

Understanding Determinants of Student Performance in K-12 Education System in Canada: A
Behavioural Approach

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By

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ABSTRACT

This thesis examines the performance of 15-year-old students in Canadian public schools in the 2012 math examination organized by the Program for International Student Assessment (PISA). The research aims to determine the level of influence three actors (the province, schools, and students) have on students' performance in the 2012 PISA mathematics examinations. Due to the nested nature of the data, the three-level Hierarchical Linear Model (HLM) method was used to address the research questions. The study found that of the three levels of influence, the strongest influence on math achievement (81%) is the individual students, followed by school (17%) and the province (2%). Among the variables at the individual level, gender and socioeconomic status of students are statistically significant. At the school level, parent expectations, school enrolment, class size, and teacher qualification variables were used. Parent expectations and school enrolment were found to impact student math achievement. The results from the study suggest that policies such as establishing parent engagement offices in schools, instituting gender equity programs and providing support for students from low socioeconomic backgrounds are key in enhancing student learning in Canada.

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DEDICATION

I dedicate this work to my family, friends, and individuals who have helped in one way or the other to make this work and my journey as a student a great success. God bless you all.

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LIST OF ABBREVIATIONS

- 1.1.1** PISA – Program for International Student Assessment
- 1.1.2** OECD – Organization for Economic Co-operation and Development
- 1.1.3** HLM – Hierarchical Linear Model
- 1.1.4** OLS – Ordinary Least Squares
- 1.1.5** ESL – English as a Second Language
- 1.1.6** ICC - Intra-Class Correlation
- 1.1.7** SES – Socio-Economic Status

1 INTRODUCTION

Society receives many benefits from an educated population. Education can bring about poverty reduction, higher income, low crime rates, and economic growth. Recognizing the importance of education in the development of knowledge, the Organization for Economic Cooperation and Development (OECD) and its allies have developed a tool to measure the skills and knowledge of 15-year-old students. This tool is known as the Program for International Student Assessment (PISA).

PISA began in 2000 and tests students every three years. Each PISA cycle focuses more on one of the three main areas – reading, science, or mathematics. In the year 2000, reading was the area of focus followed by mathematics in 2003, science in 2006, reading in 2009, and mathematics again in 2012. PISA is mainly for 15-year old students in member countries. The reason for this target group is the belief that some skills and knowledge have been acquired by these students as they near completion of compulsory education. By this, member countries are able to tell how prepared the students are in embracing the future (Assessment & Source OECD, 2006; Ziya, Dogan, & Kelecioğlu, 2010).

By monitoring student outcomes over time, PISA has now become the lens through which policy makers scrutinize the educational system in Canada (Schleicher, 2007). PISA survey collects data on students, family, and institutions that help policy makers explain student achievement in respective countries and also compare with member countries (OECD, 2013). PISA has the potential to reveal the weaknesses and strengths of institutions and to identify what can be done to minimize these weaknesses (Agasisti, 2013).

Canada has been participating in PISA since it was first administered in 2000. This thesis studies the data of Canadian students who took the 2012 PISA math test. In 2012, there were significant variations among the provinces in math achievement. The average score for Canada in 2012 PISA math was 508.5, with the Atlantic and Prairie provinces (excluding Alberta) performing below the national average. As shown in Figure 1.1., the difference in average math scores between the top-performing province (British Columbia) and the lowest (PEI) is about 37 points.

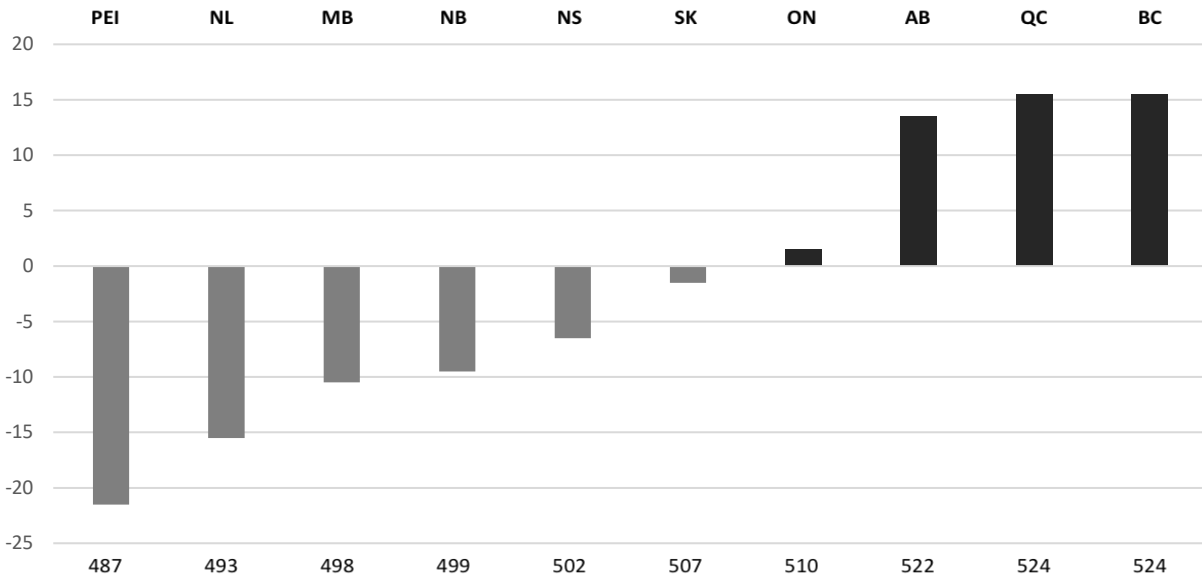


Figure 1.1: Provincial average math scores relative to the average score for Canada in the 2012 PISA

Data source: CANSIM Table 478-0014

The school boards in Canada invested approximately \$54 billion in public elementary and secondary education in 2012 (Statistics Canada Table 37-10-0065-01). Although this investment shows that provincial governments are committed to enhancing student learning, evidence from the 2012 PISA mathematics examination indicate that these investments do not necessarily result in better student performance. For instance, even though Luxembourg’s expenditure per student is higher than the other OECD countries, its average performance in the PISA 2012 mathematics examination was 486, which falls short of the OECD average by 4 points (i.e., the OECD average was 490). It stands to reason that beyond a certain minimum level of expenditure per student, building an effective education system requires something more than just money.

The picture of students’ PISA examination achievements would be incomplete if the various roles played by provinces, school divisions, and students were not understood. Student characteristics, school resources, and provinces collectively impact student achievement. Students come from diverse backgrounds and possess unique characteristics. They differ in gender, socioeconomic circumstances, and immigration status. Students’ varying characteristics and circumstances play a vital role in their PISA math achievement (Galway, Sheppard, Wiens, & Brown, 2013; McEwen, 1995; Sackett, Kuncel, Arneson, Cooper, & Waters, 2009).

The school one attends sets the parameters of a student's learning experience (Korir & Kipkemboi, 2014). For example, a school's resources, including teachers with different levels of experience and educational qualification, are counted as some of the resources a school possesses that influence student achievement. In effect, to classify a school as effective or otherwise may be due to the above-mentioned characteristics of a school (Lee, 2000).

The provinces make sure that school leadership is provided with the necessary financial and logistic support to achieve set goals and targets. For instance, the province of Ontario created the Literacy and Numeracy Secretariat that engaged teams of educationists to reshape the status of underperforming schools. These teams of experts engage in direction setting, enhancing the professional skills of teachers and principals, redesigning the organization, and managing the instructional program. In essence, they provide leadership for school leaders (Leithwood & Strauss, 2009).

Student performance on the exam is thus dependent upon provincial, school, and individual characteristics, all of which need to be taken into consideration when assessing student performance for policy purposes. An understanding of the factors affecting students' performance is key for informed policy making.

The main objective of this study is to assess the provincial-, school-, and student-related factors that influenced student performance on the 2012 PISA exam. Specifically, the study will seek to:

- Determine which of the levels – student, school, and province – had the greatest influence on 15-year-old Canadian students' mathematics performance on the 2012 PISA.
- Assess the factors that are associated with student performance on PISA.

The governance of the educational system in Canada is hierarchical. Students are nested within schools, which are, in turn, nested within provinces. The hierarchical nature of the data limits the ability of Ordinary Least Squares (OLS) to correctly estimate their impacts. In a typical study like this involving hierarchical data, estimating student achievement using an OLS model, tends to produce biased results. To avoid such biases, the hierarchical linear model (HLM) offers a solution by estimating the three levels of the education system simultaneously instead of treating each level individually.

The remainder of the study is organized as follows: Chapter 2 provides the background of the study. Chapter 3 presents the literature review. Chapter 4 describes the data, and Chapter 5 explains the methodology. The results are presented in Chapter 6, and discussion/policy recommendation are in Chapter 7. Chapter 8 concludes the thesis.

2 BACKGROUND OF PUBLIC K-12 EDUCATION SYSTEMS IN CANADA

In Canada, the education system is governed by three levels of organization – the provincial authorities, the school board, and the school. There are 13 education systems in Canada – 10 provincial and three territorial. The school systems include primary school and secondary school. Because education in Canada is managed and administered by the provinces and the territories, there is no federal department of education. Elementary education is compulsory for Canadians and immigrants who meet residency requirements. Elementary education covers 6 to 8 years of schooling. There are two main publicly funded elementary school systems in Canada; public and Roman Catholic. In elementary schools, students are taught such subjects as reading, mathematics, science, health, and physical education and art. Canada is a bilingual nation that officially recognizes English and French as acceptable media of instruction in public schools (Dunleavy, 2007). Depending on the province, students may undertake second-language learning. After students have had their six to eight years of elementary education, they proceed with secondary education. The final four to six years of compulsory education in Canada occur in secondary schools. At the secondary level, students take compulsory and optional courses. Students at the secondary level must complete a total of 30 credits, which comprise 18 compulsories and 12 optional courses. Students whose interests lie in vocational and technical studies are taught and trained in separately designated vocational training centres. In these vocational institutions, student undergoes training for a minimum of a year to a maximum of three years. Students who successfully complete their compulsory education are awarded a diploma (Council of Ministers of Education, 2008; Guven & Gurdal, 2011).

2.1 The role of provinces in public K-12 education

The province or territory is the central authority when it comes to the provision and administration of Kindergarten to Grade 12 (K-12) education in Canada. In every province/territory, departments or ministries of education are responsible for the organization of schools and delivery and assessment of education for elementary and secondary levels. This central authority grants powers, determines and distributes materials and financial resources, and oversees both school boards and school operations. The central authority sets the priorities and directions that school boards and

schools should follow. The province/territory plays varied roles in terms of school curriculum, from outlining the goals and objectives to formulating practices for student progress and creating channels to assess student performance (Lessard & Brassard, 2005).

Funding for public education in the provinces comes from the provincial government or by means of provincial transfers and local taxes. These funds are collected by the province or school boards who have the power to do so. The government leader in the province appoints the minister in charge of education. The central authority ensures that schools use these funds judiciously to achieve the overall objective of the province. Some of the factors provincial authorities consider when allocating funds include student population, location, and special needs.

A body consisting of provincial ministers of education, known as the Council of Ministers of Education (CMEC), provides a platform for discussing and promoting formal education across Canada. For instance, CMEC has launched a new initiative coded “Learn Canada 2020,” outlining strategies that will enhance educational systems, learning opportunities, and outcomes of education across Canada. This new vision is built on four core pillars: improving the accessibility of high quality early childhood education; developing world-class skills in literacy, numeracy, and science for elementary and high school students; increasing the enrolment in postsecondary education; and ensuring that adult education provides learning and skill development to Canada’s adult population (Council of Ministers of Education, 2008).

2.2 The role of school boards in public K-12 education

The school board is the second authority in the hierarchy of school governance in Canada. School boards are also known as school divisions. The school boards comprise a council of commissioners or trustees who are elected by the people of the community and are mandated by law to execute their powers. These trustees hold regular meetings with the public to solicit their views on school management. They make decisions on administration, facilities, personnel, and student enrolment (Council of Ministers of Education, 2008; Lessard & Brassard, 2005). School boards work with different agencies and stakeholders in delivering their mandate – improving the school system. The school boards ensure that their policy goals, priorities, and resource allocation conform to the province’s educational attainment goal.

In 2016, school boards in Canada spent \$60 billion (approximately) in running its programs. Funding for public education comes from such sources as local taxation, provincial government, federal government, and other private-sector sources. As shown in Table 2.1, school boards allocate funds for salaries, instructional supplies, administration purposes, transportation, school facilities, capital expenditures, and other miscellaneous items for the running of the schools. Across Canada, teachers' compensation represents by far the highest expenditure for school boards. In 2016, expenditures on teachers' salaries and wages amounted to approximately \$36 billion.

Table 2.1: Annual expenditure of school boards (\$'000)

	2012	2013	2014	2015	2016
Teachers' salary	32,732,536	33,829,213	34, 513,132	35,437,827	36,603,410
Instructional supplies	1,634,149	1,660,828	1,704,247	1,740,904	1,756,524
Administration	3,033,232	3,085,842	3,158,886	3,181,463	3,223,151
Transportation	2,293,150	2,328,071	2,367,580	2,382,496	2,407,427
School facilities services	4,580,949	4,731,482	4,882,318	4,931,123	4,986,143
Other operating expenditures	5,102,486	5,318,034	5,459,726	5,506,315	5,630,109
Capital expenditures	4,770,532	4,918,685	5,097,201	4,956,041	5,887,432
Total Expenditure	54,147,034	55,872,155	57,183,090	58,136,169	60,494,196

Source: Statistics Canada Table 37-10-0065-01

To achieve their goals, school boards hire a superintendent who manages the operations of schools in the district. This superintendent, whom the school board holds responsible for what occurs in his/her jurisdiction, works to ensure that the board's key goals remain a priority while maintaining good relationships with the members of the board. Superintendents also supervise principals of schools under their jurisdiction and address parental concerns.

2.3 The role of schools in public K-12 education

Schools are institutions that provide education services to communities. Schools are created by school boards, are required to adhere to school board rules and regulations, and are headed by a

principal. A principal is the “manager” of an individual school within a district in a province or territory. Principals oversee teachers, administer the school’s budget, ensure student discipline, oversee teaching and curriculum, maintain records about students in the school and ensure parents are informed about the progress of their wards in school. As part of their responsibilities, principals are tasked with attracting and retaining good teachers in their school. Teachers’ education qualifications and experience affect their pay. Principals and superintendent of schools decide on which teachers to bring into the classroom and how to retain and promote teachers who contribute to student achievement. In this way, principals and superintendents influence prevailing conditions in schools and classrooms (E. A. Hanushek & Rivkin, 2007).

3 LITERATURE REVIEW

Learning is not only a product of schools but also of families, communities, peers, and socioeconomic and cultural forces. Students' learning environment consists of many elements, for example, their physical location in the class and the children around them, the teacher, their home, and the community (Coleman, 1968). A student's academic achievement is potentially influenced by his/her academic foundation, learning tools at his disposal and ability to take use school resources to his/her advantage Academic achievement is also influenced by a student's pre-existing human capital, namely, the tools the individual uses to learn, as well as to convert the impact of schools and other educational institutions into acquired skills and knowledge (Rothstein, 2000). This literature review focuses on student characteristics and school resources that contribute to student achievement.

3.1 Student characteristics

3.1.1 Gender, immigration and socioeconomic status of students

The student characteristics reviewed in this study are gender, immigration status, and socioeconomic status. Earlier studies suggested that girls performed better than boys in language skills, such as reading and writing (Mead, 2006), while boys performed better in math (Geary, 1996). In this debate, the fields of differential psychology and the cognitive sciences have played a large role in explaining these differences (Stoet & Geary, 2015). However, recent studies have suggested that gender differences in educational outcomes are disappearing or have largely disappeared (Janet S Hyde & Mertz, 2009a) because of changes in social roles and the transition towards gender equality in economic and political life.

There are two main theories that explain current differences in gender and educational attainment- the gender similarities hypothesis and the stratification hypothesis (Stoet & Geary, 2015). The stratification hypothesis suggests that there is a linear relation between the size of the sex difference in mathematics performance and the extent to which men and women have equal social, economic, and political opportunities (Reilly, 2012). The gender similarities hypothesis suggests that males and females "are more alike than different" (Janet Shibley Hyde, 2005, p. 581) and that there are only a few psychological variables on which men and women vary, such as some motor and sexual behaviors (Janet Shibley Hyde, 2005). Thus, Hyde argues that the focus on sex

differences leads to an underestimation of girls' potential in mathematics. In sum, the gender similarities and gender stratification hypotheses both coherently suggest that almost all psychological sex variations are the result of social and political factors. In this context, implementing policies that create equal opportunity would remove the stratification of society by gender, and thus eliminate any sex differences in achievement (Stoet & Geary, 2015).

There have been mixed findings on gender differences in student achievement. Recent studies show that girls are outperforming boys in academic achievement (Co-operation & Development, 2010; Fortin, Oreopoulos, & Phipps, 2015). In the last three decades, the average performance of girls in high school has shifted from the “B” position to “A” while the boys have stayed with “B” in the last three decades (Fortin et al., 2015). Career expectations of girls, e.g., becoming a medical doctor and other professionals, are the strongest motivational drivers of this shift (Fortin et al., 2015). Boys, on the other hand, choose to enter the military or a vocational school which do not require any advanced educational certificate (Fortin et al., 2015).

However, boys tend to outperform girls in mathematics. A study on college preparedness of high school students in Texas for the 2006-2007 school year reveals that 52.6% of boys had high mathematics scores compared to 44% of girls. In contrast, girls had a higher score in reading (51%) in terms of their college-readiness than boys (39%) (Combs et al., 2010). This advantage of boys in mathematics may be attributed to the fact that boys are exposed to higher level mathematics than their female counterparts or that boys show greater interest than girls in mathematics and science careers. On the other hand, the more women engage in research and teaching of mathematics and science, the more likely they are to serve as role models for girls and help improve their performance in these fields (Beller & Gafni, 1996). Other studies have demonstrated gender neutrality in student performance. The widespread conviction that boys outperform girls in mathematics achievement has been challenged. When gender disparities in mathematics achievement are examined, evidence shows that “Victor is not necessarily better than Victoria in mathematics achievement” (Georgiou, Stavrinides, & Kalavana, 2007, p. 338). In the 2009 PISA results, girls outperformed boys in reading assessment, but boys performed better than girls in mathematics. However, science scores did not vary much between boys and girls (Co-operation & Development, 2010).

The number of immigrant families or children in advanced countries is increasing. Since education is important for economic mobility, factoring immigrant children into the educational system has aroused the curiosity of researchers. Earlier studies were of the view that children from immigrant families will experience reduced results from education (Zhou & Portes, 2012) as a result of cultural differences, unfamiliarity with the educational system, and language difficulties (Feliciano & Lanuza, 2017). However, recent studies have shown that immigrant children, compared with people from similar socio-economic backgrounds, perform better than children born from native families (White, 2000). This pattern is described in various terms such as ‘second-generation advantage’, ‘immigrant paradox’, or ‘super achievement’ (Feliciano & Lanuza, 2017). Several studies have tried to explain the immigrant paradox. In the US, some scholars have suggested that the culture of America has particularly negative impact on immigrant children (Coll & Marks, 2012). Some scholars have also used cultural mechanisms such as immigrant optimism, immigrant cultural capital, and immigrant ethos of hard work as the explanatory model for the immigrant paradox in education (Hsin & Xie, 2014). However, Feliciano and Lanuza (2017) have suggested that the immigrant paradox is overstated and hence discount the immigrant advantage as a paradox.

According to Feliciano and Lanuza (2017), a focus on the contextual approach can better explain the immigrant paradox. The contextual approach focuses on the class of immigrant parents, which is not well captured by standard socio-economic measures (e.g., family household incomes and parental educational and occupational attainments) alone. This approach includes the historical and geographic context in which parents’ levels of schooling are completed as the structural origins in which cultural resources emerge to push immigrant children up. Hence, the contextual approach goes beyond the common explanation that immigrants are highly motivated and achievement-oriented to suggest that most immigrants originate from higher social class locations, which provides them with a set of class-specific resources—a habitus, for example—that buttresses their children’s achievement. In other words, immigrant parents’ high aspirations influence their children’s educational attainment.

Despite the immigrant advantage, some studies have shown that some immigrants have poor educational outcomes or, in extreme cases, are unable to complete high school (Lutz, 2007). Several factors, such as ethnicity, generation, language proficiencies, family structure, and socio-economic status, have been adduced in the literature to explain this phenomenon. Lutz (2007) suggests that in the US, the popular perception is that educational outcomes among Latino students

are primarily hindered by a lack of English proficiency. Yet Lutz (2007) shows that the incidence of low levels of educational attainment among immigrants compared to other groups tends to be more complex than often assumed. Lutz (2007) suggests that although the impacts of other factors such as students' family and school context have been well documented in sociological research (Lareau, 2000), they have been less applied to immigrant children.

Socioeconomic status is one of the essential variables in education research. Increasingly, educational researchers examine academic achievement in relation to socioeconomic background of students (Davis-Kean, 2005; Fan & Williams, 2010; Lunenburg & Irby, 2002; Muller, 2018). A student's socioeconomic (SES) status can be described as the ranking of either the individual or the family on a hierarchy according to access to or control over some combination of valued commodities such as wealth, power, and social status (Mueller & Parcel, 1981). Characteristics such as family income, parental education, and a measure of family structure are some of the factors considered when looking at the SES of a student's family (Sirin, 2005).

Empirical studies that examine the relationship between student achievement and student's socioeconomic status have centered on parental education, family income, immigration status of the student, the language spoken at home, and the number of books at home. Guimarães and Sampaio (2013) investigated how family background influences students' performance in a university's entrance exam. The results clearly indicate that parental education positively impacts student performance. In another research, Acemoglu and Pischke (2001) examined the changes in the distribution of U.S family income over three decades and the effect of income distribution on college education enrolment. They conclude that a 10 percent rise in family income leads to a corresponding 1 to 1.4 percent increase in college enrolment. Hanushek and Luque (2003) studied the efficiency and equity in education around the world using data from the Third International Mathematics and Science Study (TIMSS). The authors reported that family background has a strong bearing on student performance. Students from disadvantaged families and from families where the parents themselves have lower education levels tend to perform systematically worse on the TIMSS test than do students without these deficits.

A study by Downey (1995) found an inverse relationship between the number of children sharing parental resources (such as time, energy, and money.) and children's educational performance.

Economic resources decrease rapidly, with an increase in family size. The fewer the siblings, more the parents will have to invest in each child, and the more access the child will have to resources such as computers and books. Indeed, family structure plays an important role in the educational success of students. Students from single-parent families have reading scores that on average, are 12 points lower than students from other types of families, likely because the average single-parent family has a lower income than two-parent families and must manage the double responsibility of working and raising their children (Co-operation & Development, 2003). In a Norwegian study, students from homes where the mother and father live together outperformed their counterparts from homes with just one of parents by 35 points in reading in US and by 10 points in mathematics in Norway (Pong, Dronkers, & Hampden-Thompson, 2003).

3.2 School Characteristics

The school level factors that are included in this study are parental expectations of the school, school enrollment, class size, and a teacher's qualification in math.

3.2.1 Parental expectation

For school administrators, addressing the expectations of parents is important for student's achievement, particularly to enable students to reach their academic potential. As many public schools face changing demographic conditions, schools must be equipped to address the needs of an increasingly diverse population. According to Green (2013), several strategies exist to address the needs of a diverse student population. One such strategy is to place the needs of the students at the centre of discussion which emerges when schools establish effective communication between parents and schools. Communication between schools and parents can only be effective if it is a two-way approach – i.e., it sends the right message that is easily understood by the receiving party (Green, 2013). Studies have shown that family involvement improves academic achievement in children and teenagers, inspires students' attendance, enhances school-family cooperation, and enables students to develop self-control (Hoover-Dempsey et al., 2001; Titiz & Tokel, 2015).

An effective way to improve communication between parents and the school is to determine parental expectations and understand how those expectations differ from each other and are influenced by several factors. In this context, determining parental expectations of schools can be guided by knowledge of parents' race and ethnicity, socioeconomic status, and level of educational

attainment. Improving knowledge in such areas improves strategies designed to enhance school management, teaching effectiveness and the interaction between parents and schools . Moreover, awareness of parental expectations among racial and ethnic groups can help school management to meet diverse students' needs and establish effective interaction between the school and home. Hence, a school's management team that wants to improve education- and instruction need to give importance to interrelations between parents and teachers.

One aspect of parental expectations that depends on the socioeconomic status of parents is the contribution schools make to the emotional wellness of students. Parents of different socioeconomic backgrounds differ on how schools contribute to their children's psychosocial needs. When endeavoring to facilitate a home-school relationship, parents with a low SES level have to be approached differently from parents from a high SES background. Parents with low SES who come from different cultures find it more challenging to maintain involvement in their child's educational experiences (Green, 2013; Jutras & Lepage, 2006; Phillipson, 2009). Raleigh and Kao (2010) found differences in parental aspirations between immigrant parents and native-born minority parents: Immigrant parents maintained high aspirations consistently over time, whereas minority parents did not. These findings suggest that parental preferences and family circumstances are determinants of what parents expect from school (Jacob & Lefgren, 2007). As a result, parents of high SES and parents of low SES show differences regarding expectations from the school.

3.2.2 School enrolment

School enrollment is another factor considered in this study. According to Connelly and Zheng (2003), school enrolment and completion are primarily determined by three main factors: demand, supply, and government policy. Demand refers to the individual decisions made by students or their parents in terms of the costs of staying in school (e.g., opportunity costs of wage income and/or home production forgone and non-pecuniary costs, such as, whether the child enjoys school) and benefits (higher wages available from jobs attainable with more education).. The educational level of the head of a household can impact on school attendance (Chernichovsky, 1985). Chernichovsky showed that the more educated the head of the household, the more likely a child is to be enrolled in school and the longer the stay in school. Also, community standards play a critical role in school enrolment. For instance, if few attend middle school in a community, individual students are unlikely to demand attendance. Findings by Binder (1999) suggest that in

Mexico, community of residence is a significant predictor of the desired schooling, even when household level traits are controlled. Connelly and Zheng (2003) also showed that in China, the place of residence and sex, as well as the interactions between them, are the most important categories for understanding school enrolment and graduation patterns.

Supply factors affect school enrolment through reasons such as the availability or quality of education. Government policy toward education also affects educational choices in several ways. Examples include the age at which students begin school, the years of compulsory education, funding, jurisdiction, curriculum, and governance. Thus, in every country, attendance rates can be affected by institutional constraints. For instance, findings across different countries have shown that higher national per capita income is positively correlated with initial enrolment in primary school and middle school (Brown & Park, 2002). Chyi and Zhou (2014) found that tuition control has a minimal effect on primary and junior high school enrolment, while tuition waivers, free textbooks, and living expense subsidies have a significantly positive effect on school enrolment, especially for rural girls. In summary, this review suggests that several factors, such as the expectation for future earnings community standards, supply considerations, government policy, characteristics of the child, and the child's family are essential determinants of enrolment.

3.2.3 Teacher qualification in math

Generally, teachers' qualifications encompass years of teaching experience (Mayer, Mullens, & Moore, 2001), teachers' education, content knowledge (Darling-Hammond, 2000), and participation in professional development training (Cohen & Hill, 1998). Several educational researchers have argued that teacher's qualification in math is one of the most significant determinants of their teaching practices and students' achievement (Guarino, Hamilton, Lockwood, & Rathbun, 2006). Many teacher characteristics, particularly teacher qualifications, have been examined in relation to student achievement. However, there seems to be no agreement in the literature as contrasting findings exist on the effectiveness of teacher characteristics. For example, some studies have shown that teachers' qualifications (experience and years of education) are considered necessary but not enough for improved classroom teaching or student outcomes (Early et al., 2007; Wayne & Youngs, 2003). Others have also established direct effects of teachers' qualifications on student academic performance (Croninger, Rice, Rathbun, & Nishio,

2007; Guo, Piasta, Justice, & Kaderavek, 2010; Justice, Mashburn, Hamre, & Pianta, 2008) although the observed effects are smaller.

Findings from studies on the relationship between teacher education level and student achievement are inconsistent (Goldhaber, Brewer, & Anderson, 1999; Greenwald, Hedges, & Laine, 1996). For instance, meta-analyses by E. Hanushek (1998) and Greenwald et al. (1996) revealed inconsistent evidence on the effect of teachers with master's degrees on the academic performance of high school students. However, the authors also found that there is a positive relationship between advanced teaching degrees and student achievement.

Moss (2012) used a mixed-method approach to assess differences in achievement of students taught by conventionally trained teachers (*i.e. individuals who attend and complete teacher education program prior to obtaining a license to practice as a teacher*) and those taught by alternatively prepared teachers (*individuals who do not have a bachelor's degree in education but are given the opportunity to become certified as teachers*). The findings showed that overall there was no significant difference in student achievement on Mississippi Curriculum Test 2nd Edition (MCT2) math scores for teachers who were alternatively prepared or traditionally prepared. Another study by Kane, Rockoff, and Staiger (2008) examined the relative effectiveness of teachers for students in grades 4 through 8 in math and reading test scores. The authors also found no difference between uncertified and certified teachers in math achievement.

3.2.4 Class size

The debate over the educational consequences of class size has raged for decades. Opinions are divided from academics and policymakers, with some arguing that class size reduction is not cost-effective while others suggest that class size reduction is effective and therefore should be the cornerstone of educational policy.

Some scholars agree that smaller classes have positive effects on academic performance. Such research mostly draws on quantitative, experimental (Finn & Achilles, 1999) and naturalistic studies (Blatchford, Bassett, & Brown, 2011). However, many disagree on the extent and magnitude of the impact (Grissmer, 1999; Wilson, 2006). Some also argue that the effect of classroom size is more effective youngest children are taught in smaller classes from their first year of school.

Beyond these controversies, scholars generally agree that more research is needed to understand happenings in the classrooms. Most researchers who have studied class size treat the classroom as a black box, anticipating that the effect of class size upon learning outcomes will be automatic and linear (Wilson, 2006). Thus, this research often ignores the influence of the thinking and actions of those teaching and learning inside classrooms. In this context, many scholars have called for more studies on classroom ‘processes’, and specifically, research on the interactions between teachers and pupils and pupil behavior (Blatchford et al., 2011). Research, they argue should focus on factors that significantly influence the quality of classroom teaching and learning and in a manner that is attentive to the concerns of teachers as well as students (Blatchford et al., 2011; Pedder, 2006) These arguments suggest the need for a new approach to class-size research from one of the quantitative deductive inferences to a more nuanced mixed-method approach involving both qualitative and quantitative methods. The incorporation of qualitative methods can help to unravel the kinds of teacher and pupil expertise engaged in promoting and maximizing opportunities for quality learning in both large and small class contexts (Blatchford et al., 2011; Pedder, 2006).

The best available evidence on the impact class size reduction on student performance is from Tennessee’s Student Teacher Achievement Ratio (STAR) experiment (Achilles, 2002) The STAR project was implemented in Tennessee in 1985 and involved a random assignment of about 6,500 students to smaller or regular-sized classes in 329 classrooms in 79 schools in 1985-89. Students assigned to the program stayed in classes of the same size for the next three years, after which the students moved into regular sized Year 5 classes. Teachers were also assigned at random to the class groups, and no special instructions were given to the teachers on the different-sized classes. Because the STAR experiment employed random assignments, observed differences in outcomes can be ascribed to the effect of smaller class at high confidence. The results from STAR showed that students’ accomplishment on both math and reading standardized tests inched up by around 0.15 to 0.20 standard deviations (or 5 percentile rank points) for students assigned to a class of 13-17 compared with a regular-sized class of 22-25 students. Moreover, the disaggregated results by race showed greater gain for black students in smaller classes. This affirms that reduction in class size might be an effective strategy to reduce the black-white achievement gap. Students from low socio-economic-status families also performed better in the STAR as measured by eligibility for the free or reduced-price lunch program.

All types of students (low, medium, and high achievers) benefit from being in small classes across all achievement tests. More specifically, being in small classes in grade 3 is associated with a considerable increase in student achievement that lasts to grade 8 (Flessa, 2012; Konstantopoulos & Chung, 2009; Nye, Hedges, & Konstantopoulos, 2002). The outcomes of the STAR project revealed that effect-sizes increased monotonically as students spent additional years in a small class. The effect-sizes were greater for minority students compared to white students for all achievement areas (Achilles, 2002). In another study, Blatchford, Goldstein, Martin, and Browne (2002), studied class size effect in England for 220 schools, with 368 classes and 9330 children in eight Local Education Authorities. The study followed a cohort of students over a three-year period (students aged 4–7) who were in class sizes that varied from 10 to 35 in reading, and 15 to 33 in mathematics. The evaluation revealed that decreasing class size was related to increases in math test scores for class sizes of 25 or less.

A study by (Fredriksson, Öckert, & Oosterbeek, 2012) in Sweden found that class size reduction produces long-term effects. The authors revealed that reduced class size in the last three years of primary school (aged 10 to 13) are beneficial for cognitive and non-cognitive ability at aged 13 and improve achievement at aged 16. Enrollment in a small class for grades 4 to 6 increases cognitive ability at age 13. The study further showed that a class size reduction equivalent to STAR (seven students), would improve cognitive skills at age 13 by 0.23 of a standard deviation. Placement in a small class improves non-cognitive ability with a slightly smaller effect than the effect on cognitive ability. A unit reduction in class size improves non-cognitive outcomes by 0.026 of a standard deviation (Fredriksson et al., 2012). On the other hand, a study by Cho, Glewwe, and Whitley (2012) revealed that reducing class size brings about a very small impact on math and reading test scores in Minnesota. That is, a decrease of 10 students will increase test scores by only 0.04 – 0.05 standard deviations (of the distribution of test scores). According to Asadullah (2005), the lack of impact of class size reduction on math achievement could be due to poor quality of classroom teaching or teacher absenteeism. Poor quality of classroom teaching is partially due to lack of incentives to motivate teachers in order to achieve the goal of class size reduction strategy (Asadullah, 2005).

4 DATA

This study uses datasets from the 2012 PISA examination for Canada’s 15-year-olds in public schools. Since PISA focused on math in 2012, 21,000 students from Canada were tested in this area. Scores are measured by the average of all five plausible scores a student can attain on the PISA math exam. A summary of the 2012 PISA examination in the international and domestic context is presented in Table 4.1 below.

Table 4.1: An overview of PISA 2012

	International	Canada
Participating Jurisdiction	65 countries and economies	10 provinces
Target Population	Youth aged 15	Youth aged 15
Total number of participating students	Between 5,000 and 10,000 students per country with some exceptions, for a total of 470,000 students.	Approximately 21,000
Examination medium	Major: paper-based mathematics	Major: paper-based mathematics
	Minor: paper-based reading and science	Minor: paper-based reading and science
	Computer-based problem solving	Computer-based problem solving
Language in which test was administered	47 languages	Two languages (English and French)
Assessment	Two hours of assessment of mathematics, reading, and science.	Two hours of assessment of mathematics, reading, and science
	Forty-minute computer-based assessment of problem solving.	Forty-minute computer-based assessment of problem solving.
	A contextual questionnaire administered to students.	A contextual questionnaire administered to students.
	A school questionnaire administered to school principals	A school questionnaire administered to school principals.

International options	Ten-minute discretionary questionnaire on information technology and communications administered to students	
	Ten-minute discretionary questionnaire on educational career administered to students	Forty-minute optional electronic reading and mathematics assessment.
	Twenty-minute optional questionnaire administered to parents.	
	Forty-minute optional electronic reading and mathematics assessment.	Ten-minute voluntary questionnaire on educational career administered to students
	Grade-based sampling.	
	One-hour optional assessment of financial literacy.	
	One-hour booklet directed at assessment of lower-level skills.	
National options	Other options were undertaken in a limited number of countries	Ten-minute questionnaire administered to students regarding their attitudes towards working in the trades

Source: CMEC (2013)

PISA brings to bear some of the pertinent factors responsible for student success by collecting data through a student questionnaire and a school questionnaire. In addition to the math scores, PISA also administers questionnaires to parents and teachers and compiles this data. These overall data include student demographic information, including gender, socio-economic status, immigration status, parent information, teacher information, and selected school characteristics. These variables and their descriptions are summarized in Table 4.2

Table 4.2: Description of variables used in this study

<i>Variable name</i>	<i>Variable description</i>
<i>Provincial-Level (Level 3)</i>	
Provcode	Province
<i>School – Level (Level 2)</i>	
parent expectation	A dummy that indicates the proportion of parents who expect higher academic achievements from the school; 1=none 2=minority 3=many parents
school enrolment	Total student enrolment in school
class size	Average class size of 15-year old students in a school

teacher maths qualification	Proportion of teachers with ISCED 5A in math major, among all math teachers
<i>Student-Level (Level 1)</i>	
ses	Index of economic, social, and cultural status of the family of the student
female	Sex of student: 1=female;-0=male
immigrant	Immigration status of student: 1=First/Second generation immigrants, 0=Native
pisa_math	The average of the five plausible values in PISA math of a student (a measure of student performance)

Different explanatory variables are employed at each level to explain student performance. At the student level, gender, an index of socio-economic status, and the immigration status of the student are used as explanatory variables. The immigration status of students was determined using three country-specific variables relating to the country of students and their parents. The immigrant background index comprises three categories: native student (i.e. students with at least one parent born in the country of assessment), second-generation students (i.e. students born in the country of assessment with parent(s) born in a different country) and first-generation students (students born outside the country of assessment whose parents were also born in another country). The socioeconomic status of students comprises home possessions, books in the home, highest parental occupation and highest parental education expressed as years of schooling. The socioeconomic status variable is obtained as an index with zero being the score of an average OECD student and one being the standard deviation across equally weighted OECD countries. The SES of Canada is computed as follows:

$$SES_{Canada} = \frac{\beta_1 HOMPO' + \beta_2 PARED' + \beta_3 HISEI'}{\varepsilon_f} \quad (1)$$

According to Equation (1), β_1 , β_2 , and β_3 are OECD factor loadings, $HOMPO'$ is home possession by a student's parent, $PARED'$ a student's parent education, $HISEI'$ refers to highest parental occupation and ε_f is the eigenvalue of the first principal component. PARED, HISEI, and HOMPO have been standardized by OECD (OECD, 2014).

School variables used in the study include teacher qualification, class size, school enrolment, and parent expectation. Teacher qualification in math was calculated by dividing the number of teachers with ISCED5A qualification by the total number of math teachers. The class size variable was obtained from one of nine categories ranging from less or equal to 15 students in a sampled

school to more than 50 students in a school. The midpoint of each group is used as the average class size. School enrolment is the sum of boys and girls in a school. Parental expectation can be defined as the judgments of parents about the schools their children attend – how the school is able to harness the potential of children in reaching their goal in academic pursuit. This is measured by the questionnaire answered by principals of the schools. Principals were asked, “which statement below best characterizes parental expectation toward your school?”

At the student level, gender, immigration status, and socioeconomic status were included in the study. Studies such as Janet S Hyde and Mertz (2009b) and Mead (2006) show that gender plays an important role in student achievement. Zhou and Portes (2012), Feliciano and Lanuza (2017), and Coll and Marks (2012) informed the decision to include immigration as a predictor of student math achievement. Finally, Acemoglu and Pischke (2001) and Guimarães and Sampaio (2013) provided evidence of the need to include socioeconomic status in the study.

At the school level, the inclusion of parent expectations is supported by Raleigh and Kao (2010). Connelly and Zheng (2003), Guarino et al. (2006), and Pedder (2006) informed the decision to include school enrolment, teacher qualification, and class size, respectively.

5 METHODOLOGY

A regression model, known as the Hierarchical Linear Model (HLM) is used in this study to assess the factors that influenced student performance on the 2012 PISA exam. A hierarchy with three levels -- province, school, and student -- can be identified in the research question. The province is the highest level of the hierarchy (level 3), followed by the school (level 2) and the student (level 1). Students are nested in schools and schools nested within provinces. As a result, performance is likely to be dependent on the group (school or province) to which a student belongs. Accounting for these differences is essential because schools and provinces vary from each other, with each having unique characteristics that could potentially impact a student's performance on the PISA math exam. The three-hierarchical level structure involved in this study and its accompanying predictors are summarized in Table 4.2.

5.1 An Introduction of the Hierarchical Linear Model (HLM)

Historically, aggregation and disaggregation were the methods that made analysis of hierarchical data possible. However, these methods could not correctly assign variances to variables, resulted in dependencies in data, and were prone to Type I errors (Woltman, Feldstain, MacKay, & Rocchi, 2012). As Woltman et al. (2012) assert, fixed-parameter simple linear regression methods neglect the shared variance in hierarchical data. Following the introduction of an algorithm to enable covariance component estimation for unbalanced data in the early 1980s, the application of a complex form of ordinary least squares that accounted for variabilities and dependencies in data -- the Hierarchical linear model (HLM) -- has since gained popularity in the analyses of hierarchically-structured data. Researchers have since embraced this new form of estimation procedure in explaining how differences in school policies impact student achievement (Konstantopoulos, 2005; Lee, 2000; Lee & Bryk, 1989; S. Raudenbush & Bryk, 1986; Willms & Raudenbush, 1989; Wong & Mason, 1985), and the effect of socioeconomic status on health (Adler et al., 1994; Gee, 2008; House, Kessler, & Herzog, 1990; Marmot et al., 2010; Merlo, 2003; Pickett & Pearl, 2001; Wilkinson, 1992; Williams, 1999).

Hierarchies exist in data when subpopulations are nested within larger populations. For example, a three-level hierarchy exists when two subpopulations are found within a population (a larger group). In such situations, the population becomes the macro unit and the subpopulations of the

micro-units. However, depending on the research question and what a researcher wants to achieve, a micro-unit may become a macro unit from which other micro-units can be drawn. Examples of three-level hierarchical structure include students nested in households and households nested in neighbourhoods; patients nested within doctors and doctors within clinics (Miyazaki & Stack, 2015). Such hierarchical levels are common in grouped data (Osborne, 2000).

HLM is a form of ordinary least squares regression that accounts for the shared variance in hierarchically-structured data. It correctly estimates the variance in a dependent variable when independent variables are at varying tiered levels. HLM considers the impact of factors at all levels in explaining the outcome of interest while accounting for hierarchies within data. The second feature of HLM is that the levels involved in the investigation are modelled separately. For instance, level 1 equation is modelled in such a way that the parameters show a linear relationship between level-one units. The same is true for levels 2 and 3 (S. W. Raudenbush & Bryk, 2002). Researchers from the social sciences often encounter data that are distinguished from each other by the unique patterns they possess. Hierarchical data give a researcher the opportunity to explore the relationships that exist between variables belonging to different groups (Ciarleglio & Makuch, 2007; S. W. Raudenbush & Bryk, 2002).

Woltman et al. (2012, p. 56) state:

“HLM can be ideally suited for the analysis of nested data because it identifies the relationship between predictor and outcome variables, by taking both level-1 and level-2 regression relationships into account”.

5.2 An Illustration of the fully unconditional HLM Model

A special HLM model known as a fully unconditional model is used to investigate my first research question “Which of the levels – student, school or province – has the greatest influence on 15-year-old Canadian students’ mathematics performance on the 2012 PISA?”. The setup for this hierarchical linear model is demonstrated below.

$$Y_{ijk} = \beta_{0jk} + r_{ijk} \tag{2}$$

$$\beta_{0jk} = \delta_{00k} + \mu_{0jk} \tag{3}$$

$$\delta_{00k} = \gamma_{000} + v_{00k} \tag{4}$$

Equation (2) above is known as student level or micro unit of the hierarchy. According to equation (2), Y_{ijk} the dependent variable refers to the mathematics score of a student i who is found in school j , and the school, in turn, is found in province k . β_{0jk} is referred to as the school intercept term, interpreted as the average math score of school j nested in province k and r_{ijk} is student level residual. This student level residual can be interpreted as the difference between the math score of a student and the average math score of the school that the student belongs to.

In level 2 (i.e., equation (3)), which can be labelled as an “intermediate” level equation, the average math score of a school (intercept in equation (2)) shows up as a dependent variable. This dependent variable is influenced by two main factors: a provincial average in math score (δ_{00k} i.e., the intercept in equation (3)) and school-level residual (u_{0jk}).

Finally, in level 3 (i.e., equation (4)), the intercept of level 2 (i.e., equation (3)) becomes the dependent variable. That is, the provincial average score is the sum of the grand mean (γ_{000}) and level 3 residual (v_{00k}). The grand mean is the average math score of all the students in Canada who participated in the 2012 PISA math exams. The difference between the average provincial math score and the grand mean is referred to as level 3 residual.

Substituting equations (3) and (4) into equation (2) yields a mixed level model form, as seen in equation (5).

$$Y_{ijk} = \gamma_{000} + v_{00k} + \mu_{0jk} + r_{ijk} \quad (5)$$

According to equation (5), the math score of a student in a school within a province is the sum of the grand mean, provincial residual term, school residual term, and individual residual term. The three residual terms are normally distributed with means equal to 0 and variance of σ^2 , τ^2 , and φ^2 for the individual level, school level, and province level, respectively. Therefore, the total variance for the model in equation (5) is the sum of all three variances at the three levels (i.e. $\sigma^2 + \tau^2 + \varphi^2$).

The model found in equation (5) is known as the empty or fully unconditional model. This is because the model contains no predictors from any of the three hierarchy levels involved in the study. This is an intercept-only model that focuses on determining whether there are any

performance differences among provinces or schools. This model is like a one-way analysis of variance, and the effect at the school level and the province level is random.

In estimating the null model, we test a null hypothesis of zero variance among the three levels found in the data. By so doing, we test;

$$H_0: \sigma^2 + \tau^2 + \varphi^2 = 0$$

$$H_1: \sigma^2 + \tau^2 + \varphi^2 > 0$$

The null hypothesis states that the sum of all the variances from the three levels is zero while the alternative hypothesis states that the sum of the variance among the three levels is greater than zero (Albright & Marinova, 2015). The unconditional model is necessary because it shows how the total variability in the 2012 PISA math exam performance for 15-year old students in Canada is divided among contributions from the province, school, and student levels (Nezlek, 2011).

From the null model, one can calculate the intra-class correlation coefficients (ICC). This helps us to assess the variances attributed to the province, school, and student levels. The ICC for each of the three levels involved in the study is calculated using the formula below.

$$\hat{\rho} = \frac{\hat{\sigma}^2}{\hat{\sigma}^2 + \hat{\tau}^2 + \hat{\varphi}^2} \quad (6)$$

$$\hat{\rho} = \frac{\hat{\tau}^2}{\hat{\sigma}^2 + \hat{\tau}^2 + \hat{\varphi}^2} \quad (7)$$

$$\hat{\rho} = \frac{\hat{\varphi}^2}{\hat{\sigma}^2 + \hat{\tau}^2 + \hat{\varphi}^2} \quad (8)$$

Where $\hat{\rho}$ is the correlation coefficient, $\hat{\sigma}^2$ is student level variance, $\hat{\tau}^2$ is school-level variance, and $\hat{\varphi}^2$ is province-level variance. This is also the first step in deciding between HLM and OLS. We estimate ICC for all three levels. By so doing, we can tell the percentage contribution of the three levels to math achievement. When at least one of the ICC estimations is greater than 10%, then the study necessitates the use of HLM (Lee, 2000). However, when no ICC is greater than 10%, it does not mean that HLM should be ignored in favor of OLS. This is because additional dependence can arise after the model accounts for predictors (Roberts, 2007).

5.3 An Illustration of a more complete HLM Model

I then build a more complete HLM model to achieve my second research objective: assess the factors that are associated with student performance on PISA.

The null model in equation (5) can be modified by introducing level 1 factors into the model (socioeconomic status, gender, and immigration). The introduction of level-1 explanatory variables into the model allows us to see how much of the variation in the response variable is accounted for by individual level factors. The random intercept model is as follows:

$$Y_{ijk} = \beta_{0jk} + \beta_1 ses_{ijk} + \beta_2 gender_{ijk} + \beta_3 immi_{ijk} + r_{ijk} \quad (9)$$

Where β_{0jk} and δ_{00k} areas defined in equations (3) and (4), respectively.

Putting equations (3), (4) and (9) together yields

$$Y_{ijk} = \gamma_{000} + \gamma_{100} ses_{ijk} + \gamma_{200} gender_{ijk} + \gamma_{300} immi_{ijk} + v_{00k} + u_{0jk} + r_{ijk} \quad (10)$$

The independent variables in equation (10) have two main parts- the fixed effect part ($\gamma_{000} + \gamma_{100} ses_{ijk} + \gamma_{200} gender_{ijk} + \gamma_{300} immi_{ijk}$) and the random effect part ($v_{00k} + u_{0jk} + r_{ijk}$). When the parameters of the fixed effect component are estimated, γ_{100} , γ_{200} and γ_{300} are coefficients of socioeconomic status of students, gender, and immigration status, respectively. For the random effect part, parameters estimated are the variances with v_{00k} , u_{0jk} , and r_{ijk} , which represent residual variances for the province, school, and student, respectively.

Once level 1 variables are accounted for and the model estimated, we can compare this estimation result with the estimation result of the null model and estimate R^2 statistic. This R^2 indicates the amount of variance accounted for in level 1 residual because of introducing level 1 predictors in the random intercept model. The R^2 is calculated using the following formula:

$$R^2 = \frac{(\sigma_{empty\ model}^2 - \sigma_{random\ intercept\ model}^2)}{\sigma_{empty\ model}^2} \quad (11)$$

Equation (11) provides an estimate of the proportional reduction in unexplained variance in the random parameter accounted for by level 1 predictor variables in the random intercept model (Anderson, 2012).

The impact of school-level characteristics on student performance is also assessed using a random intercept model. The school-level characteristics considered are parent expectation (*pe*), school enrolment (*sel*), class size (*cs*), and teacher maths qualification (*tq*). We account for these variables in equation (3) and substitute equation (4) to derive:

$$\beta_{0jk} = \gamma_{00k} + \beta_1 pe_{ijk} + \beta_2 sel_{ijk} + \beta_3 cs_{ijk} + \beta_4 tq_{ijk} + \mu_{0jk} \quad (12)$$

Substituting into equation (2)

$$Y_{ijk} = \gamma_{000} + \gamma_{100} SE_{ijk} + \gamma_{200} SEL_{ijk} + \gamma_{300} CS_{ijk} + \gamma_{400} SQ_{ijk} + v_{00k} + u_{0jk} + r_{ijk} \quad (13)$$

Similarly, we can compute the R^2 statistic for this new model to see to what extent school factors predict average school achievement.

The estimation results from all the HLM models discussed above are presented in the next chapter.

6 RESULTS

The results of the study are presented in this chapter. I first present the results of the fully unconditional model described in equation (5) and then describe the results of three more complete HLM models.

6.1 Estimates of the fully unconditional model

The result of the fully unconditional model that does not include any independent variables is in Table 6.1. Due to missing data, the estimation was based on a sample of 14,846 students.

Table 6.1: Result of the fully unconditional model

Mixed-effects ML regression		Number of obs		=		14846	
Group Variable	No. of Groups	Observations per Group		Minimum	Average	Maximum	
provcode	10	1048	1484.6	2572			
schoolid	621	1	23.9	210			
Log likelihood = -85601.2		Wald chi2(0)		=		.	
		Prob > chi2		=		.	
pisa_math	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]		
_cons	505.1897	4.06675	124.22	0.000	497.219	513.1604	
Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]			
provcode: Identity							
	var(_cons)	136.5822	76.62541	45.48339	410.1433		
schoolid: Identity							
	var(_cons)	1186.011	86.41787	1028.173	1368.078		
	var(Residual)	5548.94	65.8333	5421.397	5679.482		
LR test vs. linear regression:		chi2(2) = 1757.84		Prob > chi2 = 0.0000			

The output from the fully unconditional model is divided into four sections – descriptive information about the regression, fixed effect estimates, variance component estimates, and finally, the likelihood ratio test at the bottom of the output.

From the descriptive part, it is seen that there are 14846 students (level 1 units), 621 schools (level 2 units), and 10 provinces (level 3 units). The only fixed effect parameter in a fully unconditional model is the grand mean, which is estimated to be 505.2. This means that on average, Canadian students scored 505.2 points on the PISA math exam. This grand mean does not vary across schools or provinces.

The third section of the output is variance component estimates for all three levels. The variance for the province is 136.6, with a 95% confidence interval from 45.5 to 410.1. The school variance is 1186.0, with a 95% confidence interval from 1028.2 to 1368.1. The student level records a variance of 5548.9 with confidence interval from 5421.4 to 5679.5.

The final part is the likelihood ratio test statistic. The likelihood ratio (LR) test is used to determine whether there exists variability across province and school levels. The null hypothesis for the test statistic states that there are no school or provincial differences in the average PISA mathematics scores. The test compares this HLM model to an ordinary linear regression model. The test is estimated to have a chi-squared statistic of 1757.8, and the p-value associated with this test statistic is 0.000. Based on this, we reject the null hypothesis and conclude that there are variations in average PISA scores across provinces and schools in Canada. This emphasizes the need to control for the variability across the three hierarchical levels in the data using HLM.

The fully unconditional model enables us to assess the degree of correlation in performance across students. This is computed using the intra-class correlation coefficient (ICC). For example, the student-level ICC is calculated as the percentage of student-level variance in the sum of the three variances at the province, school, and student level:

$$\hat{p} = \frac{\hat{\sigma}^2}{\hat{\sigma}^2 + \hat{\tau}^2 + \hat{\phi}^2} \quad (6)$$

The intra-class correlation coefficient shows how much variation in the dependent variable (math score of a student in a school within province) is attributed to factors at the student, school, and province levels. The total variance from the null model reported in Table 6.1 is 6871.5 (i.e. 136.5822 + 1186.011 + 5548.94). The intra-class correlation at the province level is $\frac{136.5822}{6871.5332} = 0.02$. This means the correlation between PISA scores in the same province is 2% (which is a very small correlation). From the school-level variance, we calculate the ICC at the school-within-province level, i.e., the correlation between PISA math scores in the same school and province. This is calculated as school-level variance divided by total variance. That is $1186/6871.5 = 0.17$, which is a moderate correlation among students in the same school within a province. This means that 17% of the variation in student math achievement is attributed to the school attended by a student. The level-3 ICC at student-within-school-within-province level is calculated as $\frac{5548.9}{6871.5} =$

0.81. This means 81% of the variation in PISA math scores is attributed to individual differences at the student level.

6.2 Empirical Bayes Estimates

Empirical Bayes estimates help us determine and visualize the deviations of the province-specific intercepts from the national intercept. The intercept estimate for each province is shown as:

$$\hat{\delta}_{00k} = \hat{\gamma}_{000} + \hat{v}_{00k} \quad (4)$$

Where $\hat{\gamma}_{000}$ is the estimated grand mean and \hat{v}_{00k} is the difference between the grand mean and the provincial level intercept. The difference between the provincial intercept and the grand mean (Canadian mean) is visualized in the diagram below. The blue dots represent estimates for the deviations for each province, and the black lines connect the 95% upper and lower confidence intervals for the estimates.

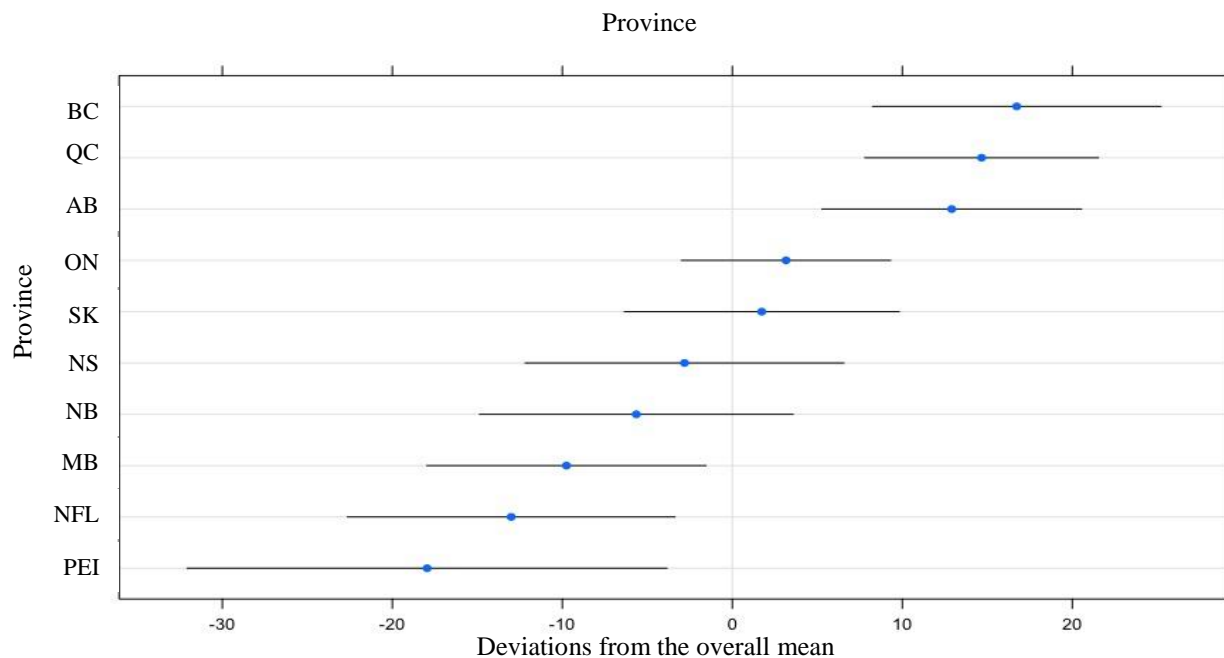


Figure 6.1: Deviations of Province-specific intercepts from the grand mean

From Figure 6.1 above, it is evident that there are variations among the 10 provinces in terms of their average PISA math scores. Quebec and British Columbia averaged 15 points above the Canadian mean whiles Prince Edward Island averaged 18 points below the Canadian mean. The confidence interval estimate is wider for PEI and narrow for Ontario.

At the school level, the deviation of school-specific intercepts from the provincial intercept are shown in the diagram below. Like Figure 6.1, the blue dots represent the difference between school-specific intercepts and provincial intercept whilst the black lines represent the 95% confidence interval limits. The estimated average math score of a school is shown as:

$$\hat{\beta}_{0jk} = \hat{\delta}_{00k} + \hat{u}_{0jk} \quad (3)$$

Where $\hat{\delta}_{00k}$ is the provincial average math score and \hat{u}_{0jk} is the school level residual.

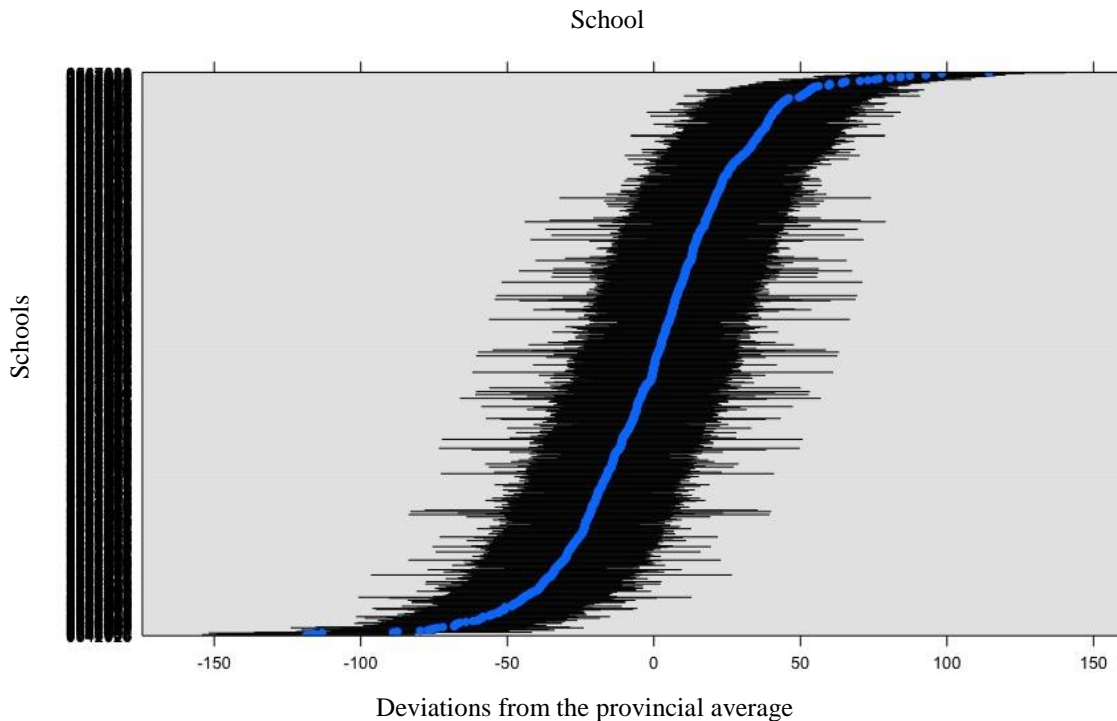


Figure 6.2: Deviations of school-specific intercepts from their respective provincial intercepts

The above plots show that the confidence intervals are wider for the school-level intercepts and show more variability compared to the province-specific intercepts. The range of variability is from -150 to 150 for schools and -35 to 30 for provinces, which aligns with the results from the model. Schools vary more on their average PISA scores compared to provinces.

6.3 Estimates of more complete HLM models

I then describe the estimation results of three alternatives, more complete HLM models that include student-level and school-level independent variables. The results are shown in Table 6.2

Table 6.2: Estimation results of three HLM models

	Random Intercept (student level)	Random intercept (school level)	Random intercept (student and school levels)
<i>student level factors</i>			
gender	-9.880*** (-8.25)		-9.909*** (-8.28)
ses	25.07*** (32.99)		24.66*** (32.42)
immigrant	-2.677 (-1.38)		-4.350* (-2.24)
<i>school level factors</i>			
parent expectation		11.63*** (5.30)	8.345*** (4.14)
enrolment		0.0170*** (4.58)	0.0147*** (4.28)
class size		0.967** (2.76)	0.785* (2.43)
teacher quality		4.149 (0.91)	3.200 (0.76)
_cons	502.1*** (132.28)	442.3*** (48.84)	453.1*** (53.72)
Variiances for all three levels			
province level	115.4*** (64.6)	36.3*** (30.3)	38.9*** (29.5)
school level	924.8*** (70.4)	982.2*** (74.5)	802.9*** (63.0)
student level	5173.2*** (61.4)	5549.7*** (65.8)	5172.8*** (61.4)
N	14846	14846	14846
R^2	10%	4.41%	12%

Standard errors in parentheses

* p<0.05, ** p<0.01, *** p<0.001

In Table 6.2, columns 1, 2, and 3 are random intercept models that include student-level factors, school-level factors, and a combination of student- and school-level factors, respectively (the complete estimation output of these three models can be found in the Appendix).

To assess the explanatory power of these factors as a group, we can compare the estimation results in Table 6.2 with the estimated model of the fully unconditional (empty) model in Table 6.1 and calculate the R^2 statistic defined in the last section. The R^2 is calculated using equation (11).

The first R^2 static indicates the additional percentage explained of the model as a result of the introduction of level 1 factors into the empty model. From the variances of the null and random (student level) intercept model, R^2 is calculated.

$$R^2 = \frac{6871.5 - 6213.4}{6871.5}$$

$R^2 = 10\%$. According to Table 6.2, the student characteristics studied explain an additional 10% of the variation in PISA math scores compared with the fully unconditional model.

In the same fashion, the school-level factors are responsible for an additional 4.41% variation in PISA math scores. The combined effects of student and school-level factors explain an additional 12% variation in student math performance.

In terms of the coefficients, Table 6.2 shows no change in the direction of influence of each of the factors across the three models. There is a consistent male-female differential, and the difference stays at approximately 10 points. Socio-economic status is positively associated with student performance. The coefficient indicates an approximately 25-point higher math score for a 1-point increase in the index of socio-economic status. The one change that is worth mentioning is the change in the influence of parental expectation from the school-level model in column 2 to the combined model in column 3. Although the positive relationship between parental expectations and student performance is still reflected in the estimation results, the coefficient decreases from 11 points to 8 points. In the following interpretation, I will focus on the 3rd column since it contains both student- and school-level factors. A variable is statistically significant if its p-value is lower than 5%.

The student level, gender, and socioeconomic status of students are all statistically significant. That is, the gender and socioeconomic status of students contribute to student achievement in math. Everything else being equal, girls' math scores average about 10 points lower than boys.

According to the results in Table 6.2, as the socioeconomic status of students improves by one unit, PISA math scores also increases by about 25 points on average. Consistent with this finding is the study by Considine and Zappalà (2002) of 3,329 students from disadvantaged backgrounds on a social intervention program called Learning for Life (LFL). According to the study, compared to students whose parents completed year 10 education, students whose parents completed year 12 and university education were 1.2 and 4.5 times more likely to achieve outstanding test results,

respectively. Students from households where parents worked to earn income were 1.2 times more likely to achieve outstanding results than students who came from a home where the parent(s)' source of income is social security benefits.

According to our study, increasing class size by one student increases math achievement by approximately one point, but this variable is statistically significant at the 10% level. Class size refers to the actual number of students taught by a teacher. Our study suggests that reducing class size does not lead to better student achievement. This contrasts with the findings of Schanzenbach (2014) on the impact of class size on academic performance. The author found that smaller class size is an important determinant of a variety of student outcomes, ranging from test scores to life outcomes.

An increase in school enrolment improves student achievement by 0.0147. Large schools affect the academic performance of students through the quality and breadth of academic curriculum available to students. Teachers can specialize and choose classes to teach. In large schools, the burden of administrative tasks teachers perform is lower because large schools can afford to hire personnel to oversee administrative tasks. Having fewer administrative tasks means more time for teachers to spend with students (Ares Abalde, 2014).

Another school attribute in this study is teacher math qualification. Our study shows that having teachers with a post-secondary degree in math does not translate into student achievement. The literature on teacher certification and student achievement shows mixed results. While some studies have found no significant disadvantage with having an uncertified teacher (Decker, Mayer, & Glazerman, 2004; Kane et al., 2008), others have found that certified teachers produce higher learning gains than uncertified teachers (Clotfelter, Ladd, Vigdor, & Wheeler, 2006; Darling-Hammond, Holtzman, Gatlin, & Heilig, 2005; Goldhaber & Brewer, 2000). Our finding is consistent with the findings from the mixed-method study of Moss (2012), which found no significant difference between the achievement of students who are taught by traditionally prepared teachers and those taught by alternatively prepared teachers.

7 DISCUSSION AND POLICY RECOMMENDATION

Our research uses a three-level hierarchical linear model to assess student achievement in the 2012 PISA math exams. It found that of the three levels of stakeholders in K-12 education in Canada (province, school, and student), only the province level had a negligible impact on student math achievement. Variations in student scores differed across the three levels, with student characteristics having the highest influence on math achievement (81%) followed by school characteristics (17%) and finally the province (2%). At the student level, gender and socioeconomic status are highly correlated with math achievement. The immigration status of a student does not affect math achievement. At the school level, parental expectations and school enrolment are statistically significant while teacher math qualification and class size are not. These findings and implications are discussed below.

The socio-economic status of a student has the greatest impact on math achievement. Our study shows that an increase in the socioeconomic index improves student math performance by about 25 points. Policies aimed at equality are essential. For example, a program by the Ontario school system supported disadvantaged students in elementary and secondary schools and improved the level of students' interest, engagement, and achievement in reading, writing, and oral language (Bodkin, 2009). Additionally, reducing the concentration of disadvantaged and low performing students in a school and providing more resources to schools with low performing or disadvantaged students are recommended to improve student performance.

The study shows a performance differential of about 10 points between male and female students. This does not come as a surprise, as generally, males outperform females in quantitative ability. Given that developed countries are interested in equal education opportunities for boys and girls, a focus on programs to improve the quantitative abilities of female students is recommended.

From our results, class size has a positive relationship with student performance. However, the variable is statistically significant at only the 10% level, and the associated gains in scores are minimal. Class size has received much attention and interest for years. Policies that focus largely on class size as a means of increasing student performance should be implemented with caution since the expected gains may not be that substantial.

Parent expectation emerged as one of the factors with high positive impacts on student performance from the study. On average, students from schools in which most parents have higher expectations tend to perform 11 points better. The expectations that parents have about their children's education motivate them to become involved in the learning and development of their children both at home and in school. Principals and school authorities are encouraged to engage parents and allow them to have a voice in the direction of the school. This engagement builds confidence, trust, and expectations and also makes education a shared responsibility out of which positive outcomes will flow.

This study has indicated that school enrolment is positively related to student math performance. The more students in the school, the higher the performance. This could be due to students encouraging each other and the sense of support they derive from one another and from parents. Also, in Canada, the funding formula, which is based on per-student, adversely affects small schools. Ways of making the funding more equitable can potentially place these schools in a better position to invest and grow. However, just like class size, though we see a significant positive relationship, the extent of the impact is not as significant.

8 CONCLUSION

K-12 education remains one of the most important services supported by provincial governments in Canada since it serves as the medium through which the next generation is provided with the foundation of knowledge, experience, and skills critical for success in later adulthood. Because of the K-12 education system plays such a crucial role in society, the sector receives significant funding and policy support. The PISA exam is one of the ways to assess the return on these investments.

This study examined the factors that impact performance among 15-year-old Canadians on the 2012 PISA math exam. The study found that factors such as socioeconomic status, gender, parental expectation, and school enrolment have significant impacts on student achievement. However, the impact of socioeconomic status has the most magnitude. The findings suggest that policies that aid female students and socio-economically disadvantaged students to reach their full potential can help improve student performance. At the school level, school boards and other stakeholders in education can design programs that strengthen schools and, at the same time, involve families in key decision making about the school.

Caution should be exercised when drawing policy recommendations based on these findings because the study could have limitations, including measurement problems and model specification problems. In addition to suffering from issues with sampling and measurement, PISA is not able to produce data on school boards, making it difficult to look at the direct impact of school boards on student math achievement. However despite these issues and although some student- and school-level variables have coefficients that are small, the study of education policy is worthwhile as education interventions have long-term effects on the economic growth and human capital development of every country (Hanushek & Woessmann, 2012; Mou & Atkinson, Forthcoming). Further research into other potential factors that impact math performance would be interesting to explore.

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Appendix

Table A.1: Summary Statistics

Estimation sample xtmixed		Number of obs = 14846			
Variable	Mean	Std. Dev.	Min	Max	
depvar					
pisa_math	508.5274	81.96081	219.902	796.939	
pisa_math					
gender	.5059275	.4999817	0	1	
ses	.3747077	.837588	-5.32	3.13	
immigrant	.1730432	.3782974	0	1	
parent expect..	2.08056	.6520507	1	3	
enrolment	785.7494	468.4935	2	2381	
class size	26.26957	4.711231	13	53	
teacher quality	.5977572	.3261779	0	1	

Table A.2: The Random Intercept model for student level factors

Mixed-effects ML regression		Number of obs = 14846		
Group Variable	No. of Groups	Observations per Group Minimum	Average	Maximum
provcode	10	1048	1484.6	2572
schoolid	621	1	23.9	210

Log likelihood = -85037.433	Wald chi2(3) = 1177.79
	Prob > chi2 = 0.0000

pisa_math	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
gender	-9.879982	1.197511	-8.25	0.000	-12.22706 -7.532903
ses	25.06561	.7599022	32.99	0.000	23.57623 26.55499
immigrant	-2.677387	1.936819	-1.38	0.167	-6.473483 1.118708
_cons	502.1007	3.795624	132.28	0.000	494.6615 509.54

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]
provcode: Identity			
var(_cons)	115.4214	64.61365	38.52813 345.7757
schoolid: Identity			
var(_cons)	924.7665	70.41855	796.5542 1073.616
var(Residual)	5173.188	61.39857	5054.238 5294.937

LR test vs. linear regression:	chi2(2) = 1386.35	Prob > chi2 = 0.0000
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Table A.3: Random Intercept model for school-level factors

Mixed-effects ML regression		Number of obs		=		14846	
Group Variable	No. of Groups	Observations per Group					
		Minimum	Average	Maximum			
provcode	10	1048	1484.6	2572			
schoolid	621	1	23.9	210			
Log likelihood = -85552.091		Wald chi2(4)		=		111.74	
		Prob > chi2		=		0.0000	
pisa_math	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]		
parent expectation	11.63365	2.19449	5.30	0.000	7.332527	15.93477	
enrolment	.0169878	.0037066	4.58	0.000	.009723	.0242526	
clss size	.9668992	.3502162	2.76	0.006	.2804881	1.65331	
teacher qual..	4.149231	4.552768	0.91	0.362	-4.774032	13.07249	
_cons	442.3497	9.056769	48.84	0.000	424.5988	460.1007	
Random-effects Parameters		Estimate	Std. Err.	[95% Conf. Interval]			
provcode: Identity							
	var(_cons)	36.24775	30.31769	7.036142	186.7358		
schoolid: Identity							
	var(_cons)	982.2435	74.53913	846.4949	1139.761		
	var(Residual)	5549.693	65.84451	5422.129	5680.258		
LR test vs. linear regression:		chi2(2) = 1296.09		Prob > chi2 = 0.0000			

Table A.4: Random intercept model for both student and school-level factors

Mixed-effects ML regression		Number of obs	=	14846	

Group Variable	No. of Groups	Minimum	Average	Maximum	
provcode	10	1048	1484.6	2572	
schoolid	621	1	23.9	210	

Log likelihood = -84999.94		Wald chi2(7)	=	1279.23	
		Prob > chi2	=	0.0000	

pisa_math	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
gender	-9.909361	1.19693	-8.28	0.000	-12.2553 -7.563421
ses	24.66498	.7607533	32.42	0.000	23.17393 26.15603
immigrant	-4.350261	1.941172	-2.24	0.025	-8.154888 -.5456337
parent expectation	8.345094	2.016834	4.14	0.000	4.392172 12.29802
school_enrolment	.0147154	.0034374	4.28	0.000	.0079781 .0214526
class size	.7850302	.3232442	2.43	0.015	.1514832 1.418577
teacher qualification	3.200298	4.184853	0.76	0.444	-5.001863 11.40246
_cons	453.1188	8.434071	53.72	0.000	436.5883 469.6492

Random-effects Parameters	Estimate	Std. Err.	[95% Conf. Interval]		
provcode: Identity					
var(_cons)	38.94376	29.5277	8.811399	172.1198	
schoolid: Identity					
var(_cons)	802.8862	63.00485	688.4267	936.3761	
var(Residual)	5172.785	61.38253	5053.866	5294.503	

LR test vs. linear regression:	chi2(2) =	1113.29	Prob > chi2 =	0.0000	