Deviation)	Metro Context	Urban Context	Rural Context
Dependent				
MathRes	**419.9**	458.87	431.71	400.88
ReadRes	**417.19**	465.95	437.82	391.34
ScienRes	**427.84**	463.81	444.04	408.43
Independent				
ESCS	-0.67 (0.9)	-0.11	-0.38	-0.99
Gender[1]	0.5	0.53	0.51	0.48
LangSch[2]	0.8	0.71	0.70	0.87
SchStart[3]	0.74	0.66	0.66	0.80
PreschEd[4]	0.77	0.86	0.81	0.72
EpistemB	-0.16 (0.77)	-0.04	-0.12	-0.21
EnwAware*	0.35 (1.09)	0.54	0.46	0.24
SSelfEff	0.07 (1.00)	0.18	0.12	0.02
TDInstr	0.05 (0.86)	0.11	0.07	0.02
DisciplS	0.38 (0.77)	0.32	0.37	0.40
TeachSup	0.45 (0.78)	0.28	0.36	0.55
InquiryB	0.51 (0.64)	0.45	0.50	0.54
PerFeedb	0.53 (0.79)	0.47	0.51	0.56
InsMotiv	0.35 (0.80)	0.23	0.31	0.42
ScienJoy	0.32 (0.78)	0.29	0.33	0.33
ScBelong	0.03 (0.74)	-0.01	0.02	0.05

The shadowed are the variables in which rural students reported higher values than urban and metropolitan students.
Means of dummy variables represent proportions of categories coded as 1:
[1] A dummy variable with 0 for boys and 1 for girls.
[2] A dummy variable with 0 for Russian medium of instruction and 1 for Romanian MoI.
[3] A dummy variable with 0 for starting the schooling before 7 y.o. and 1 for starting at 7 y.o. or later.
[4] A dummy variable with 0 for attending a pre-school institution for 12 months or less and 1 for attending a pre-school institution for more than 12 months.
*A single variable that showed non-significant differences across the contexts in one-way ANOVA.
Bold numbers are common in the tables 5 and 6

The gender variable, as opposed to ESCS, is almost constant with a regular, near-to-50/50 ratio between the boys and the girls. The age of starting schooling (SchStart input factor), on the other hand, is different across the contexts: metro- and urban students start the schooling earlier—with 34-35% of children coming to school before the age of 7 years old—while only 20% of rural students come to school before being 7 years old. The same trend, although to a smaller extent, is shown in pre-school attendance (PreSchEd input factor): 81-86 % of metro and urban students attend pre-school institutions more than 12 months (which are obligatory by the law), and only 72% of rural students do so. The difference is much smaller in this variable, because the majority of Moldovan women have to work rather than stay at parental leave due to extremally low salaries and the necessity for all members of a family (including grandparents) to earn money in order to provide the living. This is the most likely factor that makes pre-school attendance rate in Moldova comparatively high.

The language of schooling (LangSch) or the medium-of-instruction process factor reflects uneven distribution of Russian-speaking population (due to industrial migration in the second half of the 20th century) across the republic with 30% of metro/urban- and only 13% of rural 15-year-olds studying in Russian MoI.

The affective outcome of school-belonging or well-being (ScBelong) is one of seven variables where rural students reported higher values than urban and metropolitan students (shadowed in the Table 6). Stronger feelings of belonging to school manifested by rural students might be explained by small sizes of the village schools with a dozen of teachers and 30-100 students being members of a small community and knowing each other out of school settings. Rural teachers know personally every student and many of his/her relatives. Such conditions, in a long run of 7-10 years of studying in the same school, may make a small school feel like a big family. In metropolitan schools, on the contrary, pupils in the adjacent classrooms rarely know each-other's names and may never meet out of school settings. Teachers in 1000-student urban schools know only the students of the classes they teach in.

Disciplinary class environment (DisciplS), Teacher's support (TeachSup), Inquiry-based teaching (InquiryB), Teacher-directed Instruction (TDInstr), and Perceived Feedback (PerFeedb) are five process factors of the IPO model, related to science-teachers' teaching styles as perceived by the students and reported in student questionnaires. Four out of five show that rural students value the teaching approaches of their science teachers higher than the urban and metropolitan students value their teachers' teaching styles. More intimate relationship between rural students and teachers could play its role in these results too. However, such results contradict to the multiple observations that teachers working with higher-ESCS students offer more teaching support, feedback, and inquiry-based teaching than when they work with disadvantaged students (Jæger & Breen, 2016).

PISA research team suggests that students' answers may be deviated by motivated responding (presenting their teachers better than they are), reference group bias (to whom they compare their teachers' performance), response-style bias (e.g., extreme responses or modesty), and the lack of differentiation in others' ratings (Kyllonen, 2015, slide 4). Thus, the answers of rural students, although given truly, may be incomparable with those of metro/urban students.

Higher results of rural students in Instrumental motivation (InsMotiv) and the Enjoyment of learning science (ScienJoy) look also suspicious, especially taking into account that disadvantaged rural students who show high motivation for science carrier and enjoyment of science still perform at the lowest levels of PISA and significantly lower than their "less-motivated" and "less-enjoying science" urban counterparts (Table 6). Such phenomenon of better attitudes associated with lower achievement is named an "attitude-achievement paradox" and is observed mostly on between-country level when the countries with high-average-attitude scores are ones with lower-average achievement. On within-country level, positive correlations prevail, when better attitudes to the education are associated with higher academic outcomes (Kyllonen, 2015, slide 5). An outstanding instance of a within-country attitude-achievement paradox is the population of black American high-school students (Jones & Schneider,2016, p. 386) and, as three shadowed affective variables (InsMotiv, ScienJoy, and ScBelong) of the Table 6 suggest, Moldovan 15-year-olds. The attitude-achievement paradox states that “students profess an abstract belief in the value of education but have few concrete practices that demonstrate commitment to education” (Lewis-McCoy, 2015, p. 35).

The method of Anchoring Vignettes may help to fix both the “paradox” and naïvely exaggerated assessment of teachers made by rural students in near-future PISA cycles (Kyllonen, 2015, slide 9). However, there is one more plausible explanation of contradictory results on teaching approaches: what is known as the problem of reverse causality (Strietholt, Gustafsson, Rosén, & Bos, 2014), when a “dependent” variable actually causes a part of an effect in an “independent” variable. In other words, in absence of other resources and opportunities, the science teachers of rural schools may ought to manage better class discipline (DisciplS) and larger share of inquiry-based teaching (InquiryB); they might as well have to provide higher support (TeachSup) and more frequent Feedback (PerFeedb) to their students to achieve those low levels of performance that metropolitan students would have achieved due to better resources, without excessive care of teacher, but gaining more time for advanced learning. Thus, it is not a better teaching approach that is causing the worse performance, but rather poor achievement and absence of other resources require more of teacher’s attention and care (Vanlaar et al., 2015).

Two-level Modeling Techniques as Analytical Method

The given study was made via two-level modeling because this technique was purposefully designed for hierarchical data of a nested structure to estimate the relationships among latent variables with corrections to the estimated standard errors and chi-square test of model fit, which take into account stratification, non-independence of observations, and unequal probability of selection (Muthén & Muthén, 1998-2017, p. 12). All models built in the thesis are saturated models. A saturated model is one in which there are as many estimated parameters as data points, and the degree of freedom is therefore equal to zero (Hox, 2010, p.100). A saturated model is a descriptive model, by which we try to summarize our data in compact and comprehensible ways and to explain the ongoing processes described by data rather than to predict what will happened in the future. Via predictive models (which are not used in the given study but are picked for comparison) we do discriminant analysis, making assertions about what will happen with new data collected in the same settings but later in the time (Miller, 2014, p. 3).

The multiple imputation datasets of 10 plausible values representing three overall achievement scores of math, reading, and science for each student were used to carry out modeling in Mplus (Appendix 7). The parameter estimates were averaged over the set of analyses, and standard errors were computed using the average of the standard errors over the set of analyses and the between analysis parameter estimate variation.

The first model (multiple linear regression one-level Model 1) was built on the null model by adding the student background and personal factors and the teaching style as perceived by the students; what made it a school-contextual factor at the individual level. Multiple linear regression analyses were applied for traditional descriptive and predictive statistical analyses to identify features that are most important in determining performance. According to Muthén & Muthén (1998-2017, p. 19), regression analysis with univariate or multivariate dependent variables is used to model relationships among observed variables. To answer the research questions 1-3 at individual level, linear regression models (Models 1, 1G, and 2G) were built as they are suitable for continuous dependent variables (idem).

Students' performance in three areas measured by PISA 2015 were the criteria of mathematics result, reading result, and science result. Linear regression analyses for three continuous dependent variables of academic performance was carried out via ON statement describing the linear regression of the results on 16 covariates (Table 4). The means, variances, and correlations between the variables were estimated separately as the sample values (Tables 6 and 7). To compare between schools of different contexts (metro, urban, and rural), a group analysis was specified by using the GROUPING option of the VARIABLE command for individual data with CONTEXT as a grouping variable.

For every analysis, I tested whether findings held in a regression controlling for ESCS and location of school: with a grouping variable Context, which describes the community where every school is located. The models with Context as a grouping variable are identified by a G index in their titles: Model 1G, Model 2G, Model 3G, and Model 4G. A total of 16 predictors of students' performance were employed including four binary (dummy) variables (Table 6). Means of the dummy variables represent proportions of categories coded as 1. All predictors were entered into regression model simultaneously.

Maximum Likelihood Estimator with robust standard error (MLR) was applied for all Mplus models—to correct the bias in standard errors estimation due to the non-normality and non-independence of observations when data was collected by stratified multistage cluster sampling strategy—by means of TYPE=COMPLEX option in Mplus models (Muthén & Muthén, 1998-2017, p. 668).

Next, a combined latent variable of total performance (PerformT) was developed from three dependent variables of mathematical-, reading-, and science (each incorporating 10 plausible values) to test their gross change on student ESCS on both the individual- and school levels. The Confirmatory Factor Analysis (CFA) was applied as a preparatory stage for two-level modeling: to specify the structural relationship among the latent variable of total performance and its three indicators, i.e. three performance outcomes in mathematics, reading, and science. In this way, CFA allows to separate a unique variance of the indicators, the error variance (Brown, 2015, p.202).

Finally, the school-level model was expanded on with a saturated model specified for the individual level: the full models identified at the individual- and school levels respectively were combined into 2 two-level Models 3 and 4. They have the same specification as Model 1, except that they include random effects for schools, representing across-cluster variation in intercepts and slopes. As was mentioned above, IPO conceptual model provided a well-defined analytical framework for two-level modeling to manipulate hierarchical and nested data (students within schools). Two types of input variables are distinguished: resource (school) inputs and individual (student) inputs; they are further categorized in smaller divisions (Table 4). In such framework, the effects are initiated by the context, both as an unmediated influence and via its influence on student and resource characteristics (inputs) to processes that are triggered by the flow of resources. To obtain a statistical estimate of the association between academic performance and resources using regression analysis, the IPO model is simplified to a single equation where achievement is the dependent variable while the context, input and process variables are independent variables of the estimation equation (Levačić, 2007, p. 397).

Evaluation of Statistical Models

There are various parameters to evaluate statistical models—the model-fit indicators. They assess how well a model fits the data of interest. While in predictive modeling we would have to choose among several models the one that fits data at the best, in descriptive modeling on saturated models (which is the case of the given study) we have to merely confirm the good level of model-fit indicators; hence the models do fit the data (Hox, 2010, pp. 48 & 103).

A chi-square ($\chi2$) of statistically non-significant value is a common indicator of a good model fit. It shows that the difference between the sample covariance matrix and the variance matrix presented by the model is statistically non-significant, which implies that the matrices are not statistically different. This, in turn, implies that the constructed model can be neither rejected nor considered correct. Hence, the chi-square parameter is criticized as a meaningless for large samples (Kline, 2011). To address this problem, several model-fit indices were developed from the chi-square test. The given study uses the root mean square error of approximation (RMSEA), the comparative fit index (CFI), the Tucker-Lewis index (TLI), and the standardized root mean square residual (SRMR) presented in Mplus analytical software outputs (Appendices 2-3, 5,6, and 8-10).

The RMSEA is regarded as "one of the most informative fit indices" (Diamantopoulos & Siguaw 2000, p.85) because of its sensitivity to the number of estimated parameters in the model (Hooper, Coughlan & Mullen, 2008). An RMSEA value of 0.08-0.10 reflects a mediocre fit; the value below 0.08 reflects a good model fit; and if RMSEA is less than 0.06, the fit is considered perfect. The SRMR values range from 0 to 1.0 and represents a square root of the difference between the residuals of the sample covariance matrix and the residuals of the model. The perfect-fit models result in values smaller than 0.5, and the fit is considered good if values are between 0.8 and 0.5 (idem).

CFI compares the matrices on assumption that all latent variables are uncorrelated. CFI values range between 0.0 and 1.0, and those greater than 0.95 indicate a perfect model fit. The TLI compares a hypothesized model to the null model. The TLI values are not normed and may reach below 0 or above 1, but a perfect-fit model will result in the values between 1.0 and 0.95.

Validity and Reliability of the Data Source

According to Pedhazur and Schmelkin (1991), “a measure cannot be valid, if it is not reliable, but being reliable it is not necessarily valid for the purpose its author or user has in mind” (p.81). Reliability confirms that test scores are free from errors of measurement and, under the same conditions, will produce the same results (APA, 1985, p.19). Sufficient validity denotes that an instrument measures what is was designed to measure (Field, 2009) and confirms the “appropriateness, meaningfulness and usefulness of the specific inferences made from test scores” (APA, 1985, p.9).

PISA reports present the program as “most comprehensive and rigorous international program to assess student performance and to collect data on student, family and institutional factors that can help to explain differences in performance” and claim to have high degree of validity and reliability of the collected data (OECD 2009, p.21; OECD, 2016c, p.10). Thus, the leading regional experts make the decisions on the scope and nature of the assessments and on what background information to be collected. In every region, the translation, sampling and data collection are performed via high-quality mechanisms, assuring cultural and linguistic breadth and balance of the assessment materials. To enhance the validity of combined items (the indices), new scaling methods were introduced In PISA 2015. For each item within every scale, the item fit was controlled for each country-by-language group during the assessment procedure (OECD, 2016c, p.104). A coder reliability monitoring, an innovative approach of coding by item was introduced in PISA 2015 and proved itself a powerful tool to improve reliability (idem, p. 102).

However, although OECD experts devote a substantial effort and resources, several issues on sampling and data collection have been persisting in PISA circles. While the cluster- and individuals random sampling draw a simple, random sample with all schools and students having the same selection probability and the sum of school weights is equal to the number of schools in the population, the sum of the final student weights is not always equal to population numbers of students. Moreover, the final student weights vary across the schools depending on school size. Such variability inevitably reduces the reliability of the parameter estimates for population (OECD, 2009).

Results

Individual-level Multiple Linear Regression (MLR) Models 1 and 1G. Student-level Influences

To answer the first two research questions of the given study, Individual-level Multiple Linear Regression Models (Muthén & Muthén, 1998-2017, p. 22) were built in attempt to simulate the relationship between students' results and their ESCS on individual level in a total sample (RQ1, Model 1); and across three contexts or the areas the schools are situated in (metro, urban, and rural contexts, RQ2, Model 1G). A single-level regression model examines the degree to which performance scores vary within the schools and explains how much variation in performance is predicted by different sets of variables. These relationships are examined using ESCS as the predictor variable and three scores (math, reading, and science) as the outcome variables. The ESCS index has an OECD mean of zero and a standard deviation of one.

The means of Moldovan performance outcomes in math, reading, and science, which resulted from one-level Multiple Linear Regression, are compared in the Table 5 (bold) to the same results calculated by PISA team. The distribution of the means of ***all*** factors involved in the models across three types of the context—metropolitan (cities), urban (towns), and rural (villages)—is shown in the Table 6, which is composed from the results of Multiple Linear Regression models 1 (Appendix 2) and 1G (Appendix 3). Additional one-way ANOVA statistical tests (Appendix 4) were performed for all variables: out of 16 tested variables, the test showed only one variable (enjoyment of science, ScienJoy) with non-significant differences across the contexts.

Although the students of all three contextual areas show low (all negative) average ESCS in comparison with other PISA 2015 participants, the privileged status of metropolitan population clearly manifested itself in this input variable. The difference between metropolitan and rural families in this particular factor is striking—one standard deviation. Nevertheless, even in metro-cities, the correlation between ESCS and performance is modest (0.31-0.33, Table 7), and the regression coefficients of the performance on ESCS (shadowed) express only 2-6 % of explained variance, which is very little in comparison to 13-23 percent accounted by ESCS in performance across all PISA-participants' results as well as PISA-2015-calculated 12% variation in science performance explained by Moldovan students' SES (Table 1).

Table 7. Correlations Among the Outcomes and Between the Outcomes and the Predictors[1]

Variables	Sample	Correlations				
		MathRes	ReadRes	ESCS	EnvAwarn	EpistemB
MathRes	Total sample			0.34	0.32	
	Metro	1.00		0.31		
	Urban					
	Rural				0.33	
ReadRes	Total sample	0.73		0.36	0.35	0.34
	Metro	0.73	1.00	0.33	0.30	0.32
	Urban	0.69				
	Rural	0.69			0.36	0.35
ScienRes	Total sample	0.79	0.78	0.35	0.38	0.35
	Metro	0.79	0.78	0.32	0.35	0.34
	Urban	0.76	0.73		0.34	0.31
	Rural	0.77	0.75		0.37	0.34

[1] Only the correlations with Pearson r larger than .3 are presented out of all results among 22 variables tested in linear-regression models 1 and 1G.

The Table 7 shows that, in agreement with existing research (Brese & Mirazchiyski 2010; Howie 2002), all three disciplines measured as PISA outcomes (math, reading, and science) appear sufficiently correlated, meaning that the Moldovan 15-year-olds who perform well in one subject-area are also likely to perform well in other two subject-areas. And visa-versa: insufficient reading skills undermine mathematical and science performance even if there are other factors enhancing it (such as biological predisposition, instrumental motivation, or positive attitude to natural sciences). Math and Science are inter-correlated even more than each of them is to the Reading, that is also common-sensical. There is accumulated research evidence suggesting that students' reading ability[es] are related to their mathematics achievement.

According to Cohen (1988, 1992), the regression coefficients of .10, .30, and .50 are conventions for a 'small', 'medium', and 'large' size effect corresponding to 1%, 9%, and 25% of explained variance. As the regression coefficients of the outcomes on independent variables show (Table 8; Models 1 and 1G), only in math and reading, the age of beginning of schooling (at 7 years old or earlier) has some predictive power (regression coefficients are 0.04) with better result for those students who start earlier, what is supported by the existing research. Across the contexts, nevertheless, this variable has little effect on the results of tests (with the exception of urban students' reading results), which can suggest some compensatory power of Moldovan schools on this predictor.

More than one year of pre-school education, on the other hand, makes a difference in reading performance in metropolises and villages (regression coefficients: 0.05-0.07), but not in the towns (Table 8). Pre-schooling also explains a small part (0.16%) of the variance in mathematic results but not on science; that is strange, because the two are usually greatly correlated.

Table 8. Regression Coefficients[1] of the Assessment Outcomes (the first column) on Independent Variables (Models 1 and 1G)[2]

Depend. Var.	Sample	Independent Variables													
		ESCS	School Start	Preschool Education	Gender	Inqiary Base Teaching	Teacher-Direct. Instr.	Environm. Awarenes	Perceved Feedback	Joy of Science	Instrument. Motivation	Epistemol. Beliefs	Language of School.	Disciplinary Climate	Science Self-efficacy
MathRes	Total	0.23	-0.04	0.04	-0.05	-0.05	0.16	0.16	-0.08	0.06	-0.10	0.14			
	Metro	0.27			-0.09		0.15	0.13	-0.10		-0.07	0.20			
	Urban	0.22				-0.10	0.18	0.16			-0.11	0.10			
	Rural	0.16					0.15	0.19		0.08	-0.09	0.12			
ReadRes	Total	0.24	-0.04	0.07	0.21	-0.06	0.13	0.17	-0.10		-0.10	0.21	-0.11	0.04	
	Metro	0.30		0.05	0.16	-0.06	0.11	0.16	-0.10		-0.09	0.24			
	Urban	0.19	-0.07		0.24	-0.09	0.10	0.18			-0.13	0.16			
	Rural	0.16		0.07	0.22	-0.05	0.14	0.19	-0.10	0.05	-0.08	0.20			
ScienRes	Total	0.22					0.17	0.20	-0.10	0.05	-0.10	0.21	-0.08		0.06
	Metro	0.27			-0.06		0.16	0.19	-0.13		-0.08	0.25			
	Urban	0.21					0.15	0.22			-0.13	0.18			
	Rural	0.14					0.18	0.20	-0.09	0.07	-0.09	0.20			0.07

[1]Only those with z-score larger than |±1.96| and significant *p*-value (smaller than 0.05) are presented; with Y-variables in the first column and X-variables in the first raw of the table.
[2]From Standardized Model Results
Shadowed columns: the three factors that made the strongest unique contributions to explaining the dependent variables, when the variance explained by all other variables in the models 1 and 1G is controlled for.

The gender variable did not deviate from a standard picture: being a girl strongly predicts better performance in reading across all three contexts (r. c.: 0.16 – 0.24), while being a boy provides a smaller effect in mathematics (r. c.: 0.05). In science, being either a girl or a boy does not imply any advantage, even though Moldovan girls showed better results in all three disciplines (Table 6). This may confirm that Moldovan schools are more successful in addressing gender inequities in science education.

The variable of the language of schooling or MoI is a weak predictor of science- (r.c. = -0.08) and of the reading performance (-0.11) for the total sample. As Russian-medium schools stay for 0 and Romanian – for 1 in binary variable of the language of schooling, the results suggest that Russian MoI explains 0.64% of positive variation in science results and 1.2% of better performance in reading. However small is the effect, the almost-two-times difference in these numbers is not surprising. Between 1959 and 1989, Russian-speaking minority of Moldova increased from 10.2 % of the population to 13% by an influx of highly-educated migrants from Russia, Ukraine, and other Soviet republics. They were attracted by job-offers for managerial positions in industry and contingent to them advantages as accommodation, personal transport, etc. In 1990s, those new-comers accounted for two-thirds of the Russian-speaking population in Moldova; they were concentrated in urban areas, particularly in metropolitan cities, and "enjoyed disproportionately high levels of education" (Moldova – Russians, 2018).

Nowadays, although Russian-speaking population has been decimated by migration back to the lands of origin, thousands of Russians and Ukrainians in Moldova continue to convey the wealth of Russian language and culture, which for almost two centuries played a leading role in the Republic. Thus, surrounded by reading family culture and provided with an ocean of mastered literature from the birth through adulthood, Moldovan Russians are expected to perform better in reading than native speakers of Romanian, whose literature has been neglected and who are left with a handful of Moldovan writers and not-always-quality translations of world literature. Lower educational and professional levels of parents (on average) also play their role in conditioning children' reading environments in families in terms of critical factors of literacy development, such as reading-, text-, and task factors (Heath, 1986).

Students of Russian-medium metropolitan schools performing better in science are likely to bear cultural heredity of their highly-educated grandparents who were a part of the most significant Russian migration to Moldova during her rapid urbanization and industrialization in the second half of the 20th century. As was mentioned above, they were settled predominantly in metropolitan cities and their descendants have been living in the same houses and apartments granted by Moldovan authorities of the date. It should be mentioned that although Moldovan-MoI programs have been always present in higher education of Moldova, their number was small until the year 2000; hence, the modern Moldovan-speaking population of the metro areas are mostly the children of rural migrants of 1990s, when the citizens with rural domicile were allowed to live and work in cities.

The absence of correlation between ESCS and performance results in urban and rural areas (Table 7, Model 1G) suggests that the students of higher ESCS show better knowledge in all three subjects only in metropolitan areas, while in towns and rural contexts, ESCS seems not to play an important role in student performance. To exclude the possibility of non-variant ESCS in towns and rural contexts I have checked the results of Model 1G (Table 9): student ESCS is variant in all three contexts.

Table 9: Variances of Student ESCS across the Contexts (an excerpt from the Model 1G)

Context	Estimate	S.E.	Est./S.E.	Two-Tailed	Rate of Missing
Metropolitan	0.946	0.106	8.91	0.000	0.000
Urban	0.696	0.043	16.31	0.000	0.000
Rural	0.811	0.043	18.83	0.000	0.000

Both the correlation- and regression-coefficient matrices (shown respectively in the Tables 7 and 8) highlight that only three out of 19 factors—namely ESCS, Environmental Awareness, and Epistemological Beliefs—manifested moderate correlations with the outcomes and the highest values of regression coefficients between 0.14-0.24 (Table 8, shadowed).

Conclusion 1 (RQ2): There is significant difference on individual level between the answers of the students of Metro, Urban, and Rural groups across 15 out of total 16 input- and process predictor-variables (Appendix 4). ***Conclusion 2*** (RQ2): In complete accordance with existing research, in all three academic outcomes (MathRes, ReadRes, and ScienRes variables) and in all 30 plausible variables of academic performance (Appendix 7), on individual level, metropolitan students showed the highest results (as the most privileged), and rural students expectedly performed at the lowest level as the most disadvantaged in such terms as family ESCS, school's educational resources, far distance from cultural centers, museums, etc. (all differences are statistically significant, see Appendix 4). ***Conclusion 3*** (RQ5): It is noteworthy that, on individual level, teaching approach perceived by students makes little difference to the effects of ESCS and thus cannot be understood as ways in which students' cultural capital influences academic performance scores. ***Conclusion 4*** (RQ1): on individual level, the effect of ESCS is associated with the environmental awareness and epistemological believes of the students, or the attitudes that, in existing research, have been also found to be taken by children from their parents. ***Conclusion 5*** (RQ1): On individual level, the predictor-variables of ESCS, Environmental Awareness, and Epistemological Beliefs make the strongest unique contributions from 1.5 till 9% percent to explaining the variance of the dependent variables, when the variance explained by all other variables in the Models 1 and 1G is controlled for (Table 8, shadowed). Although ESCS has the strongest impact on students' performance, it is difficult to discriminate between these three variables in terms of importance, and the values of explained variance are not sufficient to name any of them a **deterministic** variable.

Accordingly, no one of the tested factors may be named deterministic for the academic outcomes of Moldovan 15-year-olds.

Confirmatory Factor Analysis (CFA) Testing. SES Differences in Achievements between Schools with Different Language Instruction. Model 2G

As MLR Models 1 and 1G could not provide a significant value for the association between students' results and ESCS while controlling for two media of instruction (LangSch) in Moldovan schools (Russian and Romanian), Confirmatory Factor Analysis model (Muthén & Muthén, 1998-2017, p. 60) with Wald Test of Parameter Constraints were used to address the third and fourth research questions.

As in the whole study, in Model 2G, only student ESCS was taken into account, to test the gross effect of its components of occupational and educational level of parents and family possessions on student's academic performance. However, the regression coefficients of performance on ESCS are 0.404 for Romanian and 0.341 for Russian MoI. If the difference between Romanian-medium ESCS, which accounts for 16.3% of the variance in performance, and Russian-medium ESCS, which does so only for 11.6%, is significantly different, this could suggest that Romanian-medium schools of Moldova are less equitable.

To test the significance of the difference between the regression coefficients, Wald Test of Parameter Constraints had been run in the Model 2G (Appendix 6). The Wald test is most commonly used to test the significance of a regression estimate (Vanlaar et al., 2015, p. 12). The test is highly analogous to the t-test in multiple regression but is tied to a theoretical distribution symbolized by χ^2 (a chi-square distribution) rather than *t* (Hox, 2010, p. 45). The test resulted in non-significant p-value of 0.7774, which confirms that there is no difference in the association between the ESCS and academic performance in relation to the medium of instruction in Moldovan schools. ***Conclusion*** (RQ3 and RQ4): On individual level, studying in either Romanian-medium- or Russian-medium schools of Moldova is equal in terms of the variance in performance accounted by the ESCS. The two-level modeling was conducted to confirm this result on multistage sampling.

Table 10. Standardised[1] Results of Model 2G (CFA). An excerpt from the model results

Model Results[2]		Language of Schooling or MoI	
		Romanian (80% in population and sample)	Russian (20% in population and sample)
Factor Loading	PerformT indicated by		
	MathRes	0.859	0.858
	ReadRes	0.848	0.829
	ScienRes	0.917	0.906
Regression coefficient of PerformT on ESCS		0.404	0.341

[1]STDYX Standardization

[2]All presented values have z-scores larger than |±1.96| and significant P-values (smaller than 0.05).

CFA also helped to specify the structural relationship among a compound latent variable of total performance (PerformT) and its three indicators, i.e. three performance outcomes in Math, Reading, and Science. As Brown (2015) states, CFA tests whether conceptualized factorial structures of scales in a measuring instrument under study are valid. If a hypothesized CFA model fits the data, the factorial structure is valid for the population (Wang & Wang, 2012). The Table 10 presents the standardized factor loadings of academic outcomes (MathRes, ReadRes, and ScienRes) on Total Performance latent variable (PerformT) which are very high, with values ranged between 0.829 and 0.917. It shows that the three outcome variables are strong indicators for PerformT (idem). Such inference is also supported by the Model 1 showing that all three dependent variables of academic performance are highly correlated: Pearson rho is equal to 0.725, 0.791, and 0.755 (Table 7 and Appendix 2).

Intraclass Correlation Coefficient

The Intraclass Correlation Coefficient rho (ICC ρ) plays two roles in the given study. Firstly, in relation to the research questions 1-4, it indicates the proportion of the variance accounted by the grouping structure of the population (Hox, 2010, p. 15) and is a well-established indicator of population equity (Gustafsson et al., 2016, p. 8). In other words, ICC is the proportion of between school variance in a variable in relation to the total variance.

Secondly, it shows the extent of group-clustering or similarity of the results within groups with p values being 0, small, large, or 1, and defines whether a two-level modeling is necessary. Using the between- and within mean square calculated with help of the values resulted in the Model 1 (Hox, J, 2010, p.5), the ICC of the given study was estimated as 0.2714. ICC expresses the between-school variance as a proportion of the overall variance in student performance, and thus measures the inequity between schools within the country. ICC equal to 0.27 means that 27% of total variance in PISA 2015 results of Moldovan fifteen-year-olds is explained by the effects of the schools.
A low value of ICC (below 0.3) of all the background variables (Table 11) indicates a small share of the between-school differences in PISA scores due to compositional differences between schools in the socio-economic characteristics of their students (RQs 1 and 6). The values of the school-factor variables of perceived teaching style are even lower (less than 0.12) and show a very small difference between Moldovan schools in terms of teaching approach (RQ5). These figures are very close to the average (around 8%) for net school effects from the existing research (Scheerens and Bosker, 1997).

Table 11. Intraclass Correlations (between-school variation)

Variables		Intra-class Correlation			
		Total Sample	Metro	Urban	Rural
Personal Factors	ESCS	0.27	0.29	0.11	0.09
	MathRes	0.20	0.27	0.14	0.11
	ReadRes	0.21	0.24	0.15	0.08
	ScienRes	0.17	0.26	0.10	0.09
	EnvAware	0.08	0.07	0.04	0.08
	EpistemB	0.05	0.07	0.07	0.03
School Factors of the Teaching Style	DisciplS	0.11	0.07	0.10	0.12
	TeachSup	0.09	0.07	0.05	0.09
	PerFeedb	0.04	0.03	0.04	0.04
	InquiryB	0.04	0.02	0.03	0.04
	TDInstr	0.03	0.02	0.02	0.04

However, ICC greater than 0.02 may result in Violation of Independence or Design Effect, which would impact the estimates of precision (lowering the standard errors) and would increase risk of Type 1 errors, that means finding a significant relationship where none actually exists (Miles, 2013, slides 16-18).

The Design Effect of the Moldovan dataset results in Variance Inflation Factor (VIF) = 6.97, which is larger than 2 and suggests that the dependent data were modelled as if they were independent (Rasbash, 2008, p. 16). Multilevel modeling is one way to obtain correct standard errors by explicitly modeling this dependency and automatically correcting for the design effect.

Two-level Models 3 and 3G. School-level Influences

To further develop an insight on the research questions 1-5, the amount of between-school variation accounted for by ESCS and by the school-factors was estimated as ICC in Models 3 and 3G. To that end, school-level ESCS and school-level teaching style were added in Model 3 (Appendix 6). A combined predictor of teaching style (defined as TeachSty at the individual level and TeachStB at the school level) was taken into account to test the gross effect of its various components: disciplinary climate, teachers' support, inquiry-based teaching, and teacher-directed instruction. In the two-level Models 3 and 3G (Appendix 8), these variables were used as indicators of the individual-level latent variable Teaching Style (TeachSty) to represent within-school differences between students in their ratings of teaching approach, and of the school-level latent variable Teaching Style Between (TeachStB) to represent shared perceptions of teaching approach in each school.

Results of Models 3 and 3G in terms of Intraclass Correlation ICC (Table 11) show that the amount of variance attributable to cluster membership (schools) ranges up to 29% (ESCS in metropolitan areas) and thus further justifies the necessity for a two-level analysis. However, these numbers are small in terms of between-school differences that suggests ***Conclusion 1*** (RQ1): the variation between schools of Moldova in averaged student ESCS and PISA outcomes in all three disciplines is small.

As was mentioned above, the ICC for between-school differences in performance is a well-established indicator of equity (Gustafsson et al., 2016, p. 15). The ICC results of the Model 3 show that there is a small part (17-27%) of overall variance in students' results and ESCS that might be explained by attending a particular school (Table 11). The values of ICC in teaching style components are even lower (3-11%) that suggest ***Conclusion 2*** (RQ5): there is almost equal distribution of teaching approach techniques across the schools.

Similar results show the regression coefficients estimated by the Models 3 and 3G (Table 12). As the table shows, few estimates, are statistically significant (those are stated in the table) and have a meaningful effect-size (values equal to 0.1 or higher). Overall, on individual level, ESCS is associated with all three disciplines individually, but it accounts only for 1.5-3% of the total variance in scores. On school level, ESCS contributes to the overall variance in math and reading only in metropolitan and urban schools, but there is no relation in the total sample. Only in science results, school ESCS has a relationship with the results of the total sample. The “within” column shows the relationship of students’ own ESCS with their cognitive results, while “between” column shows the relationship of school ESCS with students’ results (Table 12).

Table 12. Regression Coefficients from Two-level Models 3 and 3G (statistically significant only)

Y-variable	X-variable									
	ESCS		LangSch*		TeachSty		EnvAware		EpistemB	
	Between	Within	Between	Within	Between	Within	Between	Within	Between	Within
MathRes										
Total		0.16						-0.04		-0.07
Metro	1.14	0.13						-0.08		-0.09
Urban	0.67	0.18								
Rural		0.17								-0.07
ReadRes										
Total		0.14								
Metro	1.12	0.13								
Urban	0.60	0.14								
Rural		0.14								0.04
ScienRes										
Total	1.12	0.15								
Metro	0.84	0.12								
Urban		0.16								
Rural		0.15								
TeachStyB										
Total	-0.6		0.6							
Metro	-0.5		0.7							
Urban			0.6							
Rural			0.6							
Perform										
Total	N/A		N/A		N/A		N/A	0.27	N/A	0.27
Metro	N/A		N/A		N/A		N/A	0.24	N/A	0.32
Urban	N/A		N/A		N/A		N/A	0.26	N/A	0.24
Rural	N/A		N/A		N/A	0.07	N/A	0.28	N/A	0.27

The “within” columns show the relationship of students’ individual x-variables with their cognitive results and school’s teaching style, while “between” columns show the relationship of school-averaged x-variables with school-averaged students’ results and school’s teaching style.
*A dummy variable with 0 for Russian medium of instruction and 1 for Romanian MoI.

Conclusion 3 (RQs 2 and 6): In mathematics and reading on the school level, the ESCS is strongly and moderately associated with students' cognitive performance in metropolitan and urban schools respectively, while in rural schools, ESCS doesn't contribute to student's results. In science, only total sample and metro schools manifest the relation, which is strong (explaining 71% of total variation, Table 12). Because school ESCS (or ESCS on the school level) is a parameter of school compensatory power, we can also track the similarities with existing research: reading is less influenced by schooling and is more correlated with family background in comparison with mathematical and science skills.

However, the combined variable of the teaching style showed too small or non-significant values of regression coefficient on ESCS at both the individual- and school levels (Table 12). Hence the following conclusions regarding RQ5 are likable. ***Conclusion 4***: Moldovan teachers generally apply an egalitarian approach to their students, providing the same amount of support, guidance, and feedback to all students disregarding their ESCS level. ***Conclusion 5***: The level of teaching instruction does not fluctuate between the schools of Moldova.

Because the combined variable of total performance was included only in individual level of the Models 3 and 3G (Appendices 6 and 8 respectively), we can infer only about students' family background association with the results in total. As all values are insignificant, there is no variation that might be explained by Moldovan students' family background. ***Conclusion 6*** (RQs 1 and 6): differences in family ESCS do not result in corresponding differences in students' cognitive development.

Teaching style is tested in both roles in two-level models of this study: as an x-variable, which is assumed to influence the outcome; and as a y-variable, which itself is an outcome affected by other variables. As an x-variable, the teaching style resulted in no significant value except of the total performance of rural students on the individual level. The ***Conclusion 7*** is, therefore, related to RQs 2 and 5: rural Moldovan teachers tend to discriminate between the students of different socio-economical background and to favor more-wealthy ones (Table 12).

Environmental awareness and epistemological beliefs show no relationship whatsoever with any of three disciplines (Table 12). On the other hand, there is a solid contribution of these two variables to the total performance, explaining 5 to 9 % of its total variance on the both levels of the models and in all three contexts. This result may be clarified by strong correlation between two variables and cognitive performance, all being the outcomes of student's education (both formal and informal) rather than environmental awareness and epistemological beliefs as determinants of the results of the assessment.

Finally, on the research questions 3 and 4, the language-of-school variable doesn't show that any of two Moldovan media of instruction are likely to affect the learning outcomes of their students (Table 12). The ANOVA test made by SPSS resulted in the same judgment. The following three conclusions (8-10) address the research questions 4 and 5. ***Conclusion 8***: Russian and Romanian school show equal academic performance in PISA 2015 when all other variables are controlled. Nevertheless, teaching style results in significant and large values of 36-49% of explained total variance when regressed on the language of schooling at school level. At the individual level, the results are unsurprisingly insignificant because the variable of language is almost constant at the school level: the majority of schools teach in a single medium of instruction. Thus, the total sample consists of 5325 students from 227 school; out of them only 453 (8.5%) students are from 18 (8%) schools that accommodate for both Russian- and Romanian-medium sections. As the language of instruction (RQs 3-5) was coded as a dummy variable with 0 for Russian and 1 for Romanian MoI, the **Conclusion 9** is that the teachers of the Romanian-medium schools on average are more supportive, focus more on group activities and whole-class teacher-centered instruction, and provide more feedback than teachers of Russian-medium schools.

However, two factors may have deviated the results on the relationship between the school MoI and teaching style. First is the restriction of the Moldovan data to student questionnaire only. The assessment of teaching style was therefore made solely on students' perception and may well be biased for or against the quality of teaching approaches. Secondly, the reverse causality may also interfere in student-teacher relations in this case: as was described at the page 37 of the given manuscript, Russian students are historically better prepared and supported for schooling by more educated parents and grate-parents. This may result in lesser need of teacher support. Consequently, higher quality and larger quantity of teaching support at Romanian-medium schools might finally close the initial gap between two ethic groups of students, so that by age of 15, they are able to show equal cognitive outputs. If this reasoning is correct, the ***Conclusion 10*** is capable to clarify on the RQs 3-5: the two-level Models 3 and 3G show the compensatory power of Romanian-medium-school teaching style against the inequity in cultural background of Moldovan students rather than higher quality of Romanian-medium teachers.

Two-level-with-random-slope Models 4 and 4G

To answer the research question 6, the two-level-with-random-slope Models 4 and 4G were tested (Appendices 9 and 10 respectively), which are two-level regression models with student performance as the outcome and individual student ESCS (at the individual level) and averaged school ESCS (at the school level) as the explanatory (or predictive) variables. The model assumed the within-school estimates of the slopes and intercepts for the regression of performance scores on ESCS to be random coefficients, so the model estimated the mean and the variance of a slope and an intercept for every school. The idea thus was that if the relationship between individual ESCS and individual scores (i.e., the slope parameter) within some Moldovan schools is stronger than in other schools, the model would be able to capture these differences with the estimated variance of the slopes.

Thus, I tested how ESCS' association with three performance scores varies across Moldovan schools, depending on the school intake's ESCS composition. To that end, I modelled a cross-level interaction where the school-level covariate ESCS (averaged for every school from students' individual scores) moderates the influence of the individual-level covariate ESCS on the scores.

I defined three relationships between math, reading, and science results and ESCS. Then I regressed all three slopes on their respective scores via TYPE = TWOLEVEL RANDOM command of Mplus, thus creating a two-level regression model with a random intercept and a random slope varying across clusters, i.e. schools (Muthen & Muthen, 1998-2017, pp. 21 & 22).

There are three possible outputs in random-slope models on ESCS-achievement relationship. If the slope regresses on school ESCS with negative value of the coefficient, the educational system is likely to be a compensatory one. If the slope value is positive, the system enlarges the differences between students from different levels of ESCS and might be considered an anti-compensatory one. The third type of the model result—and the result of the given study—is non-significant value of the regression coefficient. This output says that there is no association between aggregated school ESCS and the strength of the relationship between student's individual ESCS and his or her cognitive performance.

All three slopes don't relate to the ESCS-performance relationship in Moldovan schools. The intercepts are non-significant too. ***Conclusion*** (RQ6): The results of the Models 4 and 4G (Appendices 9 and 10 respectively) show that school-level factors seem to be not associated with any compensatory power. This result is in line with other studies showing several non-tracking comprehensive educational systems (e.g. the Scandinavian ones) with Slope-SES estimates close to zero (Nilsen, Kaarstein, & Gustafsson, 2016). Moldovan secondary-education system is non-tracking and comprehensive too.

Evaluation of the Models and Model Fit

The present paper is focused on saturated models. A saturated model is one in which there are as many estimated parameters as data points. With few exceptions, this will lead to a perfect fit (Hox, J, 2010, p.100). However, to ascertain the good fit of the models of the given study, the model fit evaluation was conducted.

All 7 models of the present report were tested using Mplus version 7.4 (Muthén & Muthén, 1998-2015). The results of the model-fit indices are presented in the Table 13 with bold values indicating a perfect fit and with underlined values for a poor fit. All other values are considered as good-fit indicators.

As Table 13 shows, the models of the given study showed a poor-fit chi-square values, e.g. χ^2 (28) = 530 of the Model 1. Because the chi-square is sensitive to sample size and several other conditions, I examined alternative fit indices to determine whether the fit was adequate. Taken together, the alternative fit indices suggested:

1. an acceptable or perfect fit for Model 1 with RMSEA = 0.058, CFI = 0.961, TLI = 0.958, and SRMR = 0.029;
2. an acceptable fit for Model 1G: RMSEA = 0.078, CFI = .955, TLI = 0.951, and SRMR = 0.064;
3. a perfect fit for Model 2G with RMSEA = 0.03, CFI = .998, TLI = 0.998, and SRMR = 0.021;
4. an acceptable or perfect fit for Model 3 with RMSEA = 0.069, CFI = 0.958, TLI = 0.952, within SRMR = 0.088, and between SRMR = 0.252;
5. an acceptable or perfect fit for Model 3G with RMSEA = 0.068, CFI = 0.962, TLI = 0.954, within SRMR = 0.088, and between SRMR = 0.286;

Table 13. Model Fit Parameters

Models	Chi-square		RMSEA	CFI	TLI	SRMR	
	$\chi 2$	Degree of Freedom					
One-level							
Model 1	<u>530</u>	28	**0.058**	0.961	0.958	**0.029**	
Model 1G	<u>1531</u>	112	0.078	0.955	0.951	**0.064**	
Model 2G	<u>27.4</u>	8	**0.030**	**0.998**	**0.998**	**0.021**	
Two-level						Within	Between
Model 3	<u>2342</u>	88	**0.069**	0.958	0.952	**0.088**	**0.252**
Model 3G	<u>2769</u>	298	**0.068**	0.962	0.954	**0.088**	**0.286**

The bold values indicate a perfect fit and underlined values indicate a poor fit of a model. All other values are considered as good-fit indicators.
For two-level models with random slope (Models 4 and 4G), no overall fit index has been developed.

Overall, all models presented in Table 13 show good model fit, indicating that the variance-covariance matrices of the proposed models reproduced very well the corresponding observed variance-covariance matrices.

For two-level models with random slope, no overall fit index has been developed. The RMSEA, CFI, TLI, and SRMR fit indices are irrelevant for the random-slope Models 4 and 4G because the indices are based on covariance matrix fitting while the variance of a random-slope model varies across the clusters.

Conclusions

Many educationalists in the second half of the last century supported the statement of Coleman (1966) that the home factors influence student learning at most because such predictors as parenting style, parental involvement, and parental attitudes are significantly related to child's achievement and academic attitude. Bourdieu (1997) claimed that children happen to face their parents' experiences which result in developing tastes, academic motivations, and preferences similar to those of parents. Consequently, these attributes lead to differences in academic and occupational outcomes of the students.

PISA 2015 results show that across all participating countries, 26% of the variation in science performance is explained by learning at a particular school, 22% by belonging to a particular school system, and the remaining 53% by students' individual differences. This means that, even if students' individual background characteristics—e.g. the gender or ESCS—have a strong impact on their performance, what schools do, makes a crucial difference for student performance.

The results of the given study suggest the following answers for the studies research questions (RQ):

RQ1: Is ESCS a strongest predictor of Moldovan student's performance? In other words, is ESCS deterministic?

> The Index of Economic, Social, and Cultural Status cannot be deemed as a strongest predictor of cognitive performance of Moldovan students, even though it is one of three factors that make the strongest unique contributions from 1.5 till 9% percent to explaining the variance in cognitive outcomes on individual level when the variance explained by all other variables in the Models 1 and 1G is controlled for (Table 8, shadowed). The variation between schools of Moldova in averaged student ESCS and PISA outcomes in all three disciplines is also small: ICC equal to 27% (Table 11).

RQ2: Which role does the regional school location (urban versus rural context) play in equity of Moldovan secondary education?

> According to the results, the grouping variable of school location (Context) is the strongest school-level variable, which increases the inequity in cognitive results of Moldovan students, particularly in metropolitan and urban schools and in science objects (with ESCS explaining 71% of total variation, Table 12). There is significant difference on individual level between the answers of the students of Metro, Urban, and Rural groups across 15 out of total16 input- and process predictor-variables (Appendix 4). In complete accordance with existing research, in all three tested areas and in all 30 plausible variables of academic performance, on individual level, metropolitan students showed the highest results (as the most privileged), and rural students expectedly performed at the lowest level as the most disadvantaged (Appendix 7). In mathematics and reading at the school level, the ESCS is strongly and moderately associated with students' cognitive performance in metropolitan and urban schools respectively.

The three following questions were answered together:

RQ5: Has teaching style a compensatory power on ESCS-performance relationship in Moldovan schools?
RQ3: Which role does the language of schooling play in equity in Moldovan secondary education?
RQ4: Are Russian-medium and Romanian schools of Moldova equally equitable?

> On individual level, teaching approach perceived by students makes little difference to the effects of ESCS and cannot be understood as ways in which students' cultural capital influences academic performance scores. Moldovan teachers generally apply an egalitarian approach to their students, providing the same amount of support, guidance, and feedback to all students disregarding their ESCS level. There is almost equal distribution of teaching approach techniques across the schools too; the values of ICC in teaching style components are low (3-11%, Table 11), meaning that the level of teaching instruction does not fluctuate between the schools of Moldova. Similarly, the school-level models point to an equal distribution of more- and less-qualified teachers across the schools. A small exception is between-school difference in rural context with teachers of wealthier schools assessed as more qualified (Table 12).
>
> On individual level, studying in anyone of two media of instruction of Moldova (Romanian or Russian) is equal in terms of the variance in performance accounted by the variable of the language of schooling (Table 8). Similarly, on the school level, Russian and Romanian schools show equal academic performance in PISA 2015 when all other variables are controlled (Table 12). However, according to students' perception, the teachers of the Romanian-medium schools

on average are more supportive, focus more on group activities and whole-class teacher-centered instruction, and provide more feedback than teachers of Russian-medium schools (Table 12).

Finally, the two-level Models 3 and 3G (Appendices 6 and 8 respectively) may be interpreted as showing the compensatory power of Romanian-medium-school teaching style against the inequity in cultural background of Moldovan students rather than higher quality of Romanian-medium teachers.

Do different schools have different degree of educational equity, measured by the variation of the effect of SES on performance?

RQ6: Does the effect of SES on performance scores vary significantly across schools? (Or does this regression coefficient vary from school to school?)

Two-level modeling showed that, on the school level, the differences in family ESCS do not result in corresponding differences in students' cognitive development (Table 12). Moreover, the results of the Models 4 and 4G (Appendices 9 and 10 respectively) showed that school-level factors in Moldovan education system seem to bear neither compensatory- nor anti-compensatory power. This result is in line with other studies showing several non-tracking comprehensive educational systems (e.g. the Scandinavian ones) with Slope-SES estimates close to zero (Nilsen, Kaarstein, & Gustafsson, 2016). Moldovan secondary-education system is non-tracking and comprehensive too. However, it contradicts to the foresaid conclusions on the compensatory power of the teaching approach of Romanian-medium schools and anti-compensatory power of the location context of the schools. More research is needed to resolve this conundrum.

I am also uncertain how to answer the generic research question of my study: Does Moldovan formal education foster socio-economic opportunity or reproduces social inequality? I will answer it in future, via my doctoral studies.

Recommendations

Overall, the given report proves the necessity of a scrupulous analysis of each and every education system in terms of educational equity, because there are no identical templates of population distribution, and every state is a unique example of majority-minority(ies) ratio and relationship. However, after decomposition of factors into component variables, common patterns appear, allowing for more precise evaluation of the existing systems and even of those that will appear in a decade or so as a result of global migration.

The findings from this study are relevant to Moldovan educationalists and policy-makers who, reading through the findings, will apprehend that both the family background and school factors play a decisive role in student performance. Although their influence on student's learning outcomes is disproportionately different, with family socio-economic background being the key explanatory factor, this study indicates that student SES is by no means deterministic, and school-focused policies are likely to improve the performance of low-achieving students or reduce socio-economic inequalities in student performance. Additionally to that, family-focused policies are equally crucial.

The scope for school factors to exert the adverse influences of the ESCS and to uphold the beneficial ones is limited, but further research may find new ways to overcome inequity. Although socio-economic background has significant effects, its impact can be described as just moderate. Moldovan schools' socio-economic level appears to have little impact, which is the good news. PISA team defines success in education as a combination of high level of equity and high performance and consistently confirms that high performance and high level of equity in education are not mutually exclusive. On the contrary, 2015 assessment reports that, at the educational-system level, more socio-economically inclusive schools tend to improve performance of low-performing students, without negatively affecting high-performers (OECD, 2016b, p. 272). PISA revealed two ways high-performing countries do that: a) distributing the finances more equitably across "more disadvantaged" and "more affluent" schools or b) distributing disadvantaged and low-performing students across the schools, so that schools do not differ by SES in relation to each other (OECD, 2014a).

Policies based on the idea that urban-rural differences should be eliminated by developing the rural schools' resources will have an impact on reducing socio-economic inequalities in student cognitive outcomes. The recommendation of this study is as follows: to improve the outcomes of the students with low socio-economic status, the policy should be focused on both the individual students in need of assistance and on the schools they attend.

For further research, I would recommend focusing on peer relations as school-ESCS effect. For myself, I plan further work on the topic with emphasis on mediation and moderation between variables. For instance, science teaching methods for mathematical and reading performances. The variation of cognitive results between schools of a similar socio-economic status is one of such captivating topics. I also consider testing the variable of urban-rural context as a predictor and a controlled variable rather than a grouping variable as it was in the present study.

Finally, as PISA data collection takes place regularly, it is possible to study changes over time in Moldovan educational system. These will allow to draw conclusions on the effects of alteration in various aspects of education.

Limitations of the Study

Even though this study is based on a reliable OECD data, it bears certain limitations. One limitation is that only one of nine PISA 2015 questionnaires was processed in Moldova: student questionnaire. Other crucially important questionnaires such as parent-, teacher-, and school questionnaires were not included. Therefore, the whole analysis is based on the student answers exclusively. Parents' opinion on family background, or teacher's view on teaching approaches they apply, or principals' assessment of the disciplinary school-climate would have complemented the existing data substantially. There is evidence that the perception of the school-level factors by students, teachers, and principals are independent of each other, whereas within-group concepts (e.g., teacher or student opinion alone) appear to be consistent. School-level variables were particularly reduced in amount because school questionnaires completed by school-principals were absent in Moldovan assessment of PISA 2015. Thus, the present report is depleted of the information other than student's data; that might have resulted in the models less-fit to the sample- and population characteristics. That, in turn, could result in less accurate conclusions.

The second limitation is that the information on teaching style was collected from students via questions about science classes only, while in the models, these data were used as teaching style of a school in general. The reason underlying such conceptualization is that using of more-student-centered approaches is a school-level characteristic due to communication exchanges among teachers and top-downwards incentives from the principal and senior teachers to younger members of faculty. Science-teaching style, therefore, was used as a measurement of the entire-school teaching style that could further distort the results.

The third limitation of the study is that the interactions between various inputs and processes and between various processes were not examined. Mediation and moderation effects are essential parts of all social processes, but this level of command on advanced statistical methods is yet in the range of the author's skills.

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Appendix 1. List of Abbreviations

ANOVA	Analysis of Variance
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
EER	Educational Effectiveness Research
ESCS	Index of Economic, Social, and Cultural Status
IBM	International Business Machines
IEA	International cooperative of national research institutions
IPO	Input-Process-Output conceptional and analytical model
MDL	Moldovan Leu (the local currency)
MLR	Multiple Linear Regression
MoI	Medium of instruction
OECD	Organization for Economic Co-operation and Development
PISA	Program for International Student Assessment
RMSEA	Root Mean Square Error of Approximation
RQ	Research Questions
SES	Socio-economic background
SPSS	Statistical Package for the Social Sciences
SRMR	Standardized Root Mean Square Residual
TLI	Tucker-Lewis Index

Appendix 2. Mplus output
Multiple Linear Regression One-level Model. Model 1

TITLE: Multiple Linear Regression, one-level, individual-level; Student-level influences;
To simulate the relationship between students' results and their ESCS in a total sample;
Performance Scores on all variables;
DATA: TYPE=IMPUTATION;
FILE IS Imputation_Feb24.csv;
VARIABLE: NAMES ARE SchoolID StudenID Context ESCS LangSch Gender SchStart SciClass DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScCareer ScBelong HISCED MISCED FISCED PARED HISEI CultPoss HmEdRess HomePoss ICTRess Wealth Grade PreschEd LangHome AGE ST003D02 IMMIG REPEAT MathRes ReadRes ScienRes;
MISSING is ALL (-99);
USEVAR = ESCS LangSch Gender SchStart DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScBelong PreschEd MathRes ReadRes ScienRes;
CLUSTER = SchoolID;
DEFINE: IF (Gender == 2) THEN Gender = 0;
ANALYSIS:
TYPE = COMPLEX;
MODEL: MathRes ReadRes ScienRes ON ESCS LangSch Gender SchStart DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScBelong PreschEd;
[ESCS SchStart DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScBelong PreschEd]
OUTPUT: STANDARDIZED

Appendix 3. Mplus output. Multiple Linear Regression One-level Model of subgroup comparison. Model 1G

TITLE: Multiple Linear Regression, one-level, individual-level; Student-level influences;
To simulate the relationship between students' results and their ESCS in a total sample;
Performance Scores on all variables;
DATA: TYPE=IMPUTATION;
FILE IS Imputation_Feb24.csv;
VARIABLE: NAMES ARE SchoolID StudenID Context ESCS LangSch Gender SchStart SciClass DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScCareer ScBelong HISCED MISCED FISCED PARED HISEI CultPoss HmEdRess HomePoss ICTRess Wealth Grade PreschEd LangHome AGE ST003D02 IMMIG REPEAT MathRes ReadRes ScienRes;
MISSING is ALL (-99);
USEVAR = ESCS LangSch Gender SchStart DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScBelong PreschEd MathRes ReadRes ScienRes;
Grouping is Context (1=Metro 2=Urban 3=Rural);
CLUSTER = SchoolID;
DEFINE: IF (Gender == 2) THEN Gender = 0;
ANALYSIS:
TYPE = COMPLEX;

MODEL: MathRes ReadRes ScienRes ON ESCS LangSch Gender SchStart DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScBelong PreschEd;
[ESCS SchStart DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv SSelfEff EpistemB ScBelong PreschEd]
OUTPUT: STANDARDIZED

Appendix 4. SPSS Output. One-way ANOVA Statistical Tests

One-way ANOVA Statistical Tests were performed for all variables: out of 16 tested variables, only one variable—Enjoyment of science, ScienJoy (shadowed)—showed non-significant differences across the contexts.

ANOVA						
Dependent Variable	Source	Statistics				
		Sum of Squares	df	Mean Square	F	Sig.
Index of economic, social and cultural status (WLE)	Between Groups	762.456	2	381.228	566.419	.000
	Within Groups	3557.066	5285	0.673		
	Total	4319.522	5287			
Language of Assessment and Medium of Instruction	Between Groups	43.807	2	21.903	144.022	.000
	Within Groups	809.392	5322	0.152		
	Total	853.199	5324			
Student (Standardized) Gender ST004D01	Between Groups	2.586	2	1.293	5.179	.006
	Within Groups	1328.512	5322	0.25		
	Total	1331.097	5324			
How old were you when you started <ISCED 1>? Years ST126Q01	Between Groups	25.077	2	12.539	66.383	.000
	Within Groups	977.857	5177	0.189		
	Total	1002.934	5179			
Disciplinary climate in science classes (WLE) DISCLISC	Between Groups	6.731	2	3.366	5.727	.003
	Within Groups	3053.684	5196	0.588		
	Total	3060.415	5198			
Teacher support in a science classes of students choice (WLE) TEACHSUP	Between Groups	73.381	2	36.691	61.185	.000
	Within Groups	3113.481	5192	0.6		
	Total	3186.863	5194			
Inquiry-based science teaching an learning practices (WLE) IBTEACH	Between Groups	8.044	2	4.022	9.945	.000
	Within Groups	2096.438	5184	0.404		
	Total	2104.482	5186			
Teacher-directed science instruction (WLE) TDTEACH	Between Groups	6.285	2	3.143	4.261	.014
	Within Groups	3773.723	5117	0.737		
	Total	3780.008	5119			

Perceived Feedback (WLE) PERFEED	Between Groups	8.253	2	4.127	6.685	.001
	Within Groups	3170.647	5136	0.617		
	Total	3178.9	5138			
Environmental Awareness (WLE) ENVAWARE	Between Groups	80.752	2	40.376	34.249	.000
	Within Groups	6035.928	5120	1.179		
	Total	6116.68	5122			
Enjoyment of science (WLE) JOYSCIE	Between Groups	2.202	2	1.101	1.8	**.165**
	Within Groups	3127.19	5112	0.612		
	Total	3129.392	5114			
Instrumental motivation (WLE) INSTSCIE	Between Groups	31.15	2	15.575	24.335	.000
	Within Groups	3248.065	5075	0.64		
	Total	3279.215	5077			
Science self-efficacy (WLE) SCIEEFF	Between Groups	22.559	2	11.28	11.208	.000
	Within Groups	5079.254	5047	1.006		
	Total	5101.813	5049			
Epistemological beliefs (WLE) EPIST	Between Groups	24.183	2	12.092	20.636	.000
	Within Groups	2943.194	5023	0.586		
	Total	2967.377	5025			
Students' expected occupational status (SEI) BSMJ	Between Groups	61286.98	2	30643.49	93.051	.000
	Within Groups	1631440	4954	329.318		
	Total	1692727	4956			
Subjective well-being: Sense of Belonging to School (WLE)	Between Groups	4.324	2	2.162	3.934	.020
	Within Groups	2795.774	5088	0.549		
	Total	2800.097	5090			
Did you attend <ISCED 0>? ST124Q01	Between Groups	17.576	2	8.788	50.49	.000
	Within Groups	918.322	5276	0.174		
	Total	935.898	5278			

Appendix 5. Mplus Input. Confirmatory Factor Analysis Model with Wald chi-square Test of parameter difference. Model 2G

```
TITLE: Confirmatory Factor Analysis to specify the structural relationship among a
      compound latent variable of total performance (PerformT) and its three indicators;
      Wald Test of Parameter Constraints to test the significance of a regression
      estimate for two groups of MoI (LangSch);
    DATA: TYPE=IMPUTATION;
        FILE IS Imputation_Feb24.csv;
VARIABLE: NAMES ARE SchoolID StudenID Context ESCS LangSch Gender SchStart SciClass
DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv  SSelfEff EpistemB
ScCareer ScBelong HISCED MISCED FISCED PARED HISEI CultPoss HmEdRess HomePoss
ICTRess Wealth Grade PreschEd LangHome AGE ST003D02 IMMIG REPEAT MathRes ReadRes
ScienRes;
    MISSING is ALL (-99);
    USEVAR = ESCS MathRes ReadRes ScienRes;
    CLUSTER=SchoolID;
```

```
grouping is LangSch (0=Russian 1=Romanian);
ANALYSIS:
TYPE = COMPLEX;
MODEL:
PerformT By MathRes ReadRes ScienRes;
PerformT ON ESCS;
ESCS;
MODEL romanian :
PerformT ON ESCS (p1);
MODEL Russian  :
PerformT ON ESCS (p2);
OUTPUT: STANDARDIZED;
model test:
p1 = p2;
```

Appendix 6. Mplus Input. Two-level Model of school-level Influences. Model 3

```
TITLE: Two-level Model. School-level Influences. Adding school characteristics in Model 1;
DATA: TYPE = IMPUTATION;
FILE IS Imputation_Feb24.csv;
VARIABLE: NAMES ARE SchoolID StudenID Context ESCS LangSch Gender SchStart SciClass
DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv  SSelfEff EpistemB
ScCareer ScBelong HISCED MISCED FISCED PARED HISEI CultPoss HmEdRess HomePoss
ICTRess Wealth Grade PreschEd LangHome AGE ST003D02 IMMIG REPEAT MathRes ReadRes
ScienRes;
MISSING is ALL (-99);
USEVAR = ESCS LangSch DisciplS
TeachSup InquiryB TDInstr PerFeedb EnvAware EpistemB MathRes ReadRes ScienRes;
CLUSTER = SchoolID;
DEFINE:MathRes = MathRes/100;
ReadRes =ReadRes/100;
ScienRes=ScienRes/100;
ANALYSIS:
TYPE = TWOLEVEL;
MODEL:
%WITHIN%
MathRes ON ESCS;
ReadRes ON ESCS;
ScienRes ON ESCS;
TeachSty BY DisciplS TeachSup InquiryB TDInstr PerFeedb;
PerformT By MathRes ReadRes ScienRes;
MathRes ReadRes on LangSch EnvAware EpistemB TeachSty;
PerformT on LangSch EnvAware EpistemB TeachSty;
%BETWEEN%
TeachStB BY DisciplS TeachSup InquiryB TDInstr PerFeedb;
MathRes ReadRes ScienRes ON ESCS LangSch TeachStB;
TeachStB ON ESCS LangSch EnvAware EpistemB;
ESCS LangSch EnvAware EpistemB;
OUTPUT: STANDARDIZED;
```

Appendix 7. SPSS Output. Descriptive Statistics of Plausible Values.

In the given extract, in complete accordance with existing research, in all three tested areas and in all 30 plausible variables of academic performance, on individual level, metropolitan students showed the highest results (as the most privileged), and rural students expectedly performed at the lowest level as the most disadvantaged.

Plausible Values (PV)	Context	N	Mean	Std. Deviation	Std. Error
PV1 in Mathematics	Metro	1171	456.6	90.2	2.6
	Urban	1082	430.9	86.8	2.6
	Rural	3072	400.6	87.7	1.6
	Total	5325	419.1	91.0	1.2
PV6 in Mathematics	Metro	1171	458.0	89.6	2.6
	Urban	1082	429.7	88.6	2.7
	Rural	3072	400.2	87.3	1.6
	Total	5325	418.9	91.2	1.2
PV2 in Reading	Metro	1171	465.3	94.9	2.8
	Urban	1082	436.4	90.2	2.7
	Rural	3072	391.6	93.0	1.7
	Total	5325	416.9	97.9	1.3
PV4 in Reading	Big city	1171	465.5	95.0	2.8
	Urban	1082	438.0	89.8	2.7
	Rural	3072	390.5	90.8	1.6
	Total	5325	416.6	96.9	1.3
PV7 in Reading	Big city	1171	462.7	95.2	2.8
	Urban	1082	442.2	89.5	2.7
	Rural	3072	390.8	92.7	1.7
	Total	5325	417.0	97.8	1.3
PV3 in Science	Big city	1171	464.0	85.5	2.5
	Urban	1082	445.8	80.6	2.4
	Rural	3072	407.6	82.7	1.5
	Total	5325	427.7	86.4	1.2
PV5 in Science	Big city	1171	464.2	85.7	2.5
	Urban	1082	444.5	81.9	2.5
	Rural	3072	409.0	81.1	1.5
	Total	5325	428.4	85.6	1.2
PV8 in Science	Big city	1171	463.9	87.2	2.5
	Urban	1082	444.4	82.4	2.5
	Rural	3072	407.3	83.5	1.5
	Total	5325	427.3	87.5	1.2

Appendix 8. Mplus Input. Two-level Model Comparing school influences on achievement between subgroups. Model 3G

```
TITLE: Two-level Model. School-level Influences. Adding school characteristics in Model 1. Grouping
is Context;
     DATA: TYPE = IMPUTATION;
          FILE IS Imputation_Feb24.csv;
VARIABLE: NAMES ARE SchoolID StudenID Context ESCS LangSch Gender SchStart SciClass
DisciplS TeachSup InquiryB TDInstr PerFeedb  EnvAware ScienJoy InsMotiv SSelfEff EpistemB
ScCareer ScBelong HISCED MISCED FISCED PARED HISEI CultPoss  HmEdRess HomePoss
ICTRess Wealth Grade PreschEd LangHome AGE ST003D02 IMMIG REPEAT MathRes ReadRes
ScienRes;
     MISSING is ALL (-99);
USEVAR = ESCS LangSch DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware EpistemB
MathRes ReadRes ScienRes;
     grouping is Context (1=Metro 2=Urban 3=Rural);
CLUSTER = SchoolID;
     DEFINE: MathRes = MathRes/100;
           ReadRes =ReadRes/100;
           ScienRes=ScienRes/100;
     ANALYSIS:
     TYPE = TWOLEVEL;
MODEL:
     %WITHIN%
     MathRes ON ESCS;
     ReadRes ON ESCS;
     ScienRes ON ESCS;
    TeachSty BY DisciplS TeachSup InquiryB TDInstr PerFeedb;
    PerformT By MathRes ReadRes ScienRes;
    MathRes ReadRes on LangSch EnvAware EpistemB TeachSty;
    PerformT on LangSch EnvAware EpistemB TeachSty;
     %BETWEEN%
     TeachStB BY DisciplS TeachSup InquiryB TDInstr PerFeedb;
     MathRes ReadRes ScienRes ON ESCS LangSch TeachStB;
     TeachStB ON ESCS LangSch EnvAware EpistemB;
     ESCS LangSch EnvAware EpistemB;
```

Appendix 9. Mplus Input. Two-level Random Slope Model. Model 4

```
  TITLE: Random-slope analysis. Adding school characteristics in a school-level
     regression Model3 to explain variation in the within-school slopes;
     DATA: TYPE = IMPUTATION;
          FILE IS Imputation_Feb24.csv;
  VARIABLE: NAMES ARE SchoolID StudenID Context ESCS LangSch Gender SchStart SciClass
          DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv
          SSelfEff EpistemB ScCareer ScBelong HISCED MISCED FISCED PARED HISEI CultPoss
          HmEdRess HomePoss ICTRess Wealth Grade PreschEd LangHome AGE ST003D02 IMMIG
          REPEAT MathRes ReadRes ScienRes;
```

```
     MISSING is ALL (-99);
  USEVAR = ESCS LangSch DisciplS TeachSup InquiryB TDInstr PerFeedb MathRes ReadRes
ScienRes;
     CLUSTER = SchoolID;
     DEFINE:MathRes = MathRes/100;
            ReadRes =ReadRes/100;
            ScienRes=ScienRes/100;
     ANALYSIS:
     TYPE = TWOLEVEL RANDOM;
     MODEL:
     %WITHIN%
     S1|MathRes ON ESCS;
     S2|ReadRes ON ESCS;
     S3|ScienRes ON ESCS;
     %BETWEEN%
     TeachStB BY DisciplS TeachSup InquiryB TDInstr PerFeedb;
     S1 S2 S3 MathRes ReadRes ScienRes ON ESCS LangSch TeachStB;
```

Appendix 10. Mplus Input. Two-level Random-Slope Model for subgroup comparison. Model 4G

```
TITLE: Random-slope analysis. Adding school characteristics in a school-level
          regression Model3 to explain variation in the within-school slopes. Grouping is Context;
DATA: TYPE = IMPUTATION;
          FILE IS Imputation_Feb24.csv;
  VARIABLE: NAMES ARE SchoolID StudenID Context ESCS LangSch Gender SchStart SciClass
          DisciplS TeachSup InquiryB TDInstr PerFeedb EnvAware ScienJoy InsMotiv
          SSelfEff EpistemB ScCareer ScBelong HISCED MISCED FISCED PARED HISEI CultPoss
          HmEdRess HomePoss ICTRess Wealth Grade PreschEd LangHome AGE ST003D02 IMMIG
          REPEAT MathRes ReadRes ScienRes;
          MISSING is ALL (-99);
          USEVAR = ESCS LangSch DisciplS TeachSup InquiryB TDInstr PerFeedb MathRes ReadRes
          ScienRes;
          grouping is Context (1=Metro 2=Urban 3=Rural);
          CLUSTER = SchoolID;
DEFINE:MathRes = MathRes/100;
            ReadRes =ReadRes/100;
            ScienRes=ScienRes/100;
ANALYSIS:
          TYPE = TWOLEVEL RANDOM;
          MODEL:
       %WITHIN%
          S1|MathRes ON ESCS;
          S2|ReadRes ON ESCS;
          S3|ScienRes ON ESCS;
       %BETWEEN%
          TeachStB BY DisciplS TeachSup InquiryB TDInstr PerFeedb;
          S1 S2 S3 MathRes ReadRes ScienRes ON ESCS LangSch TeachStB;
```