Parental Characteristics and the Achievement Gap in Mathematics: Hierarchical Linear Modeling Analysis of Longitudinal Study of American Youth (LSAY)

Mohammad Shoraka[1], Robert Arnold[1], Eun Sook Kim[2], Geri Salinitri[1], Jeffrey Kromrey[2]

[1]University of Windsor, [2]University of South Florida

One of the most salient problems in education is the achievement gap. The researchers investigated the effects of parental education and parental occupations in science, technology, engineering, mathematics, or medical professions (STEMM) on the achievement gap in mathematics. Because students were nested within schools, two-level Hierarchical Linear Modeling (HLM) was the main analysis. Findings were consistent with another Multilevel Modeling analysis, that is, parental characteristics such as parental education had a positive effect on student achievement (Teodorovic, 2012). Moreover, parental occupations in STEMM had a positive effect on student mathematics achievement.

L'écart de rendement constitue un des problèmes les plus importants en éducation. Les chercheurs ont étudié les effets de l'éducation et de la profession des parents en sciences, technologie, ingénierie, mathématiques et médecine (STIMM) sur l'écart de rendement en mathématiques. Puisque les élèves étaient emboîtés dans les écoles, l'analyse repose sur un modèle de régression linéaire hiérarchique à deux niveaux. Les résultats correspondent à ceux d'une autre analyse basée sur la modélisation à niveaux multiples qui indique que les caractéristiques des parents telles leur éducation a eu un effet positif sur le rendement des élèves (Teodorovic, 2012). De plus, quand la profession des parents est reliée à STIMM, le rendement en mathématiques de leurs enfants a eu meilleur.

Introduction

One of the most salient problems in education is the achievement gap. This study is important because it gives scholars and policy makers a scientific reason to think and act according to equity versus equality. This research is also significant as it strives to indicate that the playing field in education is not level in the U.S. and other places such as Canada. Consequently, students who receive better education will have greater chances to be successful in society, and be upwardly mobile; for example, Canadian students of working class families still struggle to

hold professional careers such as in medicine (Kwang, Dhalla, Streiner, Baddour, Waddell, & Johnson, 2002).

According to the Organisation for Economic Cooperation and Development (OECD) higher education is crucial to advocates of social justice because there are correlations between number of years of education and health (Organization for Economic Cooperation and Development 2006) and unemployment rate (Statistics of Canada, 2004). Moreover, higher education results in higher income (Murnane, Willett, Duhaldeborde, & Tyler, 2000), and higher income has a direct correlation to student achievement. In Ontario, student achievement is measured on four levels, from one to four, with one as the lowest and four the highest. O'Reilly and Yau (2009) stated that 84% of students in the Toronto District School Board whose families earn more than $100,000 can reach level three or four in Grade 6 mathematics, compared to only 56% of students meeting that standard when their families earn less than $30,000 (O'Reilly and Yau, 2009, p. 26).

Researchers have presented longitudinal studies that reveal a direct correlation between student marks and student incomes later in their life (Lazear, 2003; Murnane, Willett, Duhaldeborde, & Tyler, 2000). That is why government intervention in education is necessary; otherwise, certain people who are in poverty may unwillingly pass on their low economic status to their children. Because education contributes to an individual's life chances, the issue of equity has been a concerning topic in society. Researchers from different disciplines including psychology, sociology, history, and humanities strive to find possible predictors to the long lasting problem of the achievement gap, as well as positing ways to reduce this gap. Curriculum enrichment (Beecher & Sweeny, 2008), equality of school profile (Edgerton, Peter, & Roberts, 2008), teachers' perception (McKenzie & Scheurich, 2004), the role of cognition (Stevens, Olivarez, & Hamman, 2006), class size (Konstantopoulos, 2008), school counseling (Bemak & Chung, 2008; Cheryl, 2007), and to some extent early childhood development (Levin, 2009) have been given attention in those studies. Achievement disparities are most often studied through two sets of variables: school associated factors such as curriculum, school profile, and so on; and the outside-of-school factors such as gender, race, language, and social class (Chatterji, 2005).

Researchers in Australia along with Statistics Canada have revealed that students with a high socio-economic status (SES) have higher achievement rates than students with a low SES in all provinces in Canada (Marks, Cresswell, & Ainley, 2006; Statistics Canada, 2007). This link between SES and achievement is similar to what other scholars have found in East Asian countries. The research on student achievement in mathematics in East Asian countries, particularly with Japan and the Four Asian Tigers (Hong Kong, Singapore, South Korea, and Taiwan), has indicated that outside-of-school factors have a larger impact on student achievement than school-associated factors (Liu, Wu, & Zumbo, 2006).

Our study is based upon sociological perspectives and on the grounds of "Concerted Cultivation" theory, which indicates that students with better resources should perform better in school (Lareau, 2003). We investigate the effect of parental education and parental occupations on student achievement in Grade 7 through Hierarchical Linear Modeling (HLM) using the Longitudinal Study of American Youth (LSAY), 1987-1994, and 2007.

Parental Characteristics and Math Achievement

Parental characteristics are social capital factors, which have been discussed in educational

settings mostly by economists (Haile & Nguyen, 2008; Schildberg-Hoerisch, 2011; Stevens & Schaller, 2011). Furthermore, Miller and Kimmel (2010) used a set of 21 variables to predict employment in science, technology, engineering, mathematics, or the medical professions (STEMM) between the ages of 34 and 37. In their results, students of college graduate parents had a higher chance to work in a STEMM field than students of parents with just high school diplomas.

Parental characteristics have usually been measured by different characteristics such as parental education, parental occupations, and other factors that comprise socio-economic (SES) background. However, different measuring of SES could result in different conclusions (Marks, 2010). For instance, Kapinga (2014) used parental income, parental education, and parental occupations to make a composite factor SES and found that parental SES has a significant correlation with student dropout. Nevertheless, the significance of the effect was not quantified. One may speculate that the difficulty of interpretation of composite factor (SES) could be the reason of not having any numbers. There are other studies that did not even specify what the SES is, while they were trying to find the effect of SES on student achievement (Farooq, Chaudhry, Shafiq, & Berhanu, 2011; Ogunshola, & Adewale, 2012). In our study parental education and parental occupations was analyzed separately for ease of interpretations and conclusions.

The literature on the effects of parental involvement and in particular parental education and its association with student life and student academic performance is rich (Dubow, Boxer, & Huesmann, 2009). Spera, Wentzel, and Matto (2009) found that student achievement was positively related to parental aspirations within all ethnic subgroups of African American, Asian, Caucasian, and Hispanic families.

Under a three-level HLM model with 5,000 students, 250 classrooms, and 100 schools, Teodorovic (2012) showed that the mathematics disparity could be explained based on many factors, among them parental education. Davis-Kean (2005) suggested that the effect of parental education is direct on student achievement compared to parental income which has an indirect effect.

Occupations have been categorized in different disciplines mainly among sociologists and economists. The think-tank institute, Organisation for Economic Co-operation and Development (OECD), asked students about their parents' occupations and classified them according to International Standard Classification of Occupations (ISCO) list from professional such as managers to non-professional such as cleaners and helpers. The authors of the OECD report commented that: "Students whose parents work in professional occupations generally outperform other students in mathematics, while students whose parents work in elementary occupations tend to underachieve compared to their peers" (OECD, 2014, p. 1). Expanding from the OECD report, we investigated specific parental occupations in science, technology, engineering, mathematics, or medical profession (STEMM) and its impact on student achievement.

Purpose of Study

The purpose of this study was to investigate the direct effect of parental characteristics, mainly the effect of parental education and parental occupation in STEMM fields, on the achievement gap in mathematics at two levels, student background and school background.

Data and Method

Instrument

Data collection. The Longitudinal Study of American Youth (LSAY), 1987-1994, and 2007 was used for the analysis. LSAY researchers collected data in 50 public schools nationally that encompassed two cohorts: Cohort One started from the tenth grade and Cohort Two started from seventh grade in public high schools throughout the United States with a national sample of 3,116 students within 44 schools for seven consecutive years. The response rate was 0.98 for mathematics test in the fall of 1987.

Ⅰ   **Participants.** The researchers divided the 3,116 students in Grade 7 into four regions: North East, North Central, South, and West. In order to maintain participant numbers, the researchers directed the school research coordinator to draw replacements from an additional list of students (about 10) when a student declined to participate "starting at the beginning of the alternate list and proceeding sequentially until a participant was secured" (Miller, 2011, p. 9). The researchers categorized the participants as: Hispanic, Black, White, Asian, and Native American (see Table 1).

Ⅰ   **Missing Data and Imputation of Mathematics Achievement.** Primary researchers conducted imputation of student achievement in mathematics. However, scores were not imputed under two conditions: First, if the student was not in the school; and second, if four or more students' scores were missing. The protocol for imputations of Cohort Two was based on two main techniques: using regression and means. With regards to the Grade 7 mathematics grade, which relates to this study, the protocol was to regress on grade eighth and ninth.

Measurement

Summary of Mathematics Achievement Score (AMTHIRT variable in data file). The dependent variable is mathematics achievement. This variable represents the mathematics score of students in the fall or spring term. There were 51 missing cases, less than 1%. The LSAY researchers regressed Grade 7 on 8 and 9 and were able to impute 23 cases. Nevertheless, the total number of missing cases that were not imputed was less than 1% so listwise deletion was applied for the analysis (Graham & Hofer, 2000). The skewness and kurtosis were within +/- 1. The mean mathematics scores in Grade 7 was 50.381 (*SD*= 10.184; Range = 27.36 to 85.07).

Table 1

Race/Ethnicity Description

Race	Frequency	Percent
Hispanic	284	9.1
Black	349	11.2
White	2,166	69.5
Asian	112	3.6
Native American	47	1.5
Not Available	158	5.1
Total	3,116	100

Parents' Occupations. We divided parents' type of employment into three categories from non-professional to professional: neither employed in technical field nor in STEMM, at least one parent employed in technical, and at least one parent employed in STEMM (see Table 2).

Parents' Education. We calculated parents' education by the highest level of education for either the mother or father. Then, we re-coded the parental education into three categories: high school or less than high school; some college; 4-year college degree or advanced degree (see Table 3).

The education level of the student's mother was based on either her self-reported highest degree earned, or, in the absence of mother, father- or student-reported mother's education. Five categories were used: Less than high school, high school diploma, some college, 4-year college degree (including advanced degrees beyond a bachelor degree). We calculated the father's education following the same procedure.

Student Gender. We gathered gender information from student self-reports in the base year questionnaire, and from coding the names of each student. These were compared, and discrepancies resolved, by further archival checks or phone calls to the students' schools (see Table 4). We then recoded gender from one and two to one and zero for better interpretation of the model intercept.

Table 2

Parent Employment in STEMM Career

Occupation	Frequency	Percent
Neither Parent Technical	2,310	74.1
At Least One Parent Technical	409	13.1
At Least One Parent STEMM	157	5.0
Not Available	240	7.7
Total	3,116	100

Table 3

Parental Education

Education	Frequency	Percent
High School or Less	1,666	53.5
Some College	433	13.9
Bachelor or Higher	957	30.7
Not Available	60	1.9
Total	3,116	100

Table 4

Gender

	Frequency	Percent
Female	1,490	47.8
Male	1,626	52.2
Total	3116	100

Data Analysis

There are two hypotheses that need to be tested. First, there is a positive significant correlation between parent's education and student mathematics achievement. Second, there is a significant positive association between parents' occupations and student mathematics achievement. Multiple regression was used to check each hypothesis. Linearity was checked through the GAM package within R software. Parents' education and occupations were treated as continuous variables; for example, parents' education was not linear so parents with less than high school education and high school diploma were collapsed together, and parents with a university degree and higher than university were also collapsed together.

Because students were nested within schools, two-level Hierarchical Linear Modeling (HLM) was the main analysis (Heck & Thomas, 2000; Raudenbush & Bryk, 2002). The first step was to match the school ID in both levels. Eight schools from the level-1 file were not in the level-2 file so they were removed from the level-1 file, which brought the total number of students to 1,766 and the number of schools to 36. However, the characteristics of participants did not change substantively: for gender, the percentage of female students increased 2.1%; for occupation, neither of parents work in technical or STEMM increased 6.4%, at least one works in technical increased 0.8% and at least one works in STEMM increased 0.5%; for education, high school and less increased 0.9%, some college decreased 1%, and advanced degree and more increased 3.0%.

The final model was built gradually, starting with no predictors, then, after checking the ICC, some predictors to level-2 were added. Because the ICC was still relatively high at 0.08, additional predictors were added to level-1. Finally, the variance of all predictors at level-1 as checked to decide whether the slopes should be fixed or random (Nezlek, 2011). The researchers of this study used the weight variable for the Grade 7 in order to match the sample with the population.

Unconditional Model

The intraclass correlation coefficients (ICC), $\rho = \tau / (\tau+\sigma^2) = 13.57/ (13.57+81.52) = .14$, explained that about 14% of variance was due to different schools, which suggested adding some predictors to the model. Note that in addition to predictors that were in the level-2, the authors put some predictors from the level-1 into the level-2 file as compositional effects, because the effect of parental education at the student level is different than parental education at the school level (Lee, 2000). In addition to parental educations, parental occupation was also examined at the school level.

The investigators purposely avoided using SES, a famous latent variable, as it would be difficult to interpret its effect compared to observed variables of education. For example, the effect of one unit change in an observed variable, such as education, can easily be understood on student's mathematics scores compared to the meaning of one unit change in SES, which is not clear.

The next step was to find out whether the characteristics of individuals in schools (level-1) accounted for the total school variance or such variance was related to the characteristics of schools in addition to the characteristics of individuals in schools (level-1 and level-2). The next model was obtained by adding some characteristics of schools at level-2 as the predictors (called the level-2 model).

Adding Level-2 Predictors

Variables at level-2, parents' education and parents' occupation were centered on the grand mean for a better interpretation. Some predictors were composed from the level-1 file; that is, school means for parental education were calculated. The variance at the school level decreased from 13.57 to 6.94 almost 51% by adding the school mean of parents' education.

Random Effect Model

Parents' occupation (POCI), parents' education (PEDU), and gender (GENDER) of student were added to the level-1 predictors and allowed to be random across schools and found to be significant. The level-1 variables and their linear correlations with mathematics scores were examined and found to be appropriate for the model. All predictors were statistically significant. The deviance of the model decreased from 12,835 to 12,719, by adding 12 degrees of freedom, which indicates significant improvement in the model. Table 5 shows the coefficients and the summary of the best model.

Summary of the model specified

Level-1 Model

$$MATH7_{ij} = \beta_{0j} + \beta_{1j}*(POCI_{ij}) + \beta_{2j}*(GENDER_{ij}) + \beta_{3j}*(PEDU_{ij}) + r_{ij}$$

Table 5

Summary of Final Model

	Unconditional Model	Level-2	Education Random
Fixed effects			
Intercept (γ_{00})	50.3	50.1	49.5
SEducation[a] (γ_{01})		6.9*	5.8*
Education[a] (γ_{10})			1.8*
Occupation			1.8*
Gender			1.2*
Random effects			
σ^2	81.5	81.5	74.7
τ_{00}	13.6	5.2	7.6*
τ_{11}			1.4*
τ_{22}			-3.2*
τ_{33}			-2.8*
Deviance (-2LL)	12,864	12,835	12,719
Estimated Parameters	3	4	16

Level-2 Model

$$\beta_{0j} = \gamma_{00} + \gamma_{01}*(SEDU_j) + u_{0j}$$
$$\beta_{1j} = \gamma_{10} + u^{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + u_{3j}$$

POCI and PEDU have been centered on the grand mean. School Education (SEDU) has been centered on the grand mean.

Mixed Model

$$MATH7_{ij} = \gamma_{00} + \gamma_{01}*SEDU_j$$
$$+ \gamma_{10}*POCI_{ij}$$
$$+ \gamma_{20}*GENDER_{ij}$$
$$+ \gamma_{30}*PEDU_{ij}$$
$$+ u_{0j} + u_{1j}*POCI_{ij} + u_{2j}*GENDER_{ij} + u_{3j}*PEDU_{ij} + r_{ij}$$

Discussion and Conclusion

This study confirmed two hypotheses. The first hypothesis stated that parental education could predict student mathematics achievement. This finding indicated that for one unit increment in educational category parents whose education are at high school or less compared to those who have some college degree, their adolescents would achieve 1.8 marks higher, controlling for parental occupation, and student gender (see Figure 1). This is consistent with the literature, as Teodorovic (2012) had suggested that mathematics disparity could be due to parental education and Davis-Kean (2005) had also found that parental education has a direct effect on student achievement.
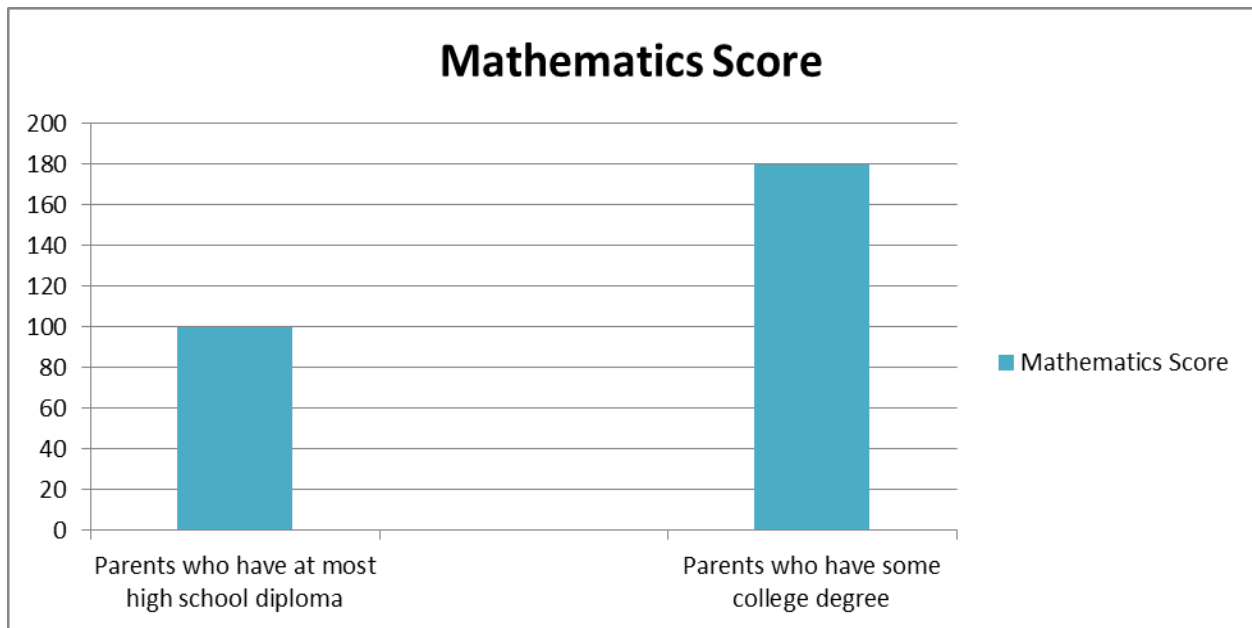

Figure 1. Parental Education and Student Mathematics Achievement

It is worth mentioning though that in addition to parental education, school means of parental education had a significant effect on mathematics disparity as well. As Lee (2000) had shown in his study, compositional effects could be influential. In this study, students who were studying in a school whose students are coming from an educated family could also benefit from the school environment and achieve 5.8 marks more than others (see Figure 2). This is roughly 60% of a standard deviation of student mathematics achievement.

The other findings, which were not at the center of the study, were related to the gender of students. Female students scored 1.2 marks higher than their male counterparts, controlling for parental education and occupation (see Figure 3).

The last findings were that for one unit increment in occupation category, regarding STEMM, for instance, students who had one parent working as technical compared to neither of the parents work as technical, achieved 1.8 marks higher, controlling for parental education and
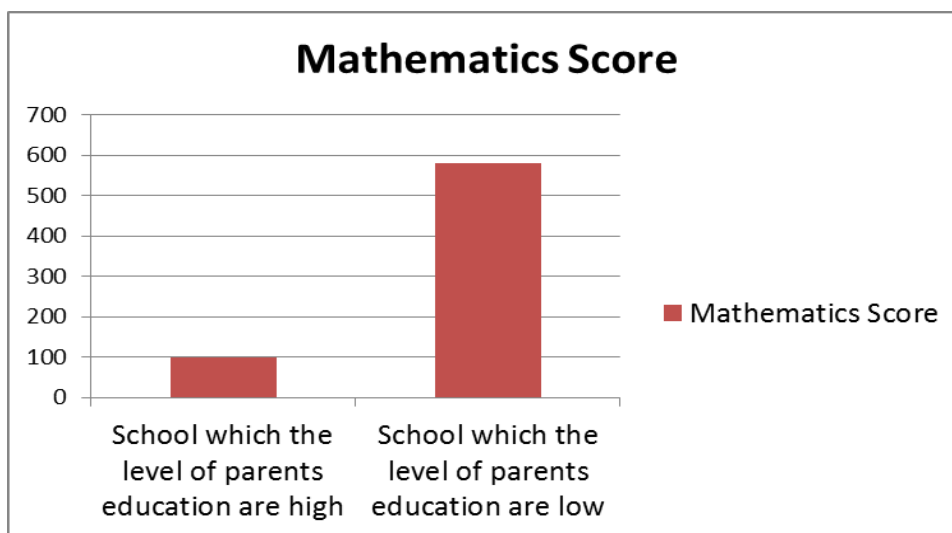

Figure 2. Average of Parents Education in School and Student Mathematics Achievement
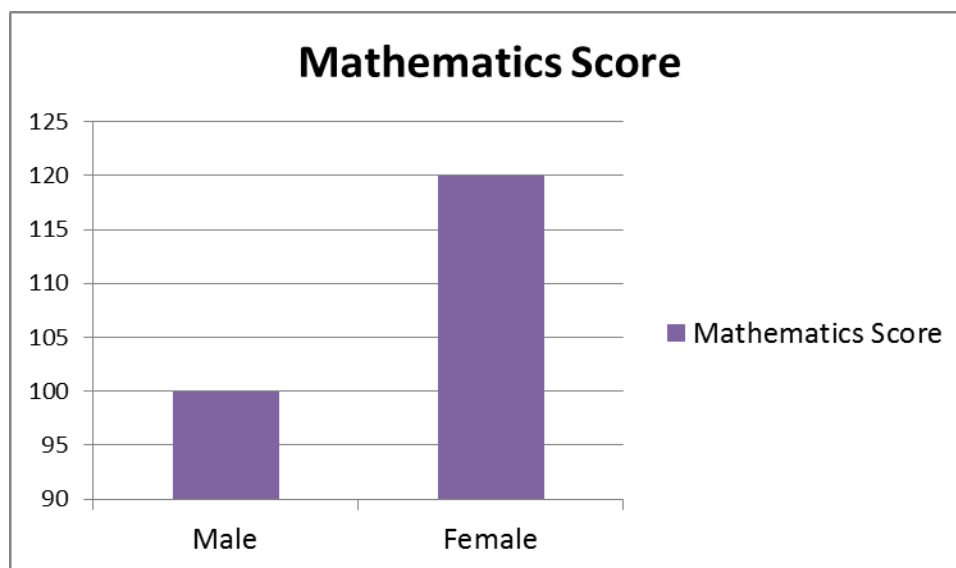

Figure 3. Student Gender and Student Mathematics Achievement

student gender (see Figure 4). This is similar to what OECD (2012) had suggested—that parents who work in professional occupations such as health, teaching, science, or business and administration have more of a positive impact on their child's achievement than children of parents who work in less technical occupations. Overall, this study suggests that more studies need to be done toward identifying the school characteristics in addition to the individual background to better understand the gap while trying to decrease it.

Implications for Practice

This study yields two implications: one at the school level and the other at the individual level. Scholars as well as research and policy makers can ameliorate the achievement gap at the school level, and practitioners can do so at the individual level. As it was mentioned earlier in this paper, parental education has a direct relation to higher income. One may wonder how parent income contributes to their children's education to the extent that intervention by government seems to be necessary. Two recent surveys shed light on the extent to which the affluent families' money would give an advantage to their children. According to the survey conducted by the Ontario Institute for Studies in Education of the University of Toronto (OISE), parents with an annual income greater than $100,000, hire tutors twice as often as parents with less than a $40,000 annual income (Livingstone, Hart, & Davie, 2005). This figure is consistent with the findings of another survey where families with more than $100,000 annual income are 2.9 times more likely to hire tutors than families with an annual income less than $40,000 (Canadian Council of Learning, 2007) (see Figure 5).

One of the main implications of this study is to provide more resources to those who are low in education either at school level or at the individual level. Policy makers could make a school education index that represents the level of parental education at the school level, then providing tutoring to the students of less educated.

Limitations and Further Study

There are many other factors that could have more effects than the current predictors. The lack of important predictors may change the impact of current factors. Because this study focused
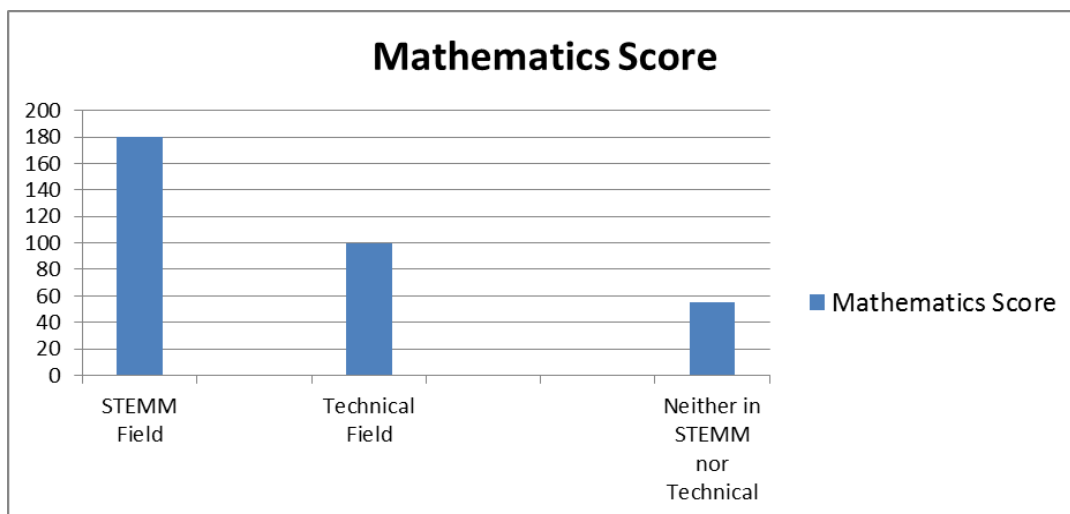

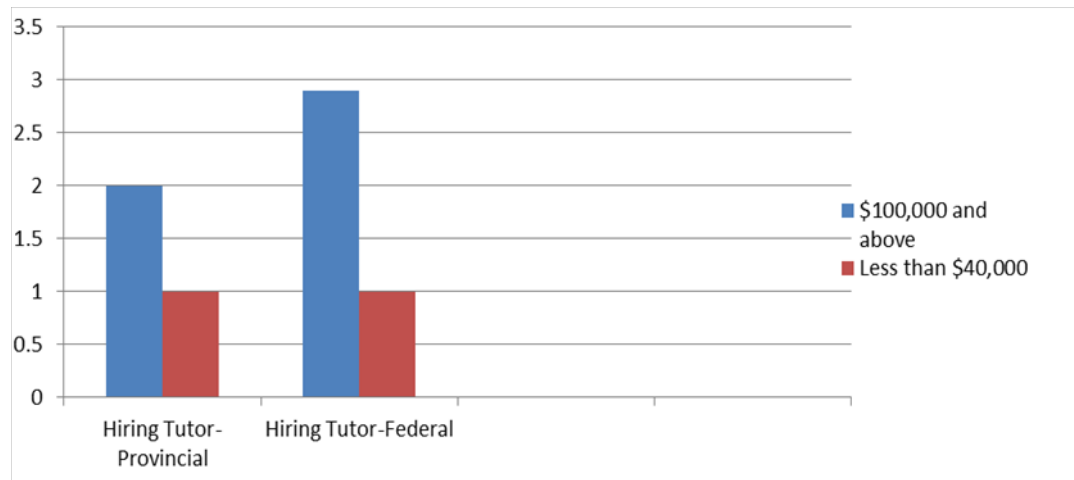*Figure 4.* Parents Occupations and Student Mathematics Achievement

Figure 5. Hiring Tutors in Canada and Ontario

just on Grade 7 mathematics, future research on other grades or subjects may yield different results. Because there are different types of tutoring, further study should be done on the impact of providing tutoring to the students of low educated parents or non-educated parents in STEMM field on the mathematics achievement gap. Although most of HLM studies deploy two-level modeling but adding one more level, that is, teacher characteristics, making three-level model may shed more light on the problem of the mathematics achievement gap.

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Mr. Mohammad Shoraka is a practitioner with teaching experience at the University of South Florida and Canadian offshore schools in China. Mr. Shoraka has also applied a factor analytic approach to the same dataset and his work been accepted to be published by Quantitative Psychology Research. New York: Springer. Mr. Shoraka has a Master of Arts in Social Data Analysis and a Master of Education in Educational Administration from the University of Windsor.

Dr. Robert Arnold had worked for 13 years in applied research before becoming a university teacher. In applied settings he was much involved in program evaluation, and so was very pleased, in 1990, to become a member of the team evaluating Better Beginnings, Better Futures, a multi-site demonstration program aimed at improving the life chances of children from disadvantaged neighbourhoods. He has taught methods and statistics from the year he received his Ph.D. to the present, in courses from the undergraduate to the doctoral level. He has taught introductory sociology (several times), social psychology, and sociology of the contemporary family, which he has offered at Windsor for the past six years. He has co-authored academic papers in criminology and sociology of health as well as others in program evaluation. He consults regularly with students and faculty who have methodological questions.

Dr. Eun Sook Kim is an Assistant Professor of Educational and Psychological Studies in University of South Florida. She has a broad interest in research methodology and psychometrics including structural equation modeling, multilevel modeling, and latent growth analysis. Her focal research interests include measurement invariance testing in multilevel and longitudinal data. She is interested in the behaviors of widely used statistical methods under various research settings and has been involved in research groups studying propensity score analysis, multilevel confirmatory factor analysis, Bayesian estimation, and ANOVA in collaboration with faculty and graduate students.

Dr. Geri Salinitri, PhD is the Associate Dean and Associate Professor with the Faculty of Education at the University of Windsor. She teaches in the area of Science Methodology, Guidance and Career Education, and Issues in Education. Her research interests include Mentoring, Social Learning, Social Justice, Teacher Education and At-Risk Youth. She has published in the areas of mentoring for 1st year university students, New Teacher Induction, learning outcomes and portfolio development in engineering cooperative education programs, and science pedagogy in collaboration with colleagues in diverse areas of education. Dr. Salinitri is currently part of a 7 year, 3.3 million dollar SSHRC partnership grant exploring the reciprocal learning of inquiry based science education between China and Canada.

Jeffrey D. Kromrey is a Professor in the Department of Educational Measurement and Research at the University of South Florida. His specializations are applied statistics and data analysis. He primarily teaches courses in applied statistics. His work has been published in Communications in Statistics, Educational and Psychological Measurement, Multivariate Behavioral Research, Psychometrika, Journal of Educational Measurement and Educational Researcher. He is a former editor of the Journal of Experimental Education and Review of Educational Research. His research has been funded by the National Science Foundation, American Association of Medical Colleges, U.S. Department of Defense, and Association for Institutional Research.