Three Essays on the Economics of Education

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Lay Abstract

This thesis examines heterogeneity in human capital outcomes across race and gender at three stages: elementary school, applications to university, and post-secondary major selection.

Analyzing data on test scores from British Columbia, I find that the gap in mean test scores between students from high- vs low-income families varies considerably across racial backgrounds. Indigenous students, in particular, exhibit a large gap in scores between students from high- and low-income families.

Using administrative data from British Columbia that links enrollment records with tax information, I investigate differences in the impacts of switching post-secondary majors on labour earnings for men and women. Relative to male students, switching has a large effect on the earnings of women conditional on initial major.

Finally, investigating university application data from Ontario, I find gender gaps throughout the application process (applications, offers and acceptances) to Engineering and Computer Science programs.

Abstract

This thesis examines heterogeneity in human capital outcomes across race and gender. Using administrative data from British Columbia, the first chapter investigates the income-achievement gap in provincial test scores among Grade 4 and 7 students of different racial backgrounds. The second chapter estimates the impact of switching post-secondary majors on labour market earnings for men and women. Finally, using university application data from Ontario, the third chapter investigates gender gaps in applications, offers and acceptances to engineering and computer science programs.

In Chapter 1, I show that there is considerable variation in test score gaps between children from families of high- and low-socioeconomic status (SES) across racial backgrounds. In particular, the gap in mean test scores between Indigenous children of high- and low SES is 0.7 standard deviations, while it is only 0.37 standard deviations for East Asian children. Further investigation into the gap among Indigenous students reveals a potential connection to broader socio-economic issues impacting Indigenous communities.

In Chapter 2, I study the impact of switching post-secondary majors on earnings. To address the endogeneity of switching, I employ a doubly-robust matching estimator to create a credible counterfactual group for switchers. Switching has a greater impact on the earnings of women, with women experiencing gains (losses) as large as \$15 500 (\$23 000) conditional on initial major. These results highlight the importance of major-choice as it relates to labour market earnings.

Finally, Chapter 3 investigates the gender gaps throughout the application process to undergraduate engineering and computer science programs. While we observe large gender gaps in applications to both programs, we also observe gender gaps in offers to engineering programs and acceptances to computer science programs. This suggests that

both programs may face unique challenges in achieving gender parity in enrollment.

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Declaration of Academic Achievement

Chapter 1 is co-authored Angela Zheng. Chapter 3 is co-authored with Arthur Sweetman and Kim Jones. The material in this dissertation consists of my research with coauthors. I conducted all of the empirical analysis, and wrote the manuscript jointly with my coauthors from 2020 to 2024. The first paper has been published in Economic Inquiry. The paper can be found online at: https://onlinelibrary.wiley.com/doi/10.1111/ecin.13182

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Chapter 1

Introduction

Education has been identified as a key component in an individual's economic well-being. Achievement in primary and secondary school has been linked to labour market outcomes later in life (Heckman et al., 2006; Heckman et al., 2010). Moreover, both college attendance (Altonji et al., 2012; Altonji et al., 2016) and college major choice (Bleemer and Mehta, 2022; Zafar, 2012) have a significant impact on earnings. Despite this, inequities (along various dimensions including racial, gender and socio-economic) continue to persist throughout the process of human capital accumulation. These inequities, often stemming from broader social issues, can impact test scores (Michelmore et al., 2017), college attendance (Pallais, 2015), and even college major choice (Kurtz-Costes et al., 2008).

In this thesis, I study inequities in the process of human capital accumulation, focusing on elementary school students, university applicants, and post-secondary students. Among elementary school students, I study the difference in test scores for students of high and low socio-economic status (SES) across different racial groups. For both university applicants and post-secondary students, I focus on differential outcomes between men and women. Specifically, for university applicants, I investigate the gender gap throughout the application process to engineering and computer science undergraduate programs. In contrast, for enrolled post-secondary students, I estimate the causal impact of switching majors on labour market earnings, focusing on the differential impact between men and women.

In Chapter 1, I explore how the income-achievement gap among elementary school children varies by race. A large literature illustrates that children from higher-income families perform better in school (for examples see Carneiro and Heckman, 2003; Hanushek et al., 2020; Chmielewski and Reardon, 2016). This is concerning as early cognitive skills have been shown to be associated with future labour market outcomes (for example Chetty et al., 2011).

I conduct a comprehensive analysis to investigate how the relationship between parental income and child academic achievement varies by racial group. To do so, I make use of administrative data from British Columbia (BC) that links child educational outcomes to parental tax records. As a measure of academic achievement, I make use of Grade 4 and 7 outcomes on the province-wide Foundational Skills Assessment (FSA) standardized exams. The FSA is an annual examination that is meant to assess a child's numeracy and literacy skills. I measure the average FSA score in reading and math across income deciles for the three largest minority groups in BC: East Asians, South Asians, and Indigenous. My primary measure of the income-achievement gap is the mean difference in test scores for students in the top-decile of before-tax household income versus the bottom decile, referred to as the P90-P10 gap, as in Reardon (2011).

I find that the P90-P10 gap varies considerably by racial group. The P90-P10 gap for East Asian students is 0.37 standard deviations, compared to 0.7 standard deviations for Indigenous students. Investigating the factors that contribute to this gap, I find that school fixed effects explain roughly 20 %-30 % of the income-achievement gaps across racial groups which suggests strong sorting by school and parental income. Furthermore, I find that special needs status is an important factor in understanding the income-achievement gap among Indigenous students. Finally, linking to the Census, I find that Indigenous students are more likely to either come from a single-parent household or reside in unsuitable housing relative to non-Indigenous children.

Chapter 2 examines the impact of major switching on labour market earnings. This investigation is motivated by two key points. First, the association between college major and post-secondary education has been well established in the education literature (for example see Kirkeboen et al., 2016). Second, switching has been identified has a common practice among post-secondary students (Astorne-Figari and Speer, 2019).

To study the impact of major switching I must address the fact that students are often able to choose when and where to switch. To address this issue, I employ a doubly-robust matching estimator (Imbens, 2015). In essence, the estimator seeks to compare the earnings of switchers to observably similar non-switchers who, thus, may have similar likelihoods of changing majors. Accordingly, in comparing students with similar predicted likelihoods of switching majors, I hope to create a credible counterfactual estimate of earnings for switchers.

To accomplish this, I employ rich administrative data from British Columbia which links high school and post-secondary enrollment records to tax information. To estimate the probability of switching for each individual, I employ a series of pre-determined covariates that have been identified in the literature as highly correlated with the switching decision including measures of academic achievement and the average earnings of previous graduates from the initial major. To further control for differences in the likelihood of switching, I separate students based on gender (male or female) and initial major. Here, majors are defined as one of four broad categories: Liberal and Fine Arts, Science, Technology, Engineering and Mathematics (STEM), Business and Health, Social Science and Education. I then estimate a carefully specified model of switching on labour market earnings using these new treatment (switchers) and control (non-switchers) groups.

Switching is a fairly common practice in my data, with nearly one-third of both men and women switching majors. There is also considerable variation in switch rates across initial majors, with nearly 50 % of students who begin in a Liberal Arts major switching while less than 20 % of those began in a Business or Health major do so. The factors that influence the switching decision also vary by initial major, with higher marks in Grade 10 Science reducing the likelihood of switching out of Science, Technology, Engineering or Math (STEM) majors while higher marks in Grade 10 English decrease the change of leaving Liberal Arts majors.

My results suggest that impact of switching varies considerably both by student gender and initial major. Specifically, switching is often a more consequential decision for women relative to men, as male students often see no statistically significant effect on their earnings from switching majors. In contrast, depending on initial major, women can experience large gains (or losses) in their earnings as a result of switching. For example, women departing STEM majors experience, on average, an increase in their earnings of nearly \$15 500, while those departing Business and Health majors experience an average loss of approximately \$23 000.

My third paper builds off two interesting observations found both in my second paper and in the literature on post-secondary education. First, that the share of women beginning in STEM majors is lower than the share of men beginning in STEM (AAUW, 2022). Second, that there is noticeable difference in STEM major selection between men and women, with female STEM students largely choosing majors relating to biology and the medical sciences while men are more likely to begin in more technologically-inclined majors. Combined, these two facts illustrate the potential difficulty in both closing the gender gap in STEM occupations and reducing the gender wage gap, as biology-oriented majors are both less likely to lead to STEM jobs (Statistics Canada, 2017) and provide lower wages than other STEM majors (Finnie et al., 2019).

Motivated by these facts, I investigate the gender gap throughout the application process (applications, offers and admissions) to engineering and computer science undergraduate programs. I study these programs, in particular, as they often exhibit the largest gender gap in enrollment among STEM programs (Wall, 2019), while also having different prerequisite requirements.

I make use of administrative data provided by the Ontario University Application Centre (OUAC) which contains demographic (including gender, age, and high school attended) and academic information (including grades in completed Grade 12 courses) on all applicants to undergraduate programs in Ontario between 1994 and 2016. I focus on students who apply between 2011 and 2016. To control for academic preparedness, I focus on applicants who have completed the typical prerequisites for engineering and computer science programs.

I find unadjusted gender gaps in applications of 35 % and 11 % to Engineering and Computer Science programs, respectively. Investigating the factors associated with these gaps, I find that high school STEM courses explain a considerable portion of both gaps. I investigate further the gaps in offers and acceptances to engineering and computer science programs.

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Chapter 2

Race and the Income-Achievement Gap

Abstract

A large literature documents a positive correlation between parental income and child test scores. In this paper, we study whether this relationship, the dependence of the cognitive skills of children on the socioeconomic resources of their parents, varies across race. Using education data linked to tax records, we find that the income-achievement gap is small for East Asian children while significantly larger for Indigenous children. School-level factors explains a large portion of the variation in the gap across race. Our results suggest that the large income-achievement gap for Indigenous students stems partially from inequality in special needs diagnoses.

2.1 Introduction

A large literature shows that there are achievement gaps based on family socioeconomic status (SES): children from higher-income families perform better in school.[1] From an inequality perspective, the existence of these SES achievement gaps is concerning because research has shown that the early cognitive skills of children are associated with their future labour market outcomes (Chetty et al., 2011; Heckman et al., 2006; Heckman et al., 2010; Hanushek, 2009). In addition, another area studies inequality in achievement across race, such as the Black-White test score gap in the United States

[1] For example, see Carneiro et al. (2003), Heckman et al. (2005), Reardon (2011), Magnuson et al. (2012), Hanushek et al. (2019), and Hanushek et al. (2020) for the U.S., and Currie et al. (2001) and Bradbury et al. (2019) for the United Kingdom. For a cross-country comparison see Chmielewski et al. (2016) and Bradbury et al., 2019.

(Magnuson et al., 2006; Jencks et al., 2011) and the achievement gap between Indigenous and non-Indigenous students in Canada (Friesen et al., 2010b; Barber et al., 2021).

To date though, there has been little focus on how the income-achievement gap varies by race. In this paper, we show that there are significant differences, and study what factors explain such variation, with a particular focus on outcomes for Indigenous children. Understanding the income-achievement gap across different minorities can shed light on whether certain children have more opportunity to build human capital, in that their test scores are less dependent on the socioeconomic resources of their parents. This work is thus related to a broader literature studying economic opportunity by race (Bhattacharya et al., 2011; Akee et al., 2019; Chetty et al., 2020), focusing instead on early childhood cognitive skills.

Our work uses administrative education data linked to tax records from the Canadian province of British Columbia. This data covers (nearly) the population of students in the province.[2] We study outcomes for the three most populous groups of visible minority students: Indigenous, East Asian, and South Asian. Our primary measure of the income-achievement gap is the average difference in test scores for students from families in the top before-tax household income decile versus the bottom decile, which we refer to as the P90-P10 gap, as in Reardon (2011). Following other work studying intergenerational mobility by race, income deciles are calculated across all racial groups (Chetty et al., 2020). Our main measure of achievement is performance on standardized tests when students are in Grade 4 (age nine) and Grade 7 (age twelve).

To start, we find that the income-achievement gaps in Canada are low compared to those documented for other countries. Our estimates indicate P90-P10 gaps ranging from 0.4-0.7 standard deviations across racial groups. In comparison, Reardon (2011) documents a gap of 1.25 standard deviations in the United States while Magnuson et al.

[2]We do not see Indigenous students who attend on-reserve schools run by the federal government. See Section 2.3 for further discussion.

(2012) finds gaps of 0.8-1.0 standard deviations for the United Kingdom. Our findings on income-achievement gaps in Canada relate to other works documenting that Canada has higher economic opportunity compared to the United States (Connolly et al., 2019).

Nevertheless, there is noticeable variation in the relationship between income and test scores among minority groups. Our most striking results are for Indigenous students: across all parental income deciles, Indigenous students score significantly lower than other students on standardized tests. In addition, Indigenous students have the steepest relationship between test scores and parental income with a P90-P10 gap of around 0.7 standard deviations.

In contrast, East Asian students have the highest performance levels on tests across all parental income deciles, and the lowest P90-P10 gap, at around 0.37 standard deviations. For South Asian students, the corresponding estimate is 0.6 standard deviations. Furthermore, we find heterogeneity in the P90-P10 gap within race by subject. While Indigenous students have large P90-P10 gaps in both reading and numeracy, the raw P90-P10 gap for East Asians is noticeably lower in the latter subject. We also show that the patterns across race at age nine are consistent three years later: in fact, the P90-P10 gap grows for Indigenous students.

Next, we turn to understanding what factors contribute to the variation in the income-achievement relationship across race. This exercise is especially important for learning what policymakers could do to improve outcomes for Indigenous students. To start, controlling for school fixed effects explains about 20-30% of the P90-P10 gap across all visible minority groups. This suggests strong sorting patterns by income and average school performance, whereby lower income students are more likely to attend schools with lower performance on standardized tests. The education data we use also identifies whether a student was ever an English as a Second Language (ESL) learner or had special needs, which include behavioural, learning, or physical needs, but not gifted ones. Our estimates show that for Indigenous students, special needs status is an important factor in understanding their income-achievement gap. In fact, we find a stark pattern between income and the probability of having a special need for Indigenous students. Lastly, we find that ESL status is an important factor for Indigenous students but also for other minority groups too. Controlling for ESL status significantly reduces the East and South Asian P90-P10 gap.

Given the low education opportunity for Indigenous students, we conduct additional exercises to investigate other possible mechanisms. About a fourth of our Indigenous students are linked to the Census, and conditional on household income, Indigenous children are significantly more likely to be from single-parent families and to live in unsuitable housing compared to non-Indigenous ones. Furthermore, while we do not find heterogeneity in the income-achievement gap between Indigenous students living on versus off-reserves, we do show that on-reserve students have lower test scores conditional on household income than off-reserve students.

Our work has several policy implications that could improve the disparity in income-achievement gaps. To start, school fixed effects explains a large portion of the income-achievement gap across all groups, indicating that sorting into schools may be an important source of inequality. School funding in British Columbia is at the provincial level and so differences in school quality do not arise due to differences in property tax funding as in the United States.[3] Nevertheless, school sorting on income still occurs as British Columbia has school zone boundaries implying that the quality of schools is capitalized into property prices (Black, 1999).

In addition, also important for the Indigenous P90-P10 gap is special needs status.

[3]The literature on inequality and education has shown that the United States' decentralized funding system has negative effects on opportunity and intergenerational mobility as district resources are tied to the socioeconomic status of residents. For example, see Durlauf et al. (1993), Durlauf (1996), Fernandez et al. (1996), Fernandez et al. (1998), Biasi (2022), Jackson et al. (2016), Eckert et al. (2019), and Zheng et al. (2022).

Indigenous students are more than twice as likely than non-Indigenous students to have a special needs diagnosis. Several works have documented the severity of the Indigenous health gap[4] and our work highlights how the link between special needs status and income worsens educational outcomes for low-income Indigenous students.

2.2 Literature Review

Our work is related to three strands of literature: research on achievement gaps, research on education inequality in Canada, and research on socioeconomic status and opportunity across race.

There are several works studying achievement gaps among students. In the United States, a wealth of research has studied the test score gap between Black and White students, with estimates ranging from 0.5-1 standard deviations (Magnuson et al., 2006; Jencks et al., 2011; Fryer Jr et al., 2004; Card et al., 2007). More closely related to our work, Rothstein et al. (2013) study the gap in Black and White test scores for students with the same permanent family income. The achievement gap between students of high and low socioeconomic status has also been extensively researched (Michelmore et al., 2017; Jerrim et al., 2012). Often, studies have used survey data without reliable family income information. Instead, these works have constructed an index of socioeconomic status from parental education (Hanushek et al., 2019), type of goods at home (Hanushek et al., 2019; Hanushek et al., 2011; Jerrim et al., 2012), or parental occupation(Haeck et al., 2021).

When using parental income as a measure of socioeconomic status, studies have also found large achievement gaps (Carneiro et al., 2003; Magnuson et al., 2012; Sandsør et al., 2021). Reardon (2011) estimates that the P90-P10 test score gap is 1.25 standard deviations for children born in 2001 in the U.S. and that the gap grew when compared

[4]For example, see King et al., 2009; Booth et al., 2008; Frohlich et al., 2006; Hajizadeh et al., 2018; Smylie, 2012; Shapiro et al., 2021.

to earlier cohorts. In a cross-country comparison of multiple countries, Chmielewski et al. (2016) find that the P90-P10 income gap is larger in the U.S. than in other OECD countries. Just like our paper, these works are descriptive, documenting the correlations between income and achievement.[5]

One of our key findings is large income-achievement gaps for Indigenous students. This result contributes to a broad literature documenting inequality for the Indigenous population in Canada. Using the same test score data as ours, Friesen et al. (2010b) study the achievement gaps between Indigenous and non-Indigenous students in British Columbia. They find that there is significant sorting of Indigenous students into lower-performing schools. Similarly, Richards et al. (2010) show that school quality explains an important component of the Indigenous test score gap in British Columbia. Across Canada, Barber et al. (2021) use a national sample of students and find an Indigenous gap of around 0.31 standard deviations that has stayed consistent from 1996 to 2008. Our main contribution here is the use of test score data linked to tax records of parental income, which allows us to study the income-achievement gap among Indigenous students.

Lastly, our work ties into the literature on economic outcomes by race. Collins et al. (2017) and Akee et al. (2019) look at historical intergenerational mobility outcomes between Black and White Americans, while Abramitzky et al. (2021) study intergenerational mobility of immigrants to the United States. Recent work on intergenerational mobility of income by Chetty et al. (2020) has highlighted that economic opportunity in the United States varies by race, with Black Americans and American Indians having worse outcomes than White and Asian Americans. We view our contribution to this literature as emphasizing that inequality in opportunity across race is a phenomenon that arises at an early point in the life-cycle. While the works mentioned above primarily

[5]For causal effects of income on achievement, see Dahl et al. (2012), who find that changes in the Earned Income Tax Credit led to improvements in test scores in the United States.

focus on income as an outcome, we show that there is unequal opportunity in child human capital accumulation across race. To the extent that child test scores are associated with future labour market outcomes, our findings may be a partial explanation for the inequality in economic opportunity during adulthood documented by other works. In Section 2.6 we discuss in detail how our results compare to those of Chetty et al. (2020). One difference to note though is that we are not able to speak to outcomes for Black students as they are a small minority in British Columbia. Instead, we shed light on outcomes for East Asian, South Asian, and Indigenous students.

The rest of the paper is structured as follows. In Section 2.3 we discuss the education system in British Columbia and Section 2.4 presents the data. Section 2.5 goes over the empirical framework and Section 2.6 presents the results. We conduct robustness exercises in Section 2.7 and Section 2.8 concludes.

2.3 Institutional Background

Our data is for the province of British Columbia (BC), the third most populated province in Canada. BC is diverse; at the time of the 2006 Census, it had a visible minority share of 25 percent. Table A2.1 in the Appendix lists demographic characteristics from the 2006 Canadian Census of BC in comparison to Canada (Statistics Canada, 2008c; Statistics Canada, 2008b; Statistics Canada, 2008a). The racial composition of BC differs in a few key ways. First, the province has a large share of Asian residents. Ten percent of the BC population is Chinese, compared to only four percent nationwide. In addition, six percent in the province are South Asian. Second, five percent of the province's population is Indigenous, which in turn implies that almost seventeen percent of the Indigenous population of Canada resides in BC. Finally, the Black population is under-represented in BC: less than one percent of residents identify as Black, compared to two and a half percent in Canada overall.

We now discuss education policy, which in Canada is set at the provincial level. BC has a traditional public school system: students are guaranteed a seat in a school based on their catchment area. Since 2003, the province has had an open-enrolment policy in which children can attend school outside their catchment area, given available seats.[6] The school financing system in BC is centralized, with roughly 94 % of the budgeted revenue for school districts coming from provincial grants (Ministry of Education British Columbia, 2015). School districts receive the same amount of funding per full-time student. Additional funds are provided for Indigenous students, students with special needs, adult learners, and English/French Language Learners (Independent Funding Model Review Panel, 2018) and again, these rates are equalized across districts (Ministry of Education, 2023). This financing system is in contrast with the U.S., where in 2013-14, funding at the district level still made up 45% of per-pupil revenue with a large share raised from local property taxes (U.S. Department of Education, 2016). Furthermore, BC has a system of independent (private) schools. These schools must hire teachers certified by the province and adhere to the provincial curriculum. Some independent schools are funded at 35-50% of their local public school rate.[7]

A key focus of this paper is on Indigenous children. In BC, education for Indigenous students can take place in two forms. Indigenous students living on reserves may attend an on-reserve school, which are funded by the federal Canadian government. We have no data on these types of schools, but they educate a only small proportion of the Indigenous student population.[8] Drawing on the literature, we can get a sense of how the lack of on-reserve school data would affect our estimates of the Indigenous income-achievement gap. Previous findings have shown that education quality and income on-reserves are lower than those of Indigenous people off-reserve (McMahon, 2014).[9] This suggests that if we

[6]See Friesen et al. (2015) for an analysis of the impact of the open-enrolment policy.

[7]See the B.C. Ministry of Education website.

[8]For instance Friesen et al. (2010b) estimate that only seven percent of Grade 7 (age twelve) BC Indigenous students attend a school operated by a First Nations band.

[9]See also https://www150.statcan.gc.ca/n1/daily-quotidien/210921/cg-d001-eng.htm

had data for federally-run on-reserve schools, our estimates of the income-achievement gap for Indigenous students would be higher.

2.4 Data

We use a unique administrative dataset that links the achievement data of students in British Columbia to income tax data. This dataset is part of the Education and Labour Market Longitudinal Platform (ELMLP) from Statistics Canada (Statistics Canada, 2021). In the Appendix, we provide further details on the ELMLP and how to access it. Replication codes are provided in the data archive associated with this paper (Bacic et al., 2023).

Education Data

Our education dataset is from the British Columbia Minister of Education and covers the universe of students who attend public or independent schools in the province (BC Ministry of Education and Child Care, 2021). It consists of student-year level observations of demographics including age, Indigenous status, gender, language spoken at home, special needs status, school attended, and test scores in Grades 4,7,10, and 12. Special needs students are those with physical, behavioural, or learning needs. For the purposes of our analysis, we do not include gifted students in our classification of special needs. We only consider school-aged learners and drop adult learners from our sample.

During the year that students are in Grade 4 (age nine) and Grade 7 (age twelve), performance on the provincial wide Foundation Skills Assessment (FSA) standardized exams are recorded. This test is given annually to all students (in both public and independent schools), and assesses their skills in literacy and numeracy. Students are graded in the form of a percentage score, which we standardize within a grade, subject, and cohort. If a student repeats a grade and retakes the FSA, we use their first attempt.

While in principle, all students should take the FSA, students can miss an exam due to illness or an emergency, and exceptions are given to certain special needs and English as a Second Language students. Moreover, recently the teacher's union has pushed to have parents opt their children out of the FSA (Boynton, 2019). This movement has had some success with participation rates falling the past few years. For example, in 2017, the participation rate was 79% whereas in 2007 it was around 89% (BC Ministry of Education and Child Care, 2021).

We focus on the cohort of students who were in Grade 4 from the academic years 2008/09 to 2012/13 and who were thus in Grade 7 from 2011/12 to 2015/16. The reason we do this is twofold. First, a fourth of our sample is linked to the 2016 Census, meaning that the census information from 2016 covers students when they are age 12 to 16 and still in school. Second, using recent cohorts is problematic due to the falling participation discussed above. In Section 2.6 we discuss how changing participation may bias our estimates.

Tax Return Data

Children in the BC education dataset are linked to the tax return data of their parents through the T1FF datafile from Statistics Canada. The tax return data covers the parents of children in the education dataset who file an income tax return, in addition to individuals who claim child benefits from the federal government. Our main definition of income is before-tax income at the household level. In robustness checks we also use household income after tax, and household income after tax scaled by family size. Income is defined as the sum of employment income, business income, income from agriculture, self-employment income, and benefits. We define a household as the two parents of a child.[10] To get a sense of the household finances during the child's early years, we take averages of total household income in the five years leading up to when the child is in

[10] A small proportion of our sample has three parents linked in certain years, in which case we take the two individuals who appear the most often.

Grade 4. We are able to match 96% of our students of interest to tax records. Of these matches, around 95% of the linkages have the full five years of income available. All income values are normalized to 2002 Canadian dollars using the Consumer Price Index (Statistics Canada, 2023).

Data on Race

The data from the Ministry of Education asks students whether they are Indigenous. We classify a student as Indigenous if a student ever answers as being so during the years observed. For other minority groups, the administrative data does not explicitly ask for a student's race. We do however, have information on the language a student speaks at home, which we use as a coarse proxy for race. We classify students who speak Chinese or Korean at home as "East Asian", and students who speak Punjabi or another South Asian language as "South Asian". For comparison, we look at students who speak English at home and who are not Indigenous; we classify these students into our "Baseline Group".

Our classification system is subject to some measurement error. While our classifications for East Asian and South Asian minorities are likely to be accurate, students who speak English at home may be White or belong to a visible minority group. This measurement error can affect our estimates in two ways. First, our classification of East Asian/South Asian students would capture those who may be less assimilated than students of the same ethnicity who speak English at home. By focusing on a less-assimilated group, we may be overstating the differences in test scores between minority groups and Whites. Second, if the degree of assimilation is correlated with parental income, our classification will miss out on East/South Asian students from higher-income families, which may potentially understate the P90-P10 gaps within these groups. In the Appendix, we show that our results are robust to using a more accurate measure of race from the Census.

Census Data

Around a fourth of our students are linked to the 2016 Census. For these students, we use their visible minority information from the Census as a robustness check. In addition, we make use of their family structure and dwelling information to understand mechanisms that may affect the income-achievement gaps.

2.5 Empirical Framework

Our baseline model is an OLS regression of standardized student test scores for child i on their household before-tax income. To start, we focus on the achievement gap between the top and bottom income decile, so that we can compare our estimates to those of Reardon (2011) for the U.S. We run the following regression separately for each of our four student groups, Baseline, Indigenous, East Asian and South Asian:

$$y_i = \alpha + \sum_{q=2}^{10} \beta_q income_{i,q} + \epsilon_i \tag{1}$$

where y_i is the average test score across reading and math of individual i in standard deviations, and $income_{i,q}$ is an indicator variable that equals one if the child's household income is in decile q. The bottom income decile is the reference level.

We calculate income deciles across all families and not within racial groups, as in Chetty et al. (2020). The coefficient β_q represents the average test score for those in income decile q relative to the bottom income decile. Standard errors are clustered at the school level to account for families sorting into schools. We call β_{10} the P90-P10 achievement gap. In certain specifications, we augment Equation (1) with controls and/or school fixed effects.

2.6 Results

2.6.1 Summary Statistics

To start, we present summary statistics for three samples of our students. Column (1) of Table 2.1 is for the entire sample of students in our cohort of interest: those in Grade 4 from 2008/09 to 2012/13. Column (2) is the sample of students who take the Grade 4 FSA. Lastly, Column (3) is the sample of students who take the Grade 4 and Grade 7 FSA. Per data-release guidelines, all counts are rounded to the nearest tenth and average income values are rounded to the nearest hundredth.

In the full sample, we have 207,120 Grade 4 students over the five years with an average household income before taxes of \$65,600. Sixty-four percent of students speak English at home and thirteen percent identify as Indigenous. Close to eight percent of students speak an East Asian language while seven percent of students speak a South Asian language at home. Around 17% have a special needs disorder and about 20% are English as Second Language (ESL) students.[11] We group students as ESL and special needs students based on if they were ever classified in the data as being in one of these groups. Lastly, twelve percent of students in our sample are in private (independent) schools.

Column (2) presents summary statistics for our cohort of students who have Grade 4 FSA scores. Out of all the students in Grade 4 during 2009-2013, 174,370 or roughly 85%, wrote the FSA. Students who do so have parents with around \$2,000 higher household income. There are lower participation rates among Indigenous, ESL, and special needs students. The representation of students in private schools increases to thirteen percent, which is in line with private schools attracting students from higher-income families. In

[11]While these ESL rates may seem high, note that populous regions in British Columbia have a significant immigrant population. For example, reporting from the Vancouver Sun in 2014 stated that ESL students make up more than 50% of their school's population in over 60 schools in Vancouver (Skelton, 2014).

Column (3), we highlight the sample of students who have both Grade 4 and Grade 7 FSA scores. Participation drops from Grade 4 to Grade 7 leaving a sample of 148,060 students. The average income is higher, now at $69,500.

Table 2.1 shows that there is selection into exam participation, which could cause our P90-P10 gaps could be biased. From the summary statistics, we see that children who do not participate are likely to be from lower-income families, since average household income rises as we condition on participation. Furthermore, we are missing students who are likely to be special needs or ESL students. Therefore, the estimates of the P90-P10 gap that we calculate should be downwards biased.

2.6.2 Raw Income-Achievement Gaps

We now present estimates of the raw income-achievement gap across race. Figure 2.1 presents a binscatter of the P90-P10 gap for students in Grade 4 across our four groups of interest: Baseline, Indigenous, East Asian, and South Asian. Each dot on the graph is the average test score from reading and math for students from a group in a certain income decile.

The first thing to note is that there are stark differences in the level of achievement among the different groups. Indigenous students perform worse on standardized tests across all parental income deciles: their test scores range from -0.6 to 0.2 standard deviations (σ). On the other hand, students in the baseline group have a minimum average performance of -0.2σ. South Asian students perform slightly worse while East Asian students perform very well: from around 0.3 to 0.8σ.[12]

Next, we present our findings on how the income-achievement gap varies by race by looking at how the slope between parental income and test scores differs among our groups of students. In particular, we look at the difference in outcomes between an

[12]In related work for Australia, Jerrim (2015) document that East Asian students perform better than Australian-born students in school.

average student whose family income is in the top income decile versus one whose family income is in the bottom decile (P90-P10 gap). For the Baseline group this is 0.54σ and South Asians have a slightly larger value, at 0.61σ. The P90-P10 gap for East Asian students is smaller, at 0.37σ . For Indigenous students though, the P90-P10 gap is noticeably larger, at 0.69σ.

While Figure 2.1 points to differences in the P90-P10 gap across race, for each of our three visible minority groups, we test whether their P90-P10 gap is statistically significantly different from the Baseline group. For example, to test differences between the Baseline and Indigenous group, we run a regression of test scores on income deciles interacted with an indicator for whether a student is in the Baseline Group or Indigenous. We test for differences between the Baseline Group and East/South Asian students in a similar way. Table A2.2 in the Appendix presents the results. In Column (1), the interaction between Indigenous and P90-P10 is 0.16 and significant. Column (2) shows that the lower P90-P10 gap for East Asian students is significant while Column (3) indicates there is no significant difference in the P90-P10 gap between South Asian and Baseline students.

Figure 2.2 shows that the patterns in test scores and parental income stay consistent when students are three years older, in Grade 7. The lowest level of test scores for East Asian students rises from 0.3σ in Grade 4 to just under 0.6σ in Grade 7. In contrast, the level of test scores decreases for Indigenous students: from -0.6σ at the bottom decile of parental income in Grade 4 to close to -0.8σ in Grade 7. Moving on to the income-achievement gap, we see that the P90-P10 difference widens to around 0.75σ for Indigenous students while for East Asian students it stays close to around 0.35σ. For both the Baseline group and South Asian, the gap is similar at around 0.6σ.

For context, we can compare the P90-P10 gap to the United States which Reardon (2011) documented to be around 1.5σ. Our results indicate that among all groups of students in BC, the income-achievement gaps are substantially lower than that in the United States. Nevertheless, there is important heterogeneity across different student groups. More broadly, our findings show that even when children are as young as nine, there are already patterns between test scores and parental income that vary across race and that are suggestive of the future relationships between child income and parental income documented by Chetty et al., 2020. Just like they find that Asians have higher relative mobility and absolute mobility, we find that East Asians specifically, have lower income-achievement gaps and higher levels of test scores. One possible reason is that our main classification of students is based on language spoken at home, and will skew towards more recent immigrants rather than East Asians who have been in Canada for longer. For those who recently immigrated to Canada, income may be a poor proxy for parental human capital as immigrants tend to experience downward occupational mobility upon arrival in a new labour market (Abramitzky et al., 2021). Furthermore, Chetty et al., 2020 find worse absolute mobility outcomes for American Indians. In a similar vein, our estimates show that Indigenous students have low test scores levels across parental income. In addition, we find that Indigenous students have the largest P90-P10 gap, at around 0.7σ. Since cognitive skills are related to future earnings, our work suggests that one way to improve economic opportunity across race is to target early stage inequalities in human capital accumulation across race.

2.6.3 Mechanisms

We then focus on understanding what factors explain the income-achievement gap across the four groups of students. To do so we utilize the richness of our administrative dataset and include different controls such as: school characteristics, peer characteristics, and individual student information. Table 2.2 presents the results for the Grade 4 exams. For reference, Column (1) contains the estimates for the raw P90-P10 achievement gaps, which were presented in the discussion of Figure 2.1.

To start, we investigate whether school resources can explain the income-achievement gaps we estimate. In British Columbia, school districts get funding largely from the provincial government, according to a formula that gives the same amount per full-time student equivalent. There is no available data on how monetary resources are distributed from a school district to individual schools, but there is data on average class size by school. Jackson et al. (2016) show that part of the benefits of increased school funding come through smaller class sizes. In Column (2), we include as controls average class sizes in the schools (British Columbia Data Catalogue, 2023). Class size reduces the income-achievement gap for our Baseline and East Asian students by about 10-15%. For South Asian students, class sizes matter more with the P90-P10 gap falling from 0.61σ to 0.49σ. On the other hand, class size does not seem to be important for the Indigenous P90-P10 gap, which only changes to 0.65σ.

There are several other factors besides class size at the school level that we cannot observe, such as quality of teachers. In Column (3), we include school fixed effects only and the P90-P10 achievement gaps fall by around 20-30% across all student groups. Thus, the sorting of high income parents into good quality schools explains a significant proportion of the raw P90-P10 achievement gap. As discussed in Section 2, British Columbia has a traditional public school system with catchment schools. Given that school quality is capitalized into house prices (Black, 1999), higher-income families are more likely to live in good school catchments. While British Columbia does have an open-enrolment policy, Friesen et al. (2015) showed that in 2006, the majority of students still attended their in-catchment school. Focusing on Indigenous students, the importance of school fixed effects in explaining the P90-P10 gap is in line with work by Friesen et al. (2010b) who study the test score gap between Indigenous and non-Indigenous students. They show that school characteristics account for around half of the raw difference in the Indigenous and non-Indigenous test score gap.

Another factor that may be correlated with both parental income and test scores is peer composition. In earlier work, Friesen et al. (2010b) do not find that peer composition is an important factor in explaining the Indigenous test score gap. However, Friesen et al. (2011) do find that having more Chinese speaking peers raises the test scores of Chinese students, while having more Punjabi speaking peers lowers the test scores of Punjabi students. In Column (4) we keep school fixed effects and then include variables to capture peer effects: the percentage of Baseline, Indigenous, East Asian, and South Asian students in a grade-school-year. Note that we cannot see the classroom assignments of students and therefore, our peer effects capture interactions among students of the same grade in a school, including those in the same classroom. Comparing Column (4) to Column (3), we see that adding peer fixed effects explains very little of the P90-P10 gap above what school fixed effects did. The coefficients do not change. This could be because there is little fluctuation in the composition of peers from year to year within a school-grade, and so school fixed effects essentially capture peer effects as well.

In Column (5) we keep school fixed effects as a control, but add in an indicator variable for if a student is ESL. Since our student population includes those who speak a language besides English at home, many of them may be immigrants who are learning English. As expected, ESL status does little to explain the income-achievement gap for English-Language students. However, ESL status explains about ten percent of the P90-P10 Indigenous gap, reducing it from 0.49 to 0.44σ. More striking, for East Asian students, including a control for ESL reduces the P90-P10 gap from 0.29 to 0.14σ. For South Asians, the gap falls from 0.42 to 0.32σ.

To get a deeper understanding of how ESL status affects income-achievement gaps, we present the share of ESL students by income quintile for our four student groups in Figure 2.3.[13] As expected, for our baseline group of students, very few are ESL since they speak English at home. For the rest of the students, there is a clear link between

[13]Due to data disclosure reasons we use income quintiles here instead of deciles.

ESL status and income. Twenty percent of Indigenous students from families in the bottom income quintile are ESL compared to around five percent in the top income quintile. For East Asian speaking and South Asian speaking students, the relationship is even starker. We see that the majority of both groups in the bottom income quintile are ESL students. Thus, the relationship between income and ESL explains why when controlling for ESL status, the income-achievement gap falls substantially.

Lastly, in Column (6) of Table 2.2 we add an indicator for special needs status. Controlling for special needs has little effect on the P90-P10 achievement gap (comparing Columns (4) and (6)) except for Indigenous students. For them, the gap falls from 0.49 to 0.44σ. The link between special needs and income is highlighted in Figure 2.4, which presents the proportion of special needs students by income quintile for each student group. Almost forty percent of Indigenous students in the bottom income quintile have special needs in comparison to twenty percent in the top income quintile. This explains why controlling for special needs status reduces the P90-P10 income achievement gap for Indigenous students but not for other groups of students. The higher prevalence of special needs among Indigenous students is related to work on the health disparities between Indigenous and non-Indigenous children.[14] Work by Smylie, 2012 highlights that the rate of pre-term births and low-weight births among Indigenous mothers is higher compared to the rate for all Canadians, and both these conditions may lead to developmental disabilities. We also find that there is a pronounced decrease in the rate of special needs diagnosis for Indigenous students as income increases. In line with our findings, Booth et al. (2008), Frohlich et al. (2006), and Hajizadeh et al. (2018) document a large health gap between Indigenous and non-Indigenous Canadians, of which income can be an important mediator.

[14] Relatedly, Elder et al. (2021) study the identification of special needs students among Black and Hipsanic children in the United States.

2.6.4 Achievement Gaps across Time and Subject

We now study how income-achievement gaps vary by subject and across time. Panel A (B) in Table 2.3 presents the raw P90-P10 gaps in numeracy (reading) results for Grade 4, and Panel C (D) presents the raw P90-P10 gaps in numeracy (reading) results for Grade 7.

We start by discussing subject differences. First, for English Language speakers, there is more inequality in test scores by income for numeracy with a gap of 0.59σ in Grade 4 (Column (1) Panel A) compared to 0.49σ in reading (Column (1) Panel B). On the contrary, the P90-P10 gap for Indigenous students is large for both numeracy (Column (2) Panel A) and reading (Column (2) Panel A) at around 0.7σ.

Differences across subjects are most pronounced for East Asian students. In Grade 4, the East Asian P90-P10 gap in numeracy is 0.33σ (Column (3) Panel A) compared to 0.48σ in reading (Column (3) Panel A). Relatedly, previous work has documented that East Asian students outperform other racial groups in mathematics (Kao, 1995). Part of this difference may stem from the fact that lower-income East Asian students are more likely to be ESL and thus may struggle more in reading comprehension. For South Asian students, we also see slightly higher gaps in reading though there is less of a difference (Column (4) of Panel A and B).

How do the income-achievement gaps change as students progress through school? Jerrim et al., 2012 study the difference in achievement gaps by socioeconomic status for Canada and find no significant increase from ages ten to fifteen.[15] However, we find that the gaps from Grade 4 to Grade 7 change differently by subject and student group. For English Language students, the Numeracy gap widens by 0.1σ, to 0.69σ (Panel C

[15] While they use parental education and number of books at home as a measure of socioeconomic status, we use before-tax household income. We also use panel data and our time frame is from ages nine to twelve.

Column (1)) while the Reading gap only grows slightly, to 0.52σ (Panel D Column (1)). We saw in Grade 4 that Indigenous students have the largest P90-P10 gap among the groups of students we study and this holds true in Grade 7 as well. The P90-P10 gap in Reading for Indigenous students grows to 0.76σ in Grade 7 (Panel D Column (2)). For East Asian students the gap in Numeracy in Grade 7 falls to 0.29σ (Panel C Column (3)) while the reading gap is similar at 0.46σ (Panel D Column (3)). For South Asian students, the gap in numeracy narrows to 0.46σ (Panel C Column (4)) while the gap in reading stays around 0.54σ (Panel D Column (4)).

In summary, our findings point to important differences in the relationship between income and achievement across different minority groups. For Indigenous students, there is the biggest disparity in test scores across income, while the gap for East Asian students is almost twice as small. Students who speak English at home and South Asian students have similar income-achievement gaps. These gaps arise by the fourth grade, when children are aged nine, and they persist into the seventh grade, three years later.

2.7 Robustness

Census Race Classification: To get a more accurate measure of race, we can restrict our sample to those who are linked to the census. The census has a question explicitly asking for the visible minority group that a student belongs to. We recalculate our income-achievement gaps using racial groups based on the census definition, but do not find large differences in our results. Section 2.10.1 in the Appendix goes into more details on the estimation and presents the results. Figure A2.1 shows binscatters of average test scores across parental income and Table A2.7 presents estimates of the income-achievement gap using Census data.

Alternative Measures of Income: Here we show that our results are robust to two different definitions of income. In our main results, the measure of income we used was before-tax household income. We check the sensitivity of our results using after-tax household income. We group our students into deciles based on the after-tax household income across the entire distribution. Then, we separately calculate the P90-P10 gaps using our new definition of income for each student group. In Panel A of Table A2.6 in the Appendix we have our original P90-P10 estimates using before-tax household income for comparison, and Panel B presents the new P90-P10 gap estimates using after-tax household income results. Comparing our estimates between Panel A and Panel B, we see that using after-tax household income hardly changes our results. The P90-P10 gaps for each group of students is essentially the same as our original estimates.

Another check we do is to scale our measure of income by household size. Children in our dataset come from families varying in size and a household income of $40,000 for a family of three is not equivalent to the same income for a family of six. Controlling for household size may also be important since one of our subgroups of interest is Indigenous students. The Indigenous population in Canada has lower-income and higher birth rates than non-Indigenous people (Smylie et al., 2014). Therefore, using income that is not scaled by household size may overstate the resources that can be allocated to each child in the family. We follow the Statistics Canada guidelines for scaling and divide after-tax household income by the square root of family size, which takes into consideration that resources can be shared among household members[16]. We then calculate each student's decile of scaled after-tax family income across all students.

Panel C of Table A2.6 presents our results using the scaled measure of income. Again, using this definition of income does not changes our measures of the P90-P10 gap substantially. Thus, our estimates of the income-achievement gap across racial groups are robust to different definitions of income.

[16]See `https://www23.statcan.gc.ca/imdb/p3Var.pl?Function=DEC&Id=103386`

2.8 Conclusion

In this paper we studied the income-achievement gaps among race using administrative education data from British Columbia. We find income-achievement gaps between the bottom and top income decile ranging from 0.37 to 0.7σ at age nine. The range in gaps widens slightly when children are aged 12. While these magnitudes are lower than the average of around one standard deviation documented for the United States, there is important heterogeneity.

East Asian students have the lowest income-achievement gaps and the highest level of test scores, while Indigenous students have the highest gaps and the lowest level of test scores. We note that school factors explains a significant part of the income-achievement gap across all student groups, while ESL status is important for East Asian and South Asian students.

We are able to link the high income-achievement gap among Indigenous students to special needs status: conditional on being low-income, Indigenous students are much more likely to be diagnosed with special needs. Further, we present some suggestive evidence that the gap may also be associated with family structure. In all, our findings point to the need for policies targeted at creating more equitable outcomes for Indigenous students, and students with special needs.

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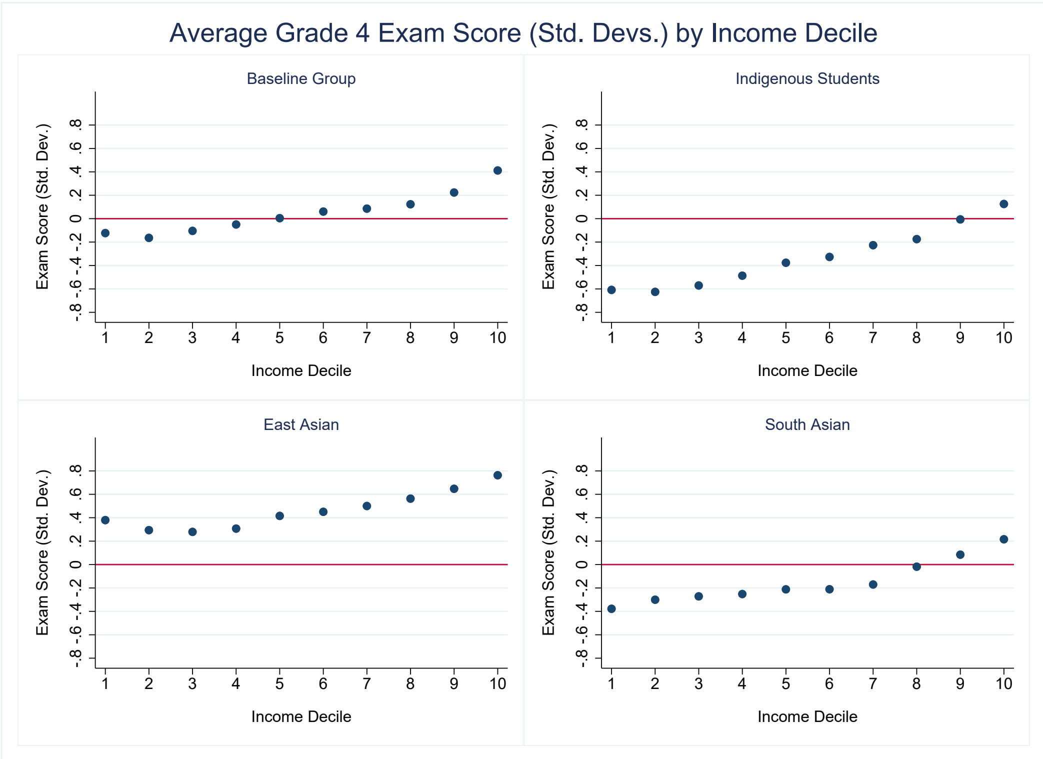
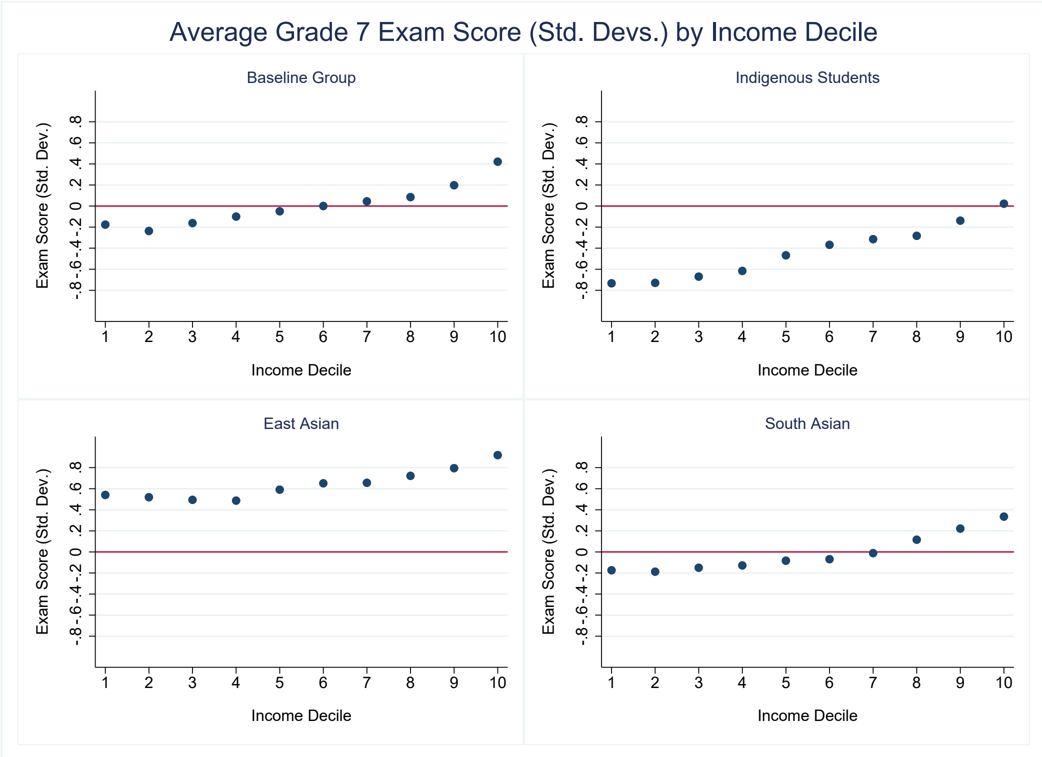
2.9 Tables and Figures

Figure 2.1: Income-Achievement Gaps in Grade 4



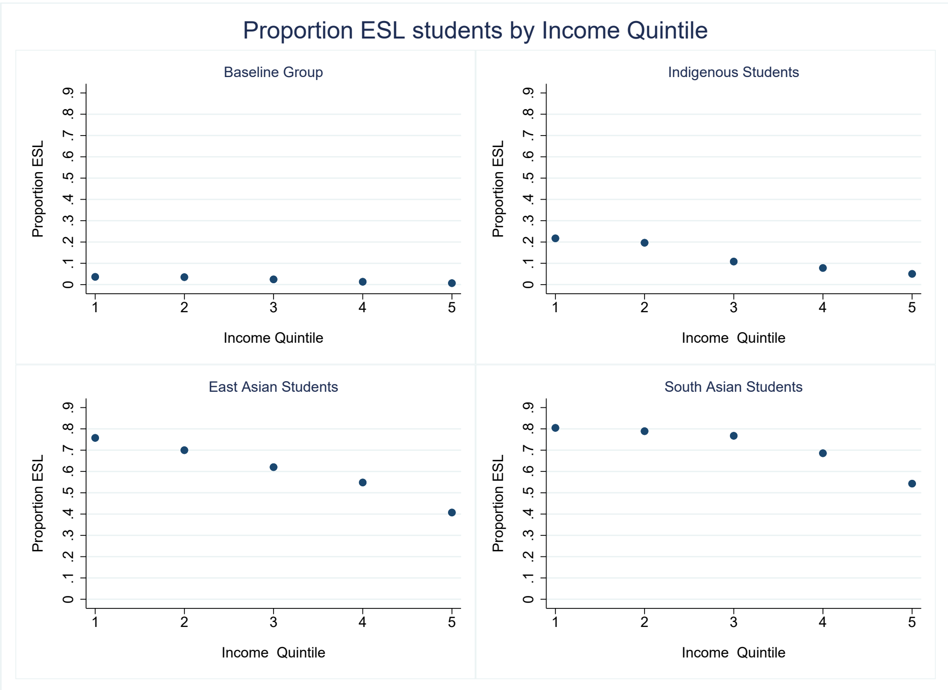
Notes: Each figure plots the average Grade 4 FSA score across both reading and numeracy by each income decile. Top left figure is for the baseline group of students, who speak English at home. Top right figure is for Indigenous students. Bottom left figure is for students speaking Chinese or Korean at home. Bottom right figure is for students speaking a South Asian language at home. Income deciles are calculated from before-tax household income and the deciles are calculated across the entire cohort of students.
Source: Author's own calculations using data from B.C. Minister of Education, Statistics Canada.

FIGURE 2.2: Income-Achievement Gaps in Grade 7



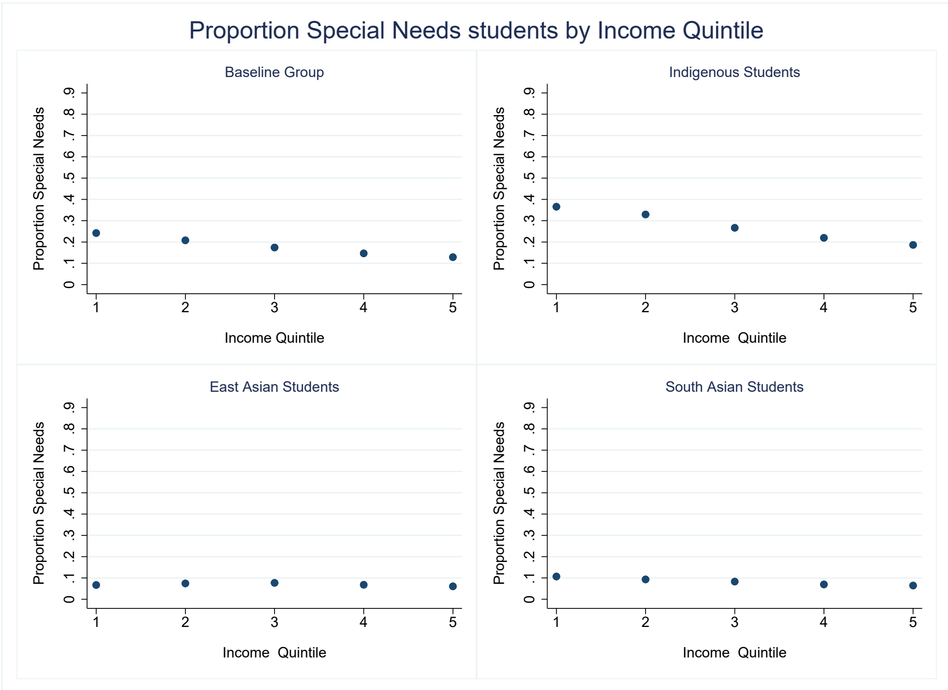
Notes: Each figure plots the average Grade 7 FSA score across both reading and numeracy by each income decile. Top left figure is for the baseline group of students, who speak English at home. Top right figure is for Indigenous students. Bottom left figure is for students speaking Chinese or Korean at home. Bottom right figure is for students speaking a South Asian language at home. Income deciles are calculated from before-tax household income and the deciles are calculated across the entire cohort of students.
Source: Author's own calculations using data from B.C. Minister of Education, Statistics Canada.

FIGURE 2.3: Proportion ESL by Income Quintile



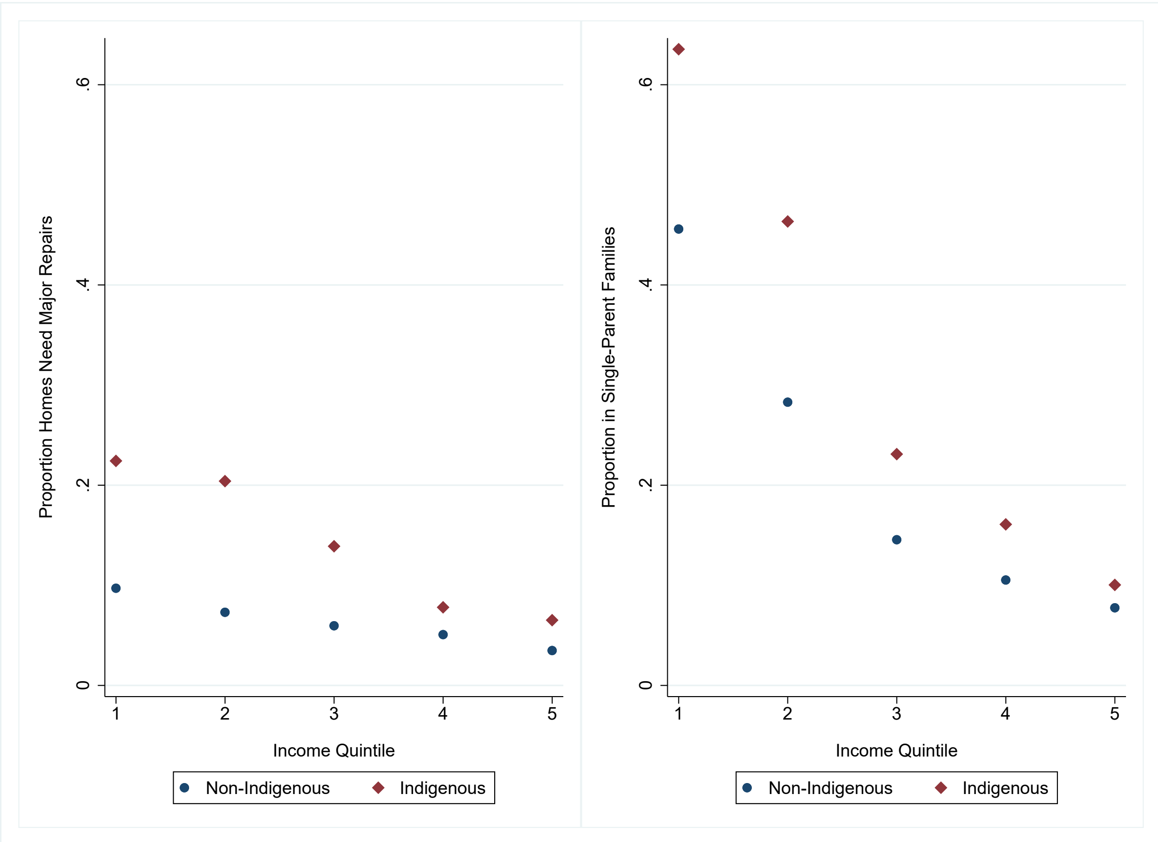
Notes: Each figure plots the share of ESL students each income quintile. Top left figure is for the baseline group of students, who speak English at home. Top right figure is for Indigenous students. Bottom left figure is for students speaking Chinese or Korean at home. Bottom right figure is for students speaking a South Asian language at home. Income quintiles are calculated from before-tax household income and the quintiles are calculated across the entire cohort of students.
Source: Author's own calculations using data from B.C. Minister of Education, Statistics Canada.

FIGURE 2.4: Proportion Special Needs by Income Quintile



Notes: Each figure plots the share of special needs students each income quintile. Top left figure is for the baseline group of students, who speak English at home. Top right figure is for Indigenous students. Bottom left figure is for students speaking Chinese or Korean at home. Bottom right figure is for students speaking a South Asian language at home. Income quintiles are calculated from before-tax household income and the quintiles are calculated across the entire cohort of students.
Source: Author's own calculations using data from B.C. Minister of Education, Statistics Canada.

FIGURE 2.5: Home Condition and Family Composition by Income Quintile and Indigenous Status



Notes: The left figure plots the share of students from each income quintile who live in a house that needs major repairs by Indigenous status. Major repairs are defined as defective electrical wiring, plumbing, or structure. The right figure plots the share of students from each income quintile who live with a single parent. Indigenous classification is based on the 2016 Census. Income quintiles are calculated from before-tax household income and the quintiles are calculated across the entire cohort of students.
Source: Author's own calculations using data from B.C. Minister of Education, Statistics Canada.

TABLE 2.1: Summary Statistics

	Full Sample	Grade 4 FSA	Grade 4 and 7 FSA
	(1)	(2)	(3)
Number of Students	207,120	174,370	148,060
Average Household Income ($)	65,600	67,900	69,500
% English Language	64	65	65
% Indigenous	13	12	11
% East Asian	7.6	7.2	7.4
% South Asian	7.5	7.7	8.2
% Special Needs	17	13	11
% English as Second Language	20	19	19
% Private School	12	13	14

Notes: Column (1) contains summary statistics for the cohort of students in Grade 4 from 2008 to 2012. Column (2) is the subset of the full sample who wrote the FSA in Grade 4. Column (3) is the subset of students who wrote the FSA in Grade 4 and Grade 7. Source: Author's calculations from the BCK-12 linked to T1FF dataset from Statistics Canada (BC Ministry of Education and Child Care, 2021; Statistics Canada, 2021).

Table 2.2: Income Achievement Gaps: English-Language, Indigenous, East Asian, and South Asian Students

	Grade 4					
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Baseline						
P90-P10	0.54***	0.46***	0.34***	0.34***	0.33***	0.31***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
N	113170	92410	113170	113170	113170	113170
R^2	0.040	0.037	0.184	0.184	0.186	0.216
Panel B: Indigenous						
P90-P10	0.69***	0.65***	0.49***	0.49***	0.44***	0.44***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
N	19820	17950	19820	19820	19820	19820
R^2	0.055	0.059	0.243	0.243	0.280	0.270
Panel C: East Asian						
P90-P10	0.37***	0.33***	0.29***	0.29***	0.14***	0.29***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)
N	11630	9520	11630	11630	11630	11630
R^2	0.025	0.026	0.156	0.157	0.219	0.175
Panel D: South Asian						
P90-P10	0.61***	0.49***	0.42***	0.42***	0.32***	0.41***
	(0.08)	(0.08)	(0.07)	(0.07)	(0.06)	(0.06)
N	12560	10350	12560	12560	12560	12560
R^2	0.013	0.021	0.294	0.294	0.334	0.314
Average School Size	No	Yes	No	No	No	No
School Fixed Effects	No	No	Yes	Yes	Yes	Yes
Peer Effects	No	No	Yes	No	No	No
English as a Second Language	No	No	No	No	Yes	No
Special Needs Status	No	No	No	No	No	Yes

Notes: This table presents the average test score gap in standard deviation units between the top and bottom income decile for the Grade 4 FSA. FSA scores are averaged across subjects. Column (1) presents results with No Controls, Column (2) adds school fixed effects, with peer effects also included in Column (3). Column (4) includes school fixed effects and an indicator for whether the student is English as a Second Language. Column (5) includes school fixed effects and an indicator for whether the student has special needs. Panel A presents the P90-P10 gap for our "baseline" group: students who speak English at home. Results for Indigenous students are in Panel B. Panel C presents results for East Asian students and Panel D for South Asian students. In the case of multiple FSA attempts, the first attempt is used. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021).*

Table 2.3: Income-Achievement Gaps by Subject Across Grades 4 and 7

Panel A: Grade 4 Numeracy				
	English Language	Indigenous	East Asian	South Asian
	(1)	(2)	(3)	(4)
P90-P10	0.59***	0.71***	0.33***	0.61***
	(0.02)	(0.05)	(0.04)	(0.10)
Number of Students	113860	20100	11820	12630
R^2	0.04	0.04	0.02	0.01
Panel B: Grade 4 Reading				
	English Language	Indigenous	East Asian	South Asian
	(1)	(2)	(3)	(4)
P90-P10	0.49***	0.69***	0.48***	0.62***
	(0.02)	(0.05)	(0.05)	(0.08)
Number of Students	114320	20190	11690	12630
R^2	0.03	0.04	0.02	0.01
Panel C: Grade 7 Numeracy				
	English Language	Indigenous	East Asian	South Asian
	(1)	(2)	(3)	(4)
P90-P10	0.69 ***	0.73***	0.29***	0.39 ***
	(0.03)	(0.05)	(0.05)	(0.09)
Number of Students	105060	18010	12260	12660
R^2	0.05	0.06	0.02	0.01
Panel D: Grade 7 Reading				
	English Language	Indigenous	East Asian	South Asian
	(1)	(2)	(3)	(4)
P90-P10	0.52***	0.76***	0.46***	0.54***
	(0.02)	(0.06)	(0.04)	(0.07)
Number of Students	105940	18290	12240	12710
R^2	0.03	0.05	0.020	0.01

Notes: P90-P10 achievement gaps by for numeracy (reading) for Grade 4 in Panel A (B). P90-P10 achievement gaps by for numeracy (reading) for Grade 7 in Panel C(D). Columns (1)-(4) present the raw P90-P10 gaps for English Language, Indigenous, East Asian and South Asian students. Standard errors in parentheses. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021).*

2.10 Appendix

Table A2.1: Demographics in British Columbia and Canada, 2006 Census

	British Columbia	Canada
% Indigenous	4.8	3.7
% Chinese	10	3.9
% Southeast Asian	1.0	0.8
% South Asian	6.4	4.0
% Black	0.7	2.5
% No High School	12	15
% University Degree	23	24

Notes: Demographic shares from British Columbia in Column (1) and Canada overall in Column (2). *Source: Statistics Canada, 2008a; Statistics Canada, 2008c; Statistics Canada, 2008b*

2.10.1 Results using the Census

The results in the main body of the paper characterized East Asian and South Asian students using language spoken at home. While it seems likely that students who speak an Asian language at home are likely to be of an East Asian or South Asian race, students who speak English at home may also be East or South Asian. Section 2.4 discussed possible biases from this measurement error. Here, we use the subsample of our data that is linked to the census. The census asks respondents to identify which visible minority group they belong in and we focus again on East Asian (Chinese/Korean)[17], South Asian and Indigenous students. As our baseline group, we use students who identify as White.

Figure A2.1 below presents the average test score across both subjects in Grade 4 for White, Indigenous, East Asian, and South Asian students as defined by the Census. Due to the smaller sample size and data reporting guidelines, we bin income by before-tax household quintile (instead of decile). We see very similar patterns across race for the

[17]We select these two groups so that it matches with the language groups in the BC administrative data

TABLE A2.2: Income-Achievement Gap by Baseline and Visible Minority Group

	(1) Grade 4 Test Score	(2) Grade 4 Test Score	(3) Grade 4 Test Score
P90-P10	0.53^{***}	0.53^{***}	0.53^{***}
	(0.02)	(0.02)	(0.02)
P90-P10 · Indigenous	0.16^{***}		
	(0.05)		
P90-P10 · East Asian		-0.16^{***}	
		(0.04)	
P90-P10 · South Asian			0.08
			(0.08)
Indigenous	-0.49^{***}		
	(0.03)		
East Asian		0.52^{***}	
		(0.03)	
South Asian			-0.26^{**}
			(0.08)
Constant	-0.12^{***}	-0.12^{***}	-0.12^{***}
	(0.02)	(0.02)	(0.02)
N	133160	124970	125900
R^2	0.086	0.049	0.048

Notes: This table presents regression results that test the difference in income-achievement gaps between Baseline students and Indigenous (Column (1)), East Asian (Column (2)), and South Asian (Column (3)) students. Income deciles are interacted with an indicator for the minority group in question. Standard errors are in parentheses. The dependent variable is the average of Grade 4 numeracy and reading FSA in standard deviations. Income deciles are calculated from before-tax household income. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021)*

TABLE A2.3: Indigenous Income-Achievement Gap: Housing and Family Composition Controls

	(1) Grade 4 Test Score	(2) Grade 4 Test Score	(3) Grade 4 Test Score
P80-P20	0.69^{***}	0.67^{***}	0.63^{***}
	(0.06)	(0.05)	(0.06)
Controls	None	Major Repairs	Single-Parent
N	5030	5030	4850
R^2	0.060	0.063	0.060

Column (1) presents the raw P80-P20 estimates for Indigenous students in the Census. Column (2) includes an indicator for if the student lives in a dwelling that needs major repairs. Column (3) includes an indicator for if the student is from a single-parent family. Standard errors in parentheses. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021)*

TABLE A2.4: Income-Achievement Gap for Indigenous Students by On/Off-Reserve

	(1) Grade 4 Test Score	(2) Grade 4 Test Score
P80-P20	0.59^{***}	0.44^{***}
	(0.03)	(0.03)
On-Reserve	-0.38^{***}	-0.28^{***}
	(0.05)	(0.04)
P80-P20 ·On-Reserve	-0.26	-0.10
	(0.14)	(0.12)
Constant	-0.56^{***}	-0.53^{***}
	(0.02)	(0.01)
School Fixed Effects	No	Yes
N	19820	19820
R^2	0.08	0.25

Notes: This table presents regression results that test for heterogeneity in the income-achievement gap between on versus off-reserve Indigenous students. Income quintiles are interacted with an indicator for an Indigenous student living on-reserve. Standard errors are in parentheses. The dependent variable is the average of Grade 4 numeracy and reading FSA in standard deviations. Income deciles are calculated from before-tax household income. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021)*

TABLE A2.5: Income-Achievement Gap for Indigenous Students by Class Size

	(1) Grade 4 Test Score	(2) Grade 4 Test Score	(3) Grade 4 Test Score	(4) Grade 4 Test Score
P80-P20	0.65^{***}	0.59^{***}	0.63^{***}	0.59^{***}
	(0.07)	(0.07)	(0.04)	(0.04)
Special Needs		-0.36^{***}		-0.36^{***}
		(0.03)		(0.02)
Sample	Small Class Size	Small Class Size	Large Class Size	Large Class Size
N	7630	7630	12190	12190
R^2	0.051	0.084	0.053	0.081

Standard errors in parentheses

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

Notes: This table presents regression results that split the sample of Indigenous students into those attending schools with class sizes below the median (Columns (1) and (2)) and above the median (Columns (3) and (4)). Columns (1) and (3) present the raw P80-P20 gap, while Columns (2) and (4) include a control for special needs. Standard errors are in parentheses. The dependent variable is the average of Grade 4 numeracy and reading FSA in standard deviations. Income quintiles are calculated from before-tax household income. $^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021)*

Table A2.6: Income Achievement Gaps: English-Language, Indigenous, East Asian, and South Asian Students: Different Measures of Income

	Grade 4			
	Baseline	Indigenous	East Asian	South Asian
	(1)	(2)	(3)	(4)
Panel A: Before- Tax				
P90-P10	0.54***	0.69***	0.37***	0.61***
	(0.02)	(0.04)	(0.04)	(0.08)
N	113170	19820	11630	12560
R^2	0.04	0.05	0.03	0.01
Panel B: After Tax				
P90-P10	0.55***	0.68***	0.38***	0.58***
	(0.02)	(0.04)	(0.04)	(0.08)
N	113170	19820	11630	12560
R^2	0.04	0.05	0.02	0.01
Panel C: After Tax Scaled by Family Size				
P90-P10	0.55***	0.71***	0.42***	0.55***
	(0.02)	(0.04)	(0.040)	(0.07)
N	110820	18970	11620	12540
R^2	0.04	0.06	0.03	0.01

Notes: This table presents the average test score gap in standard deviation units between the top and bottom income decile for the Grade 4 FSA. FSA scores are averaged across subjects. Column (1) presents estimates for the Baseline group (those who speak English at home), Column (2) for Indigenous students, Column (3) for East Asian Students and Column (4) for South Asian Students. No controls are included. Panel A presents estimates where income deciles are computed across all students using before-tax household income. Panel B presents estimates where income deciles are computed across all students using after-tax household income. Panel C presents estimates where income deciles are computed across all students using after-tax household income scaled by family size. The scaling is done by dividing after-tax household income by the square root of family size. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021)* level of test scores and the income-achievement gradients in the census as previously reported using the administrative data. Namely, the slope of the gradient for East Asian students is the lowest among the four groups of students, and they also have the highest intercept. White and South Asian students have similar gradients, while Indigenous students have the lowest test scores in terms of level and also the steepest income gradients.

Table A2.7 presents the average score in the top quintile relative to the bottom quintile (P80-P20 gap). The first column uses the administrative data and the definition of the student groups from that dataset. The second column presents P80-P20 estimates using the definitions of students from the census. We start with Panel A, which compares English-Language speaking students in Column (1) from the administrative data to students identifying as White in the Census in Column (2). We find similar estimates among these two groups. Over eighty percent of students who speak English at home identify as White in the Census and the remainder are mostly East Asian or South Asian. The P80-P20 gap for White students is similar to that for English-speaking students (0.48σ versus 0.47σ).

Panel B of Table A2.7 calculates the P80-P20 gap for Indigenous students in the administrative data (Column (1)) and the Census (Column (2)). The Census point estimate is slightly higher, though not statistically significantly different. In Panel C, for East Asian students, we find that using the Census definition reduces the P80-P20 gap by 0.1σ. On the other hand, the gap for South Asian students (Panel D) only changes by 0.01 σ.

Thus, whether using language at home as a proxy for race from the administrative education data, or visible minority definitions from the census we find that the following facts are consistent: East Asian students have the smallest income-achievement gradients. The relationship between income and test scores is similar between White students and South Asian students. Indigenous students have significantly larger income-achievement gaps.

Table A2.7: Grade 4 Income Achievement Gaps: Group classification from Administrative Data and Census

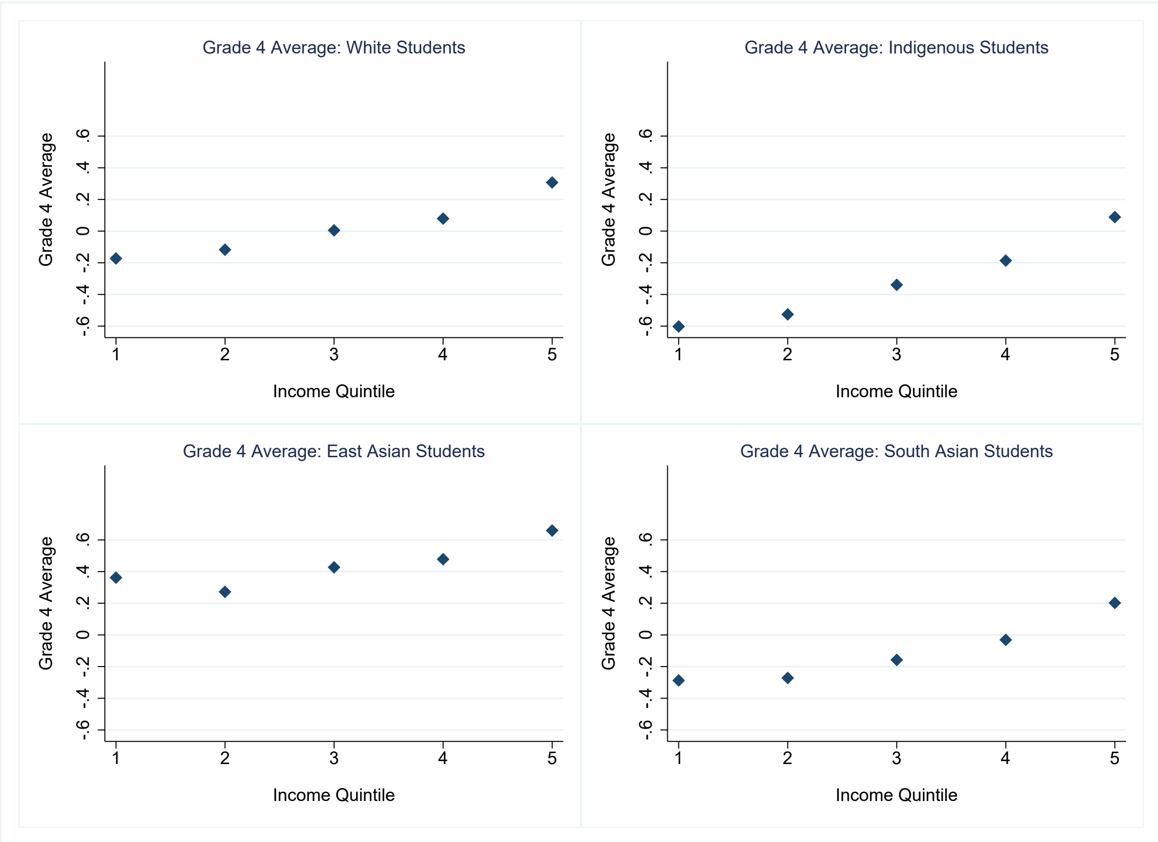
	(1) Admin	(2) Census
Panel A: English Language and White		
P80-P20	0.47***	0.48***
	(0.01)	(0.02)
N	113170	22410
R^2	0.04	0.04
Panel B: Indigenous		
P80-P20	0.65***	0.69***
	(0.03)	(0.06)
Number of Students	19820	5030
R^2	0.054	0.053
Panel C: East Asian		
P80-P20	0.38***	0.30***
	(0.03)	(0.04)
Number of Students	11630	4200
R^2	0.022	0.026
Panel D: South Asian		
P80-P20	0.48***	0.49***
	(0.05)	(0.06)
Number of Students	12560	4210
R^2	0.01	0.03

Notes: Column (1) presents the raw P80-P20 estimates using student classification groups from the Administrative data. Column (2) presents the raw P80-P20 estimates using student classification groups from the 2016 Census. *Source: BC Ministry of Education and Child Care (2021) and Statistics Canada (2021)*

2.10.2 Accessing the BCK-12 Data

The data used here comes from the Education and Labour Market Longitudinal Platform (ELMLP) run by Statistics Canada. The ELMLP links administrative data on the education and labour market outcomes of Canadians. This paper utilized linkages

Figure A2.1: Income-Achievement Gaps: Census



Notes: Each figure plots the average Grade 4 FSA score across both reading and numeracy by each income quintile. Top left figure is for the group of students who identify as White. Top right figure is for Indigenous students. Bottom left figure is for students who are East Asian. Bottom right figure is for students who are South Asian. Visible minority classifications are based on the census. Income quintiles are calculated from before-tax household income and the quintiles are calculated across the entire cohort of students.
Source: Author's own calculations using data from B.C. Minister of Education, Statistics Canada.

of tax records to test scores from British Columbia and census responses. Other linkages available, but not utilized here include: apprenticeship information, post-secondary enrolment, student loans, and immigration records. For more information on accessing data from the ELMLP, see `https://www150.statcan.gc.ca/n1/pub/37-20-0001/372000012021006-eng.htm`.

There are several previous papers that have used the BC K-12 data (without the tax linkage) including: Friesen et al. (2011), Friesen et al. (2010b), and Friesen et al. (2010a). At this time, several projects are using various datasets from the ELMLP and Statistics Canada has a repository of current projects at `https://www.statcan.gc.ca/en/microdata/data-centres/data/projects#wb-auto-2`.

Chapter 3

The Impact of Switching Majors on Earnings

Abstract

I investigate the impact of switching post-secondary majors on labour market earnings, focusing on the differential impact between men and women. Estimation of the causal impact of switching is made difficult by the endogeneity of the switching decision; students can often choose both when, and where, to switch. I address this difficulty using rich administrative data from the Canadian province of British Columbia that allow me to track individual high school grades, post-secondary enrollment decisions and earnings. Using covariates that are closely associated with the switching decision, I construct a matching estimator that allows me to create a credible counterfactual group for switchers. I find that switching increases the earnings of men by approximately 5 % on average, while it decreases the earnings of women by 1 %. There is considerable heterogeneity in the impact of switching for women across initial major, as women departing STEM majors increase earnings by approximately 50 % while those departing Business and Health majors experience a decline in earnings of 49 %.

3.1 Introduction

The choice of college major is consequential for future earnings. The earnings gap between college majors can be as wide as the gap between college and high school graduates (Altonji et al., 2012; Altonji et al., 2016). Moreover, gendered differences in college major selection account for a substantial portion of the gender gap in earnings among workers with a college education (Altonji, Arcidiacono and Maurel, 2015; Bleemer and Mehta, 2022; Zafar, 2012; Brown and Corcoran, 1997). However, major selection is not a one-shot decision as students may decide to change majors before graduation. Indeed, major switching is common in post-secondary education with over a third of US students doing so during their time in college (US Department of Education, 2017).

While a growing body of work examines the academic and social factors associated with the switching decision, no work thus far has examined the relationship between major switching and labour market earnings. I study this relationship and provide causal evidence of how labour market earnings change given switches in major, with an emphasis on the differential impact of switching between men and women. Specifically, I estimate the impact of changing majors on labour market earnings post-graduation. I use administrative data from the Canadian province of British Columbia (BC) that links high school outcomes, post-secondary enrollment, and individual tax information. Following Arcidiacono (2004) and Quadlin (2017), I group majors into four broad fields: Liberal and Fine Arts (LFA), Science, Technology, Engineering and Math (STEM), Social Science and Education (SSE), and Business, Health and Professional Services (BHPS). In the main part of my analysis, a switch is defined as a change between these aggregate fields. In what follows I use the word "major" to refer to lower levels of aggregation (i.e., engineering vs. computer science).

To study the impact of major switching on post-graduation earnings I must address the endogeneity of the switching decision. Namely that switchers are (for the most part) able to choose when they switch and there may be systematic differences between switchers and non-switchers. This presents a challenge for causal identification as these differences between switchers and non-switchers may also drive differences in earnings outcomes (Kirkeboen et al., 2016). To address this endogeneity issue, I employ a double-robust matching estimator which re-weights individuals by their estimated likelihood of switching majors using a credible set of predictors. I then estimate a carefully specified model of switching on labour market earnings using these re-weighted observations. To study the potential gendered differences in the impact of major switching on earnings I apply my empirical methodology separately on men and women.

Switching is a fairly common practice in my data, with nearly one-third of both men and women changing majors. Moreover, there is considerable variation in switch rates across fields, with nearly 50 % of LFA students switching fields compared to only 12 % of BHPS students. Both male and female switchers possess lower average levels of academic achievement than non-switchers, as measured by performance in the mandatory Grade 10 courses of English, Math and Science.

My results suggest the impact of switching majors on earnings is heterogeneous, both by gender and initial field of study. Both men and women switching out of LFA majors experience an increase in their earnings (an average increase of $10 000 for men and $6000 for women), while switching out of SSE majors has no statistically significant impact on earnings for either men or women. There is a noticeable gendered difference when switching out of the higher-earning fields of STEM and BHPS. Men departing majors in either field experience no statistically significant effect on their labour market earnings. However, women departing STEM experience a large increase in their earnings (approximately, $15 500) while those departing BHPS experience a large decline (approximately, $23 000). Accordingly, switching majors appears to be a more consequential decision for women relative to men.

My empirical strategy relies on two key assumptions. First, there is sufficient overlap in the likelihood of switching. For each field of study, I demonstrate that there is sufficient overlap in estimated propensity scores across switchers and non-switchers. Balance tests conducted across a range of baseline academic and demographic characteristics following the matching procedure support this assumption. Second, the identifying assumption is that, conditional on the covariates, assignment to treatment is essentially randomized. This assumption is not violated so long as the covariates incorporated into the estimation procedure address all the factors associated with the decision to switch. To this end, I incorporate covariates that have been identified in the switching literature as key to understanding the motivation to switch including academic and social factors, and the potential earnings of original majors.

My results have several implications for student pathways through post-secondary education. To start, while I am unable to examine the motivations for major switching, switchers from traditionally low-earning majors appear more likely to switch into majors with higher labour-market returns. This is in line with survey evidence reported by Arcidiacono et al. (2012) who find that approximately ten percent of students would change to a higher-earning major if they could. This may suggest that some students focus on, or learn about, the pecuniary benefits of majors once enrolled in higher education. This result highlights the need to improve information on the earnings consequences of switching majors for post-secondary students.

The remainder of this paper is structured as follows. In Section 2, I discuss the contribution of this paper to the existing literature. Sections 3 and 4 discuss the institutional setting and data, respectively. Section 5 presents my empirical methodology, while Section 6 provides descriptive results. Finally, Section 7 discusses the results of the causal estimation.

3.2 Literature Review

This paper contributes to three strands of literature involving research on: major switching, field of study and earnings, and major choice in post-secondary education. Research on major switching has identified three categories most closely associated with the switching decision: academic, social, and future earnings. Students may be uncertain about their own ability when enrolling in a major and, in response to grades received in major-related courses, may choose to leave if their grades provide a signal of academic mismatch (Altonji, 1993; Arcidiacono, 2004; Stinebrickner and Stinebrickner, 2013; Hsu, 2017). Moreover, Astorne-Figari and Speer (2019) demonstrate that students departing majors for academic reasons most often enroll in majors of similar difficulty, suggesting there is limited chance to “switch up" academically if a student is falling behind in their initial major.

Beyond academic reasons, social factors may also contribute to the switching decision. Smart, Feldman and Ethington (1999) emphasize that a match between a student's personality and the culture of a major may increase the probability of graduation. Further, Kugler et al. (2021) show that women in male-dominated majors are more sensitive to negative academic signals than women in female-dominated majors, suggesting academic signals may be moderated by a program's culture. Finally, students' concerns over the future earnings potential of their major has been identified as a possible motivator for the switching decision. Using administrative data from Montana State University, Schemiser et al. (2016) show that students informed of their potential inability to pay back student loans are likely to switch into majors with higher mean earnings than their current major. Moreover, Wright (2018) uses survey data on American college students to illustrate that concerns over future earnings become a key motivator for switching majors once individuals are enrolled in higher education. All of these factors (academic, social and earnings) are taken into consideration in the empirical methodology of this paper.

To this literature I make the key contribution of providing causal estimates for the impact of switching on labour market earnings. While some research has found the pecuniary benefits of a major to be a potential motivator for switching, no work has examined how the earnings of students change when they switch majors. Moreover, limited work in the switching literature has examined the consequences of changing majors. An exception that is closely related to this work is by Liu et al. (2021) who examine the academic consequences of major changes in US community colleges. The authors find statistically significant increases in completion among switchers, suggesting that switching allows students to find a better academic match. My work contributes to the switching literature by examining the earnings consequences of switching fields.

A key finding from my analysis is the differential impact that switching out of various majors has on average labour market earnings. In particular, the differential effect of switching out of similar majors between men and women. This contributes to the broader literature on the impact of major-choice on earnings. Prior work in this literature has employed novel methodologies to identify the causal impact of field of study on labour market outcomes. Bleemer and Metha (2022) study the return to an economics degree by exploiting a GPA cutoff for declaring a major, finding that those students just above the threshold earned 46 percent higher annual wages than they would have in their second choice majors. Using ranked application lists and admission cutoffs into preferred fields, Kirkeboen et al. (2016) find widely different payoffs to alternative fields of study. Other research makes use of selection-on-observable methodologies to identify major specific returns (e.g. Hamermesh and Donald, 2008; Hasting et al., 2014).

Finally, this work ties into the literature on major choice in post-secondary education. The factors influencing major choice are many including future economic returns (Delaney and Devereux, 2019), preferences for work environment (Wiswall and Zafar, 2018), and the influence of peers (Mouganie and Wang, 2020). Moreover, gendered differences in major selection have resulted in the under-representation of women in key high-earning STEM fields, including Engineering and Computer Science (Shi, 2018). To this literature, this work contributes a documented pattern of major-choice convergence among switchers. Indeed, the majority of switchers enroll in programs in the field of BHPS, which offers the largest labour market returns among all fields. While this work does not analyze the factors motivating the switching decision, the convergence of switchers onto a high earning field may speak to the influence that pecuniary benefits have on major choice after initial enrollment.

3.3 Institutional Setting

The province of British Columbia provides an ideal setting for this study for two main reasons. First, the province has a large and interconnected post-secondary education sector. While universities and community colleges largely offer Bachelors degrees and Diplomas, respectively, it is not uncommon for either institution-type to offer a mix of accreditations' (i.e., both Bachelors and Diplomas). Moreover, institutions often have "transfer programs" designed to move students from community college to university and vice versa, reducing the costs of inter-institution transfers. The interconnected nature of BC's post-secondary system allows for the incorporation of community colleges into my analysis, a sector of the post-secondary market that is often ignored in the switching literature (for an exception see Liu et al., 2021). Specifically, while this work focuses on those students who begin in a Bachelors programs I follow students who switch into community college programs.

Second, during the time period of my study, high school students in BC took mandatory courses in Science, Math and English in Grade 10. This combination of courses measure students' literacy and numeracy skills providing a multidimensional measure of academic ability in contrast to solely using in-program GPA. Furthermore, there are two distinct marks available for each course. Marks assigned by teachers for work during the term and also marks from a province-wide exam in each subject worth 20 % of the final grade. These different marks potentially allow for the coverage of both cognitive and non-cognitive skills (for example see, Kautz et al., 2014; Korthals et al., 2021; DeAngelis, 2021), both of which may be important determinants for persistence in a university program.

3.4 Data

I make use of three linked sources of individual level administrative data: high school records, post-secondary enrollment data, and longitudinal earnings information from tax records. The first, provided by the British Columbia Ministry of Education, covers the universe of students attending public and independent schools in that province between 1994 and 2020.[18] These data include student-year level demographic information including gender, age, school attended, and home and school postal codes. Academic information includes marks (in percent) from provincial exams, teacher assigned high school marks in certain subjects, and courses taken in high school. The empirical strategy I employ requires measures of students' academic ability as control variables to predict major switching. To this end, I employ the teacher-assigned and provincial exam marks from mandatory Grade 10 courses in Science, English and Mathematics. Percent marks for both the provincial exam and teacher-assigned work are standardized to have mean zero and variance one within each year-subject cohort.

Second, the Postsecondary Student Information System (PSIS) collected by Statistics

[18]Independent schools are privately-operated schools that operate in British Columbia. These independent schools must hire teachers that are certified by the province and adhere to provincial curriculum.

Canada provides annual post-secondary enrollment records for students in Canadian universities and community colleges. The dataset covers 2008 to 2020 and includes student-year information on enrollment status, field of study, degree-type, institution, program start and end dates, and province of study. As British Columbia's post-secondary sector is highly integrated, with some college-level accreditation awarded at universities and vice versa, I refer to programs by accreditation awarded (either Bachelor's or Diploma) rather than institution-type. I restrict attention to those who begin their post-secondary education at a university in British Columbia but do not restrict where they can switch to in Canada.[19] I restrict the number of degrees an individual can complete to one in order to focus on the early-career earnings of persons who transition into the workforce upon graduation.

I create two field-of-study groupings based on the 2-digit Classification of Instructional Program (CIP). The first, referred to as majors, consists of eighteen programs listed in Appendix Table A3.1 (examples include English and Engineering). The second, referred to as fields, aligns with work by Arcidiacono (2004), and groups together the eighteen programs into four large groups: Liberal and Fine Arts (LFA), Science, Technology, Engineering and Math (STEM), Social Science and Education (SSE) and Business Health and Professional Service (BHPS). The majors that are incorporated into each group are shown in Appendix Table 3A.1. A switch is defined as movement between one of the four fields (e.g. moving from LFA to BHPS) prior to graduation from one's first degree. This movement may be between fields across accreditation-types (e.g. moving from LFA at a Bachelor's level to BHPS at a Diploma level). In a robustness exercise I relax the definition of switch to include movements between majors within a field.

Finally, for information on earnings, I employ longitudinal tax data from Statistics

[19] 96% of individuals in my sample begin their studies in British Columbia.

Canada which contains information from individual tax returns. This includes individual's before-tax, after-tax, employment and self-employment income from 1994 until 2020. My primary dependent variable is individual labour-market earnings. Labour-market earnings are defined as the sum of employment income and positive self-employment income. To align with Kirkeboen et al. (2016) and conform to the limitations of my dataset, I measure labour-market earnings eight-years after the individual begins post-secondary education. Using earnings at this point in time has two advantages. First, relating earnings to time of initial enrollment, rather than time of degree-completion, avoids endogeneity issues concerning time to graduation. Second, by eight-years after beginning their studies many students have made the transition into work. However, the estimated impact of major-switching on earnings should be interpreted as earning changes early in the working career (Kirkeboen et al., 2016). All income values are inflation-adjusted to 2020 Canadian dollars using the Consumer Price Index.

The main sample consists of 27,300 students who began a Bachelor's program between 2007 and 2012. All of these students completed at least one post-secondary Diploma or Bachelor's program, graduated from a high school in British Columbia, and can be linked to labour market earnings eight-years after starting their post-secondary studies. Finally, students are classified in accordance with their initial field of study.

3.5 Descriptive Statistics

The following section provides key descriptive statistics for individuals in each field. Per data-release guidelines, all counts are rounded to the nearest ten and average income values are rounded to the nearest hundred.

3.5.1 Prevalence of Switching

Figure 3.1 displays both the distribution of men and women starting in each field (as represented by the height of each bar) as well as the share of switchers and non-switchers within each field. There is a clear difference in the distribution of men and women across initial fields as nearly 40 % of men start in STEM compared to approximately 20 % of women. In contrast, while nearly half of all women start in the field of LFA only 30 % of men do the same. The stark difference between the share of women beginning in LFA majors compared to STEM is similar other findings in the literature on college major choice (e.g. Bartolj and Polanec, 2012; Altonji, Arcidiacono, and Maurel, 2015; Card and Payne, 2021).

Looking at patterns of switching, there is considerable variation in the share of students that switch out of their initial major across fields of study. Switching is a common practice in my sample with approximately 33 % of men and 40 % of women switching majors. These aggregate figures, however, hide considerable variation in switch rates across fields. As seen in Figure 1, nearly half of all students who begin in LFA switch into an alternative field. In contrast, switching is much less common among students whose initial major is in the field of BHPS with only 15 % of men and 11 % of women switching out. These figures conform with Astorne-Figari and Speer (2019) whose survey-data for American college students finds that only 19 % of students who start in Business change their major. Of particular note from Figure 1 is the gendered difference in switch-rates in STEM, where nearly 40 % of women who begin in a STEM major switch fields, compared to less than a quarter of male STEM students.

A key factor in determining how switching may impact earnings is the eventual destination of switchers. Figure 3.2 shows the share of switchers (for both men and women) in each destination field given the switchers initial field of study (shown along the x-axis). BHPS is the most popular destination field for switchers, with approximately a quarter of all male and half of all female switchers choosing a BHPS major. In addition, men are more likely to switch into STEM majors when compared to women, with approximately 20 % of men switching into a STEM major compared to less than 10 % of women.

3.5.2 Switching and Earnings

The switching patterns illustrated above suggest that switching is common among undergraduate students. A consequence of this movement is that students may be changing the trajectory of their post-graduation labour earnings, relative to their initial major, given the heterogeneity of earnings outcomes across college majors. To that end, Figures 3.3 and 3.4 present earnings profiles for male and female students, respectively, across three different categories of students for each field of study. These categories are "Non-Switchers", "Switch-Outs", and "Switch-Ins", where "Switch-Ins" are those students who switch into the particular field of study. Earnings for each category of student are profiled in years relative to their start of post-secondary education. The largest share of Non-Switchers and Switchers (approximately 53 % and 43 %, respectively) graduate between 4 and 5 years after starting their post-secondary education.

Focusing on Figure 3.3, it is clear that Switch-Outs and Non-Switchers across all fields exhibit alternative earnings profiles from the moment of graduation and, in some cases, even before entering the workforce. For example, looking at both BHPS and STEM students in Figure 3, Non-Switchers and Switch-Outs exhibit similar earnings up to five years after starting post-secondary education, at which point the annual labour earnings of Non-Switchers begins to rise past those of the Switch-Outs. In contrast, Switch-Outs in both LFA and SSE exhibit a higher level of earnings prior to graduation (at around 3-4 years after starting post-secondary education) potentially suggesting they are moving into programs with greater opportunities to work while enrolled. The earnings profiles of female Switchers and Non-Switchers follow a similar pattern, as seen in Figure 3.4.

Expanding on the earnings information presented in Figures 3.3 and 3.4, Table 3.1 displays the mean earnings of Switchers and Non-Switchers given their initial field of study. There are two important insights from Table 3.1. First, on average, male switchers earn \$3000 less than male non-switchers (\$47 200 versus \$50 200), while female switchers and non-switchers exhibit similar earnings (\$43 000 versus \$42 700). Second, the overall figures presented belie significant heterogeneity across fields. For example, women who switch out of BHPS earn, on average, \$37 900 while those who remain earn \$52 200. Similarly, men who depart STEM exhibit earnings that are nearly \$8000 lower than those who remain. In contrast, women who switch out of STEM earn almost \$4000 more than those women who stay. It would appear, therefore, that the difference in earnings between switchers and non-switchers varies both across field of study and student gender.

Figure 3.5 illustrates this further, presenting the unconditional difference in log earnings between switchers and non-switchers across field of study and gender. Corroborating the results in Table 1, the magnitude of the earnings difference between switchers and non-switchers is often quite large and varies considerably across fields of study and student gender. For example, men (women) switching out of LFA experience an increase in annual earnings of 26 % (14 %). In contrast, men (women) departing BHPS see a decline in annual earnings of 21 % (47 %).

3.5.3 Academic Achievement

Table 3.2 presents measures of academic achievement for Non-Switchers (Panel A) and Switchers (Panel B). Columns 1-4 (5-8) are for men (women) who begin their studies in LFA, BHPS, STEM and SSE majors, respectively. Rows 1-3 (4-6) display the mean grades on provincial exams (teacher-assigned) in Grade 10 Science, Math and English, respectively. Both exam and teacher-assigned grades are standardized to mean zero and standard deviation one for all students, regardless of PSE enrollment, within each subject and cohort and year.

There are two important takeaways when examining the high school marks of students in Table 3.2. First, there is clear sorting of students into their initial field of study. STEM and BHPS students exhibit the highest average marks on these common courses for both men and women. As will be discussed below, I address this initial sorting problem by estimating the likelihood of switching separately for each field. Second, the decision to switch is an extension of this non-random sorting as switchers exhibit, on average, lower levels of academic ability. This presents a problem for the estimation of the causal impact of switching on earnings, if academic ability is related to future earnings, it may be the case that switchers would have experienced below average earnings if they remained in their initial majors. Accordingly, any effort to produce causal estimates would need to compare switchers to students of similar characteristics who chose to remain in the switchers' initial major.

3.6 Empirical Methodology

To account for the endogeneity of the switching decision, I employ a double-robust estimator (Imbens, 2015). In essence, the estimator seeks to compare the earnings of those who switch their major to those of non-switchers who are otherwise observably similar and, thus, may have similar likelihood of changing majors. Accordingly, by comparing students who have a similar predicted likelihood of changing majors I hope to create a credible counterfactual estimate of earnings for those students who switched.

This estimation strategy consists of two stages. First, I reweight non-switchers by their probabilities (or propensity scores) of switching majors so that the mean characteristics of switchers and non-switchers are statistically equivalent. Second, I estimate an ordinary least squares (OLS) model using these reweighted observations. Given differences in switch rates and initial major selection across student gender and within fields of study, I repeat this procedure eight times (once for each gender and field combination).

A particular advantage offered by the double-robust methodology, over a traditional OLS approach, is the flexibility of the functional form assumptions. This estimator produces consistent estimates so long as at least one of the first stage propensity score or the second stage OLS models is correctly specified (Woolridge, 2002; Imbens, 2015). In contrast, if covariate distributions differ between treatment and control groups, results produced by a traditional OLS approach are quite sensitive to small changes in specification given strict functional form assumptions and a heavy reliance on extrapolation (Imbens, 2015).

The double-robust estimator identifies the causal effect of interest so long as the reweighted non-switchers are a credible counterfactual for those who switch majors (Imbens and Rubin, 2015). This requires fulfilling or meeting the conditional independence assumption (CIA) whereby the counterfactual earnings of switchers would be equal to the observed earnings of non-switchers with the same propensity score, conditional on covariates in the second-stage regression (Rosenbaum and Rubin, 1983; Lechner, 2000). To this end, the reweighting procedure should produce statistical equivalence for characteristics across both groups. In Section 5, I provide balance tests to demonstrate the similarity between the two groups after re-weighting.

3.6.1 Double-Robust Estimator - First Stage

In the first stage, for each combination of initial field and student gender, I use a logit regression to estimate the conditional probabilities of switching majors. Specifically, I estimate the following:

$$p(x) = Pr(Switch_i = 1|X_i) \tag{1}$$

where p(x) is the propensity score; $Switch_i$ is a binary variable equal to 1 if observation i switches majors and zero otherwise; X_i includes variables that have been previously shown to be associated with the switching decision. These include flexibly specified individual student characteristics, variables relating to the earnings and social characteristics of majors as well as institutional and neighbourhood fixed effects. A complete list of covariates can be found in Appendix Table A3.2. Given that the correct specification of at least one of the two stages is necessary to generate consistent estimates, I implement a series of Wald tests to arrive at the functional form described below.

There are three categories of covariates in the propensity score estimation. First, a set of six variables, are the exam and teacher-assigned grades for students in Grade 10 Science, Math and English, all of which are specified quadratically. As mentioned in Section III, incorporating all three subjects provides a multidimensional representation of student ability that captures their proficiency in numerically- and literary-intensive subjects. Further, while exam grades provide a standardized measure of a student's ability in a given subject, the partly subjective marks provided by teachers may reflect skills not captured by exams including persistence, collaboration and adaptability. These skills may prove to be important in the determination of a student's persistence in a given major (Kautz et al., 2014; Feldman, Smart and Ethington, 1999).

Second, I include the average earnings of prior graduates from each major, specified as a cubic specification. Specifically, these are the earnings of students who graduated from each major between 2004 and 2010, measured eight-years after these students began their studies, averaged at the major-level. These values are included to capture the effect that post-graduation labour market prospects may have on the decision to switch majors. Indeed, prior research has demonstrated that future earnings, as a marker of labour market prospects, play a role in both initial major-selection and major-switching (e.g. Zafar, 2012; Wiswall and Zafar, 2015a). Moreover, the information that students are likely to possess on labour market earnings for their major is likely to be a composite mean consisting of information from family, friends, career counsellors and web sources (Wiswall and Zafar, 2015b). Accordingly, the earnings values included in this specification act as proxy for the information that students have on their labour market prospects as a function of major.

Third, I include indicators for a student's exposure to science courses in high school. Specifically, I include seven binary variables that indicate the type and number of science courses a student has taken in Grade 12 (with "No Science Courses" as the base category). Apart from acting as a measure of a student's interest in STEM, these courses also serve as prerequisites for a number of science-related programs at the university-level, even for those transferring between programs. Accordingly, completion of Grade 12 science courses can provide a wider array of transfer-opportunities to university students, which may raise the likelihood of switching.

To reweight observations, I employ a kernel-matching procedure to generate weights based on the proximity of the non-switcher's propensity scores to the target score of a switcher. I employ an Epanechnikov kernel with a bandwidth of 0.12 for all four groups, giving increasing weight to the propensity scores of non-switchers that are closer to the target score. I replicate the reweighting procedure with a bandwidths of 0.06 and 0.03, which results in no significant change for either the matching results or the results of the subsequent linear regression (Figures A3.2 and A3.3, respectively). To ensure credible comparisons between switchers and non-switchers a common support condition is imposed and a certain percentage of switchers are trimmed from each sub-sample, with trimming percentages in Appendix Table A3.4.[20] Inference across specifications is nonstandard since the weights employed are estimated. Accordingly, I bootstrap the entire estimation procedure (both stages one and two) using a nonparametric percentile-t bootstrap. I follow the method of Davidson and Mackinnon (2004) in selecting the

[20]The trimming percentage differs across models as the likelihood of switching varies dramatically across both gender and initial field of study.

minimum number of bootstrap replications, resulting in 599 replications for the entire procedure.

3.6.2 Double-Robust Estimator - Second Stage

Once observations have been reweighted, I estimate the following linear regression model,

$$ln(earnings_{ij}) = \alpha + \beta Switch_{ij} + \delta X_{ij} + \varepsilon_{ij} \ \forall \ j \tag{2}$$

where $ln(earnings_i)$ are log earnings of individual i who began their Bachelor's degree in field j, measured eight years after starting their post-secondary education. The model is estimated separately for men and women and for each field.[21] The binary variable $Switch_i$ is equal to 1 if individual i changed their field while in post-secondary, zero otherwise. The vector X_i contains the following covariates; Grade 10 teacher-assigned and exam grades, specified quadratically; work experience, measured as the difference between i's age when earnings are measured and their age at graduation from post-secondary, specified linearly; a binary variable, indicating whether or not i is Indigenous; a binary variable, indicating whether or not i speaks English at home; a categorical variable indicating the year in which i graduated from post-secondary; a categorical variable indicating whether i completed their post-secondary studies at a Research or Teaching University, a Community College, or at a post-secondary institution out of the province. The main coefficient of interest is β which captures the effect of switching majors on labour market earnings conditional on the included covariates. It should be noted that β can be interpreted as the causal impact of switching majors on earnings (for those individuals who are not trimmed in the first stage) so long as the CIA is satisfied and at least one of the two stages of the estimation procedure is correctly specified.

One potential concern regarding equation (2) is that the dependent variable is the

[21] Earnings are winsorized at the 5th and 95th percentile.

earnings of individuals early in their working career, a period in which some individuals may be unable to find work. As seen in Appendix Figure A3.2, this may be of concern since, while half of non-switchers complete their Bachelor's at either age 22 or 23, only a third of switchers do the same. This matters since a difference in job acquisition rates between switchers and non-switchers may bias results downwards. To account for this, in a robustness exercise, I change the dependent variable to $zeroincome_i$ a binary variable equal to 1 if the individual reports no labour income eight years after starting post-secondary education, and zero otherwise. As shown in Appendix Table A3.3 only students who depart BHPS majors demonstrate an increased likelihood of having zero income, while students who depart STEM are less likely to have zero income relative to those who remain. This provides some evidence that switchers and non-switchers are both equally likely to be working at the eight-year mark.

3.7 Results

3.7.1 Propensity Score

Table 3.3 (Table 3.4) shows the logit model estimates from equation (1) used to generate the propensity scores for men (women), where the dependent variable is a binary variable equal to one if individual i switches fields, zero otherwise. As the number of covariates in equation (1) is quite large, I display only those covariates that warrant further discussion. Columns (1) - (4) in Table 3.3 (Table 3.4) show the estimates from LFA, STEM, BHPS and SSE fields, respectively, for men (women). The pseudo-R^2 across all fields of study and gender combinations is quite high, suggesting that the model does a good job at explaining the likelihood of switching for students regardless of initial field. I will briefly discuss some of the key factors and their association with the likelihood of switching.

Focusing on men (Table 3.3), the importance of academic factors appears to vary based on initial field of study. Indeed, for LFA students (Column 1), students who have completed nearly any science course in Grade 12 appear more likely to switch relative to those students who have taken no Grade 12 science courses. In contrast, among STEM students (Column 2), it appears that those who took only Grade 12 Biology or Chemistry are more likely to switch majors. Moreover, LFA students who perform better in Grade 10 English (as measured by either teacher-assigned or exam marks) are less likely to switch their major.

Academic factors play a similar role in the determination of switch-likelihood for women (Table 4). Women who complete Grade 12 Science courses are more likely to switch out of LFA majors (Column 1). In contrast to men, however, it would appear that the completion of Physics does not increase switch likelihood. Moreover, the decision to switch for women in STEM (Column 2) is more sensitive to their outcomes on the Grade 10 Science exam than is the case for male STEM students.

There are some commonalities in factors associated with the switching decision between men and women. Indeed, switchers across all fields are likely to be older upon admission to an undergraduate program. Moreover, while students in LFA are more likely to remain as expected earnings rise, students from BHPS and STEM majors tend to leave from higher earning majors. Finally, the likelihood of switching appears to differ by starting year with students beginning their studies between 2010 and 2011 more likely to switch than other cohorts.

The distribution of propensity scores for each field for men (women) are presented in Figure 3.6 (Figure 3.7). Panels A-D are for LFA, BHPS, STEM and SSE students respectively. There are noticeable differences in the distribution of propensity scores for switchers (above the x-axis) across fields, with those for LFA switchers skewing right while those for BHPS students skew left. This reflects the existing differences in switch rates across fields, presented in Figure 3.1. The difference in propensity score distributions across fields (and gender) creates varying levels of overlap between switchers and non-switchers so varying levels of trimming were implemented for each field of study and gender combination, as presented in Appendix Table A3.4.

3.7.2 Re-Weighting Non-Switchers

Prior to re-weighting the characteristics of non-switchers and switchers are statistically significantly different from one another. Table 3.6 (Table 3.7) presents the p-values and t-statistics from tests of mean equality of high school marks across switchers (after trimming) and non-switchers for each field for men (women). Panel A displays the difference in mean characteristics prior to re-weighting, calculated as switcher minus non-switcher. Importantly, the characteristics of switchers and non-switchers are significantly different from one another.

Following the re-weighting procedure (Panel B), non-switchers more closely resemble switchers on average (for both men and women). The mean values of achievement in exams and courses are now statistically equivalent for most fields. Overall, propensity score matching has effectively minimized pre-treatment imbalances between switchers and non-switchers. In summary, the model presented in Section 3.5 has done well in matching the switchers and non-switchers. This statistical equivalence between the groups lends further credibility to a causal interpretation of the estimates from Stage 2.

3.7.3 Main Results

Figure 3.8 presents estimates of the impact of switching on labour market earnings (eqn. 2), estimated for each field of study and gender combination. The coefficients presented display the conditional difference in log earnings between switchers and non-switchers. For the fields of LFA and SSE, the impact of switching on labour market earnings has the same sign for both men and women, albeit the magnitudes differ. Specifically, departing LFA has a positive impact on an average individual's earnings, with the typical male switcher experiencing an approximate 27 %(or $ 10,000) increase in their annual earnings over male non-switchers of equivalent characteristics in LFA. Similarly, the average female switcher from LFA experiences an approximate 17 % (or $6,000) increase in earnings over similar female LFA students who do not switch. In contrast, switching does not have statistically significant impacts on the earnings of either men or women who begin in SSE.

There are noticeable differences in the impacts of switching across men and women who start in STEM and BHPS. Switching out of either of these fields has no statistically significant impact on the earnings of men. This stands in stark contrast to the unadjusted results presented in Figure 3.5, which suggest that men departing either field experience a sharp decline in earnings. For women departing either STEM or BHPS, however, switching constitutes a impactful decision on future earnings. Women switching out of STEM experience an average increase in earnings of approximately 50 % ($15,500), while switching out of BHPS produces an average reduction in earnings of about 49 % ($23,000). The gaps between the conditional and unconditional impacts of switching on earnings suggests that switching is of limited financial consequence for men, but it remains a highly consequential decision for women. This may be attributable to differences in the starting and ending majors of male and female switchers.

While the results presented in Figure 3.8 capture the average impact of switching majors on one's earnings, switchers may experience differential impacts depending on their destination. Figure 3.9 provides insight into the impact of switching into each field depending on an individual's starting field, for both men and women. Panel A and B are for those students who begin in LFA and BHPS fields, respectively, while Panel C are for those who begin in STEM and Panel D are for those who begin in SSE. Appendix Table A3.7 (Table A3.8) provides the point estimates for all coefficients for men (women).

Figure 3.9 makes clear that the impact of switching on earnings is, as expected, partly dependent on the field an individual switches into. Indeed, in nearly all cases switching into BHPS provides a large and positive impact on earnings while switching into LFA produces a negative impact. Interestingly, men and women appear to experience differential impacts on their earnings for certain switching combinations. For instance, among those who start in LFA and switch to STEM (Panel A), men experience a positive impact on their earnings while women experience no statistically significant effect on earnings. In contrast, for those who begin in STEM and switch to BHPS (Panel C), women experience a larger positive impact on their earnings compared to male switchers. This may be a product of gendered differences in starting/destination majors within each field. For example, within STEM, women are often over-represented in Biology programs, a major which has low labour market returns relative to other STEM majors (Finnie and Frenette, 2003).

3.8 Robustness

3.8.1 Changing the Definition of a Switch

The definition of a “switch" employed in the previous sections may be too conservative. In reality, students can change majors within the same broad field of study (i.e. from History to English within LFA). For the results that follow I change the definition of “switch" to incorporate those who change majors within the same field of study. I will refer to this new switch classification as a “Small Switch", while switchers under the previous definition are referred to as “Large Switchers". It should also be noted that the category of “Large Switchers" encompasses “Small Switchers".

Table 3.7 presents the share of students in each field who are “small switchers", “large switchers" and non-switchers. Columns (1)-(4) present results for LFA, STEM, BHPS and SSE respectively, with Panel A (Panel B) showing results for men (women). There is a clear difference in the share of small switchers across fields of study. For instance, nearly 18 % of men who start in STEM switch between subjects within STEM, while approximately 16 % of women in SSE do the same.

Figure 3.10 presents the coefficients of interest from equation (2) where the coefficient Switch is 1 for Small Switchers, 0 otherwise. To control for the endogeneity of the switching decision I, again, make use of the double-robust procedure discussed in Section 3.6. Two clear differences emerge when compared to results presented in Figure 3.9. First, male switchers who begin in STEM now experience a statistically significant gain in earnings of approximately 18 %, or $7,000 on average. This would suggest that male “small switchers" in STEM are changing between high-earning majors, relative to those switchers who leave STEM entirely. Second, for women who begin in LFA, switching no longer has a statistically significant impact on earnings. Accordingly, women who are “small switchers" within LFA are switching between low-earning majors, in contrast to most of those women who switch out of LFA.

3.9 Conclusion

This paper studied the impact of switching post-secondary fields of study on labour market earnings using administrative data from British Columbia. To do so, I employ a double-robust matching estimator which controls for the endogeneity of the switching decision. I find heterogeneity in changes to labour market earnings across both gender and initial field of study. In general, departing lower earning majors in the field of LFA increases the earnings of both men (by approximately, $10 000) and women (by approximately, $6000). In contrast, departing higher earning majors in the fields of STEM and BHPS has a more significant impact on the earnings of women, then does it for men. This may suggest that men are switching between majors of similar earnings potential where they are more likely to match the earnings outcomes they would have experienced had they remained in their original majors. In contrast, women may be departing majors from the tails of the potential earnings distribution where any switch away results in a dramatic change in earnings. In general, my results suggest that switching majors is a more consequential decision for the future earnings of women.

The impact of switching also varies by both initial and final major. Indeed, for both men and women, departing majors in LFA produces either no statistically significant effect on earnings or results in an increase in earnings. In contrast, departing STEM majors reduces the earnings of men if they switch into an LFA major, but not if they chose a major in the field of BHPS. That the impact of switching is partly dependent on the combination of initial and final major is unsurprising, as there is significant heterogeneity of earnings across majors (e.g. Altonji et al., 2012). This does, however, provide interesting provide an interesting focal point for both future research and policy recommendations.

The policy implications of this research depends on a broader understanding of the labour market outcomes associated with various majors. The, on average, large increases in earnings associated with switching into BHPS majors may suggest that reducing barriers of entry into BHPS majors may greatly improve the labour market outcomes of students. If there is insufficient change in the demand for BHPS graduates, however, an increase in their supply may not improve the earnings prospects of BHPS students.

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3.11 Tables and Figures

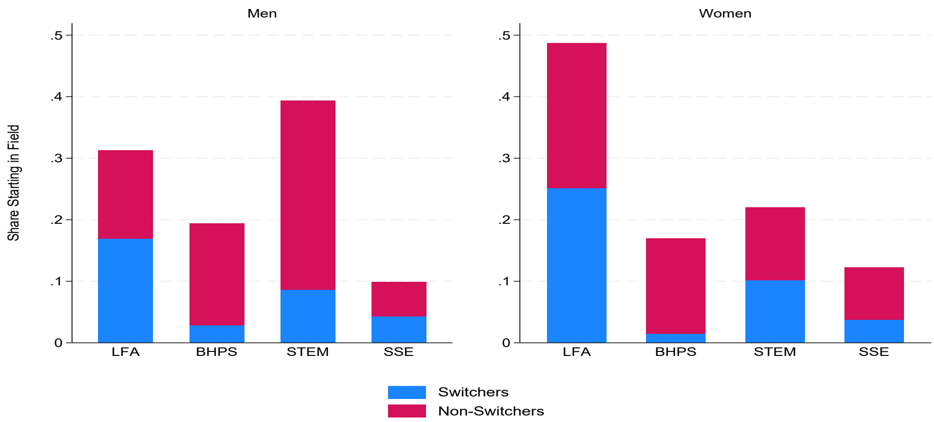

FIGURE 3.1: Share in Each Field

Notes: The share of students initially enrolled in each field of study for both men and women, shown by the height of each bar. Each bar displays the share of Switchers or Non-Switchers. All students started began a Bachelor's program between 2007 and 2012 at a university in British Columbia. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

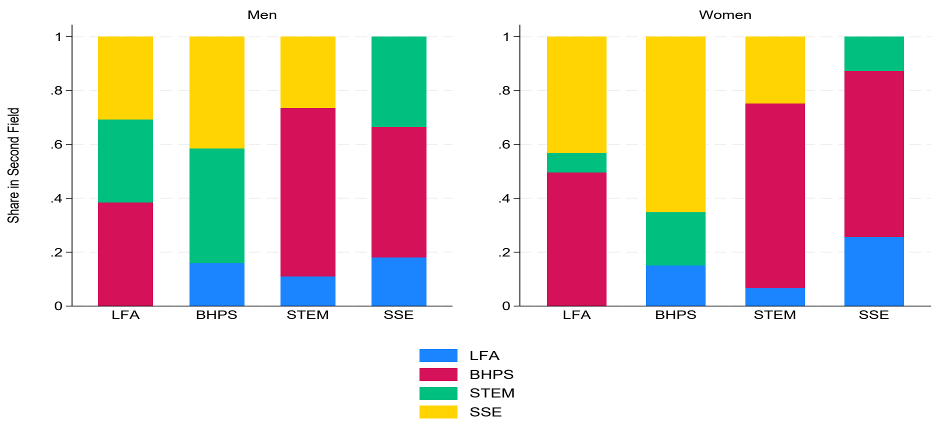

FIGURE 3.2: Destinations of Switchers

Notes: The share of switchers from each initial field of study that enroll in each alternative field, for both men and women. All students started began a Bachelor's program between 2007 and 2012 at a university in British Columbia. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

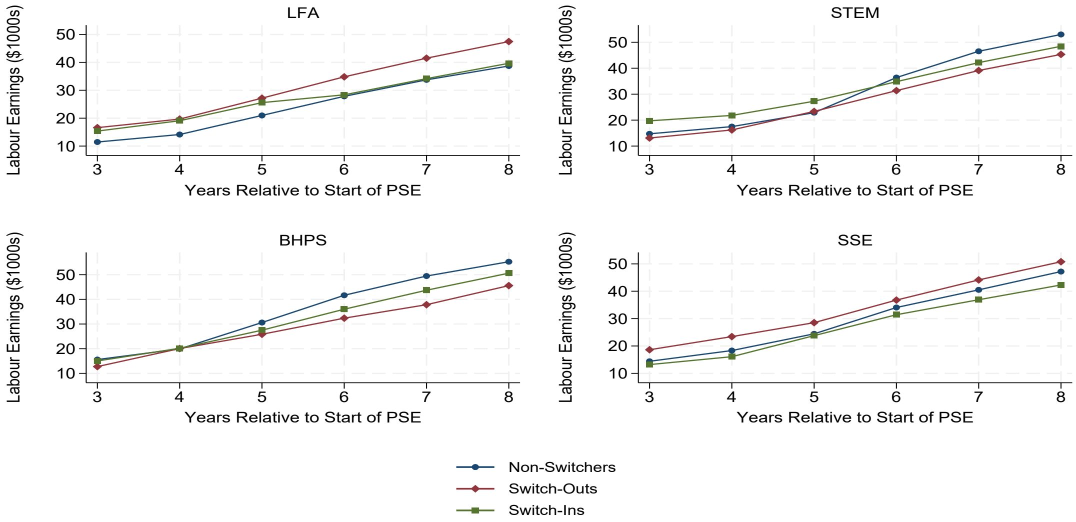

FIGURE 3.3: Earnings Profiles - Men

Notes: Earnings profile for male non-switchers, switch-outs and switch-ins across initial field of study. Earnings are tracked in years relative to the start of post-secondary education. Each point represents the mean earnings of all men in each category who began (in the case of non-switchers and switch-outs) or switched into (in the case of switch-ins) a major in each particular field of study. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

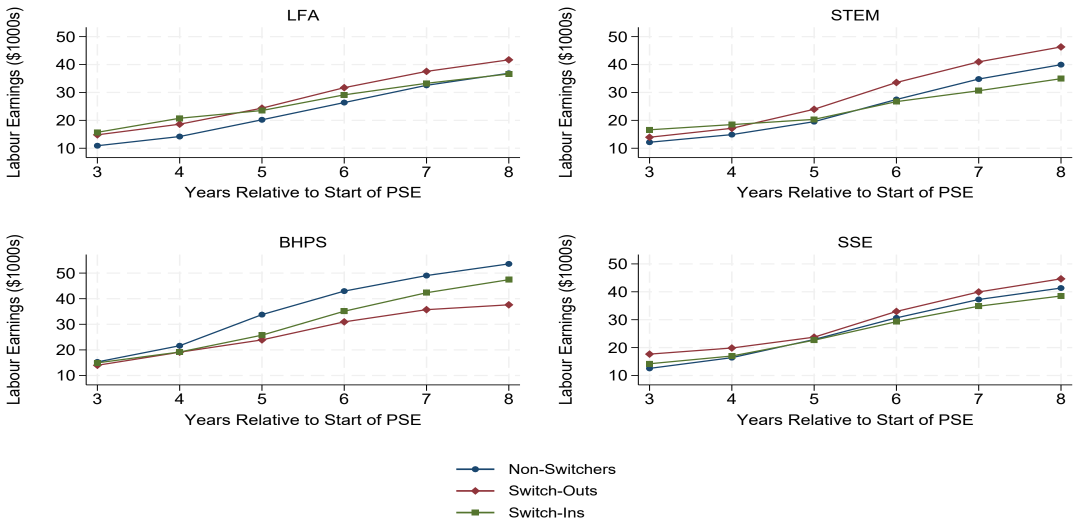

FIGURE 3.4: Earnings Profiles - Women

Notes: Earnings profile for female non-switchers, switch-outs and switch-ins across initial field of study. Earnings are tracked in years relative to the start of post-secondary education. Each point represents the mean earnings of all women in each category who began (in the case of non-switchers and switch-outs) or switched into (in the case of switch-ins) a major in each particular field of study. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

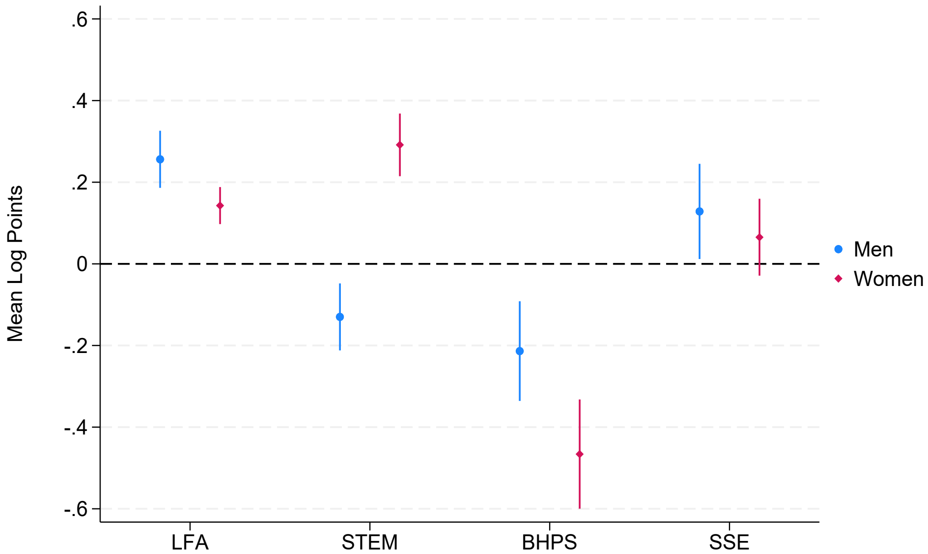

FIGURE 3.5: Unconditional Difference in Log Earnings

Notes: Average difference in log earnings between switchers and non-switchers (measured as ln(switchers) - ln(non-switchers)) across both field of study and student gender. Students began in a Bachelor's degree between 2007 and 2012 at a university in British Columbia. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

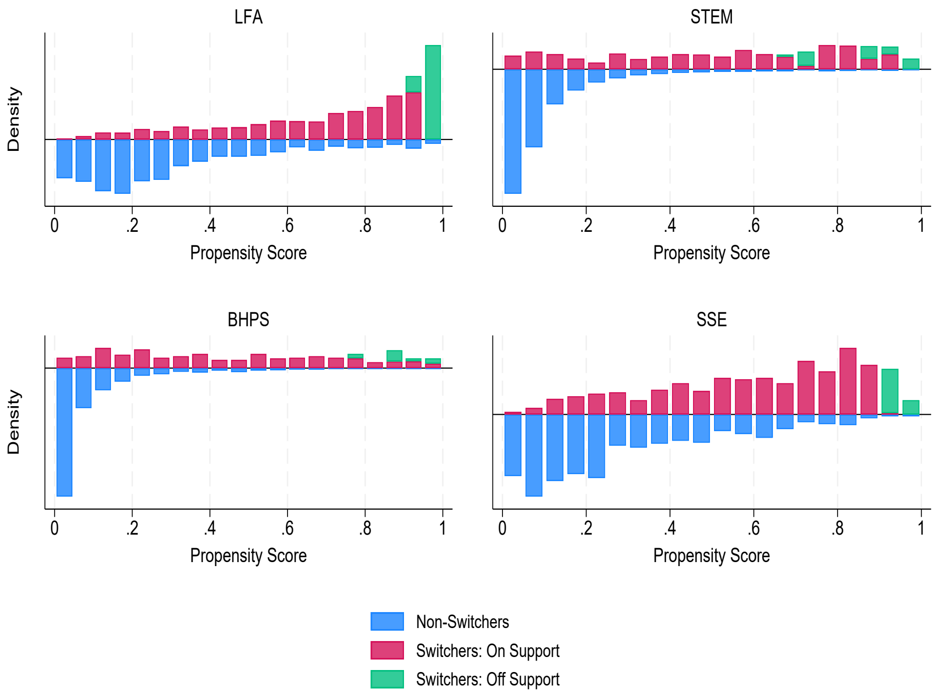

FIGURE 3.6: Estimated Propensity Score Distribution - Men

Notes: This figure displays the distribution of estimated propensity scores for male switchers and non-switchers, as determined by equation (1). Trimmed (or Off Support) observations are removed from the subsequent estimation of equation (2). The top-left figure are for those who begin in a major in LFA, while the top-right are for those who begin in a STEM major. The bottom-left figure are for those who begin in a BHPS major, while the bottom-right are for those who begin in a SSE major. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

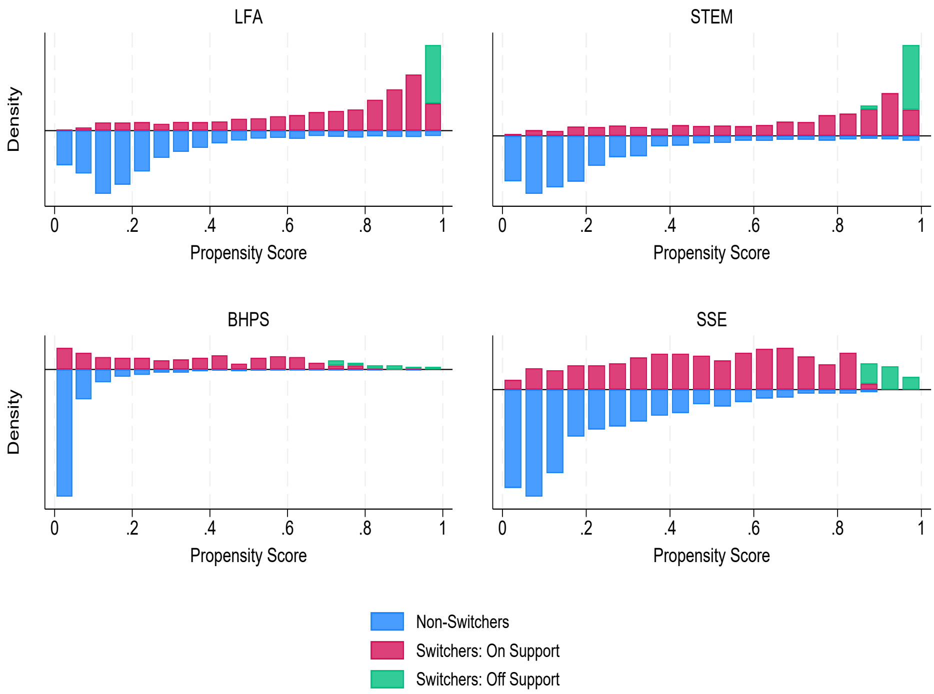

FIGURE 3.7: Estimated Propensity Score Distribution - Women

Notes: This figure displays the distribution of estimated propensity scores for female switchers and non-switchers, as determined by equation (1). Trimmed (or Off Support) observations are removed from the subsequent estimation of equation (2). The top-left figure are for those who begin in a major in LFA, while the top-right are for those who begin in a STEM major. The bottom-left figure are for those who begin in a BHPS major, while the bottom-right are for those who begin in a SSE major. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

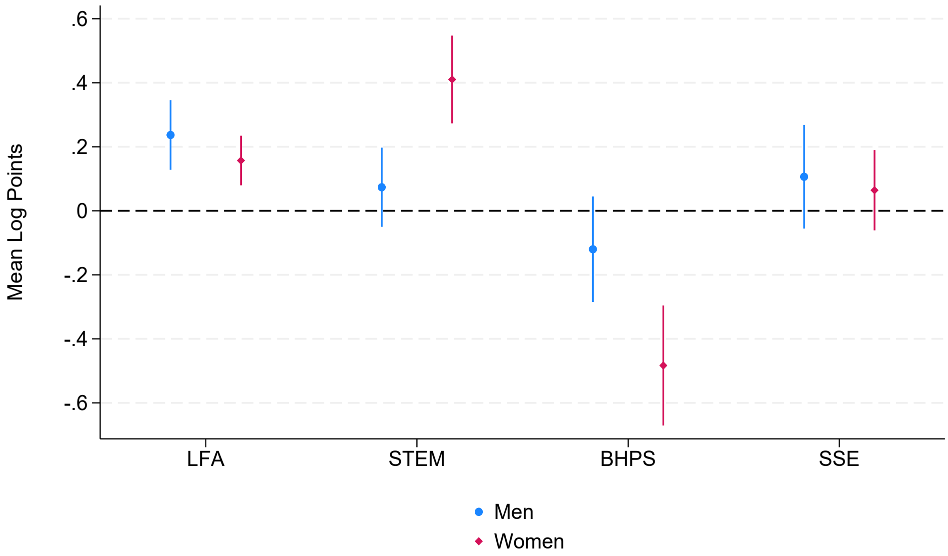

FIGURE 3.8: Impact of Switching

Notes: This figure displays the average difference in log earnings between switchers and non-switchers (measured as ln(switchers) - ln(non-switchers)) across both field of study and student gender. Determined in equation (2), estimated for each combination of student gender and field of study. Controls are for Grade 10 marks, work experience, Indigenous status, English-language skills, year of graduation, and type of post-secondary institution the person graduated from. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

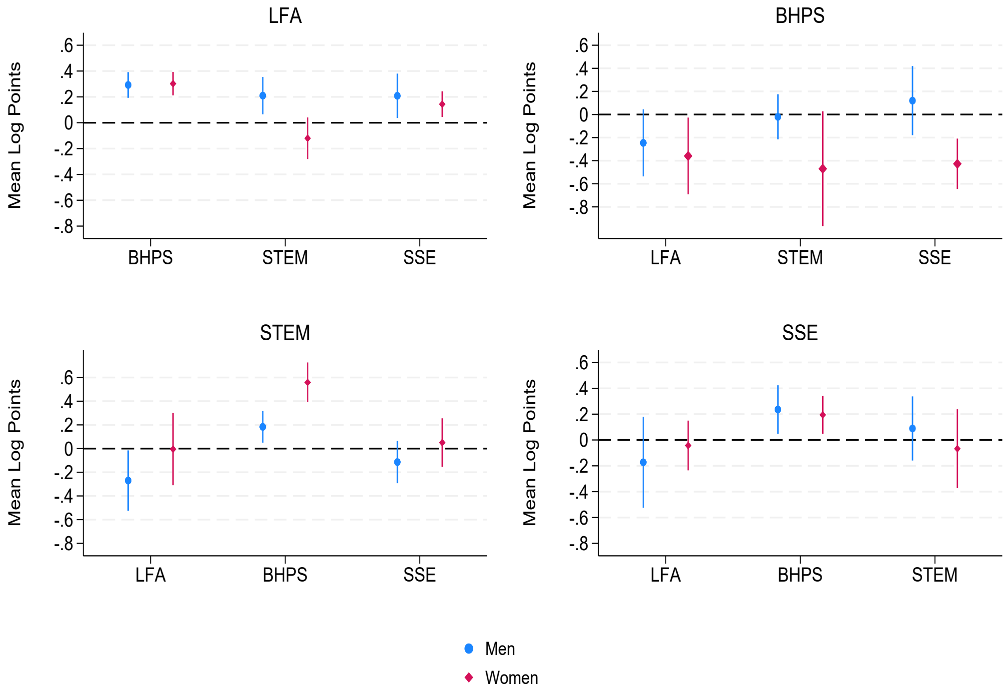

Figure 3.9: Impact of Switching into Each Field of Study

Notes: This figure displays the average difference in log earnings between switchers and non-switchers (measured as ln(switchers) - ln(non-switchers)). Estimated for each combination of initial and final field of study and student gender. Controls are for Grade 10 marks, work experience, Indigenous status, English-language skills, year of graduation, and type of post-secondary institution the person graduated from. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

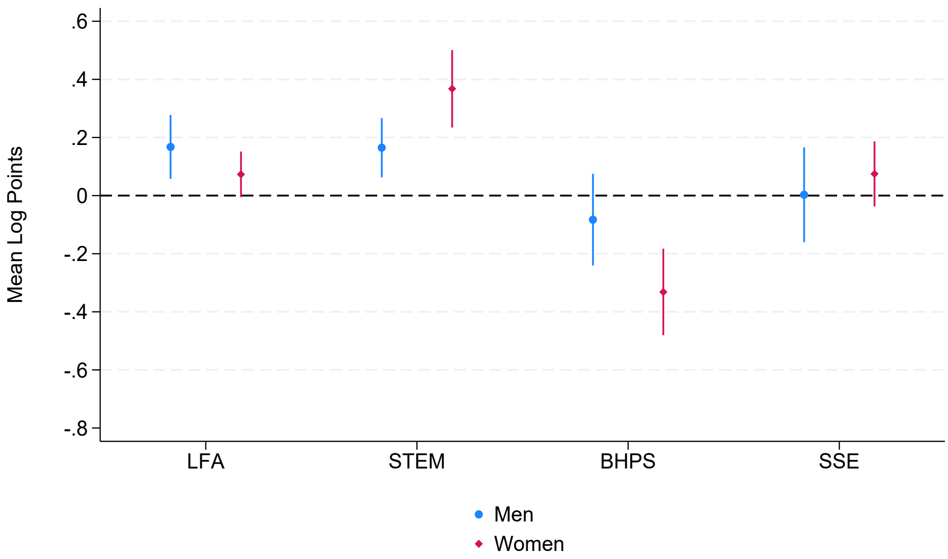

FIGURE 3.10: Impact of Switching, Including Small Switchers

Notes: This figure displays the average difference in log earnings between switchers and non-switchers (measured as ln(switchers) - ln(non-switchers)). Here, I apply the definition of a “small switch" which includes persons who switch between majors within the same field of study. Estimated for each combination of initial field of study and student gender. Controls are for Grade 10 marks, work experience, Indigenous status, English-language skills, year of graduation, and type of post-secondary institution the person graduated from. Source: Authors’ calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

Table 3.1: Average Earnings of Switchers and Non-Switchers

	Men		Women	
	Non-Switchers	Switchers	Non-Switchers	Switchers
Starting Field	(1)	(2)	(3)	(4)
LFA	39000	47500	39400	41700
BHPS	55200	45500	52200	37900
STEM	53100	45300	42900	46300
SSE	47200	50900	42500	44800

Notes: Earnings presented in 2020 Canadian Dollars. This table displays average earnings for switching fields across all Bachelor students who began their studies between 2007 and 2012. Column (1) and (2) are for male non-switchers and switchers, respectively. Columns (3) and (4) are for female non-switchers and switchers, respectively. Source: BC Ministry of Education and Child Care, 2021; Statistics Canada, 2021.

Table 3.2: Means of Standardized Grade 10 Exam and Teacher Assigned Marks by Initial Field of Study

	Men				Women			
	LFA	STEM	BHPS	SSE	LFA	STEM	BHPS	SSE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Non-Switchers								
Standardized Exam Scores								
Science 10	0.18	0.88	0.38	-0.06	0.11	0.86	0.32	-0.01
Math 10	0.07	0.78	0.37	-0.19	0.01	0.89	0.40	0.00
English 10	0.21	0.28	0.08	-0.11	0.43	0.59	0.28	0.21
Standardized Teacher Assigned Scores								
Science 10	0.03	0.71	0.34	-0.14	0.21	0.87	0.46	0.09
Math 10	-0.07	0.70	0.34	-0.19	0.12	0.88	0.48	0.00
English 10	0.06	0.30	0.12	-0.21	0.46	0.76	0.53	0.28
Panel B: Switchers								
Standardized Exam Scores								
Science 10	0.00	0.50	0.16	-0.02	-0.24	0.36	0.04	-0.06
Math 10	-0.10	0.43	0.05	-0.03	-0.22	0.37	0.11	-0.02
English 10	-0.05	0.10	-0.11	-0.25	0.11	0.29	0.15	0.20
Standardized Teacher Assigned Scores								
Science 10	-0.13	0.41	0.03	-0.13	-0.05	0.51	0.26	0.10
Math 10	-0.18	0.37	0.00	-0.11	-0.11	0.46	0.17	0.07
English 10	-0.20	0.12	-0.11	-0.25	0.20	0.53	0.33	0.30

Notes: Panel A are for Non-Switchers while Panel B are for Switchers. Column (1)-(4) are for male students who start in LFA, STEM, BHPS and SSE, respectively. Column (5)-(8) are for female students who start in LFA, STEM, BHPS and SSE, respectively. All students began in an Bachelor's program between 2007 and 2012. "Teacher Assigned" refers to teacher assigned grades. "Exams" refers to grades obtained on provincial examinations. All marks are standardized, with mean zero and variance one, within subject and year of high school graduation cohort including those who do not pursue university. Source: Author's calculations from the BC-K12 linked to the PSIS (BC Ministry of Education and Child Care, 2021).

Table 3.3: Logistic Regression Coefficients - Men

	(1) LFA	(2) STEM	(3) BHPS	(4) SSE
Dependent Variable: Switch Majors = 1; Remain in Major = 0				
Grade 12 Science Courses (Base - No Science)				
Physics Only	0.651**	-0.173	-0.220	-0.296
	(0.204)	(0.282)	(0.382)	(0.409)
Biology Only	0.311**	0.555*	-0.268	-0.390
	(0.117)	(0.260)	(0.245)	(0.212)
Chemistry Only	0.157	0.558*	-0.309	0.844*
	(0.207)	(0.257)	(0.353)	(0.364)
Biology & Chemistry	0.504**	0.328	-0.215	-0.461
	(0.174)	(0.173)	(0.293)	(0.319)
Biology & Physics	1.433***	0.279	-0.801	0.382
	(0.336)	(0.283)	(0.500)	(0.578)
Physics & Chemistry	0.606**	-0.0257	0.165	0.0948
	(0.210)	(0.160)	(0.326)	(0.354)
All Three	1.020***	0.119	0.316	0.0500
	(0.279)	(0.163)	(0.417)	(0.480)
Standardized Exam Grades				
Science 10	-0.0411	-0.254*	0.102	-0.144
	(0.0839)	(0.107)	(0.165)	(0.157)
Math 10	0.00410	0.0509	0.0610	0.234
	(0.0794)	(0.107)	(0.157)	(0.150)
English 10	-0.186**	0.119	0.285*	-0.0685
	(0.0636)	(0.0733)	(0.125)	(0.125)
Standardized Teacher Assigned Grades				
Science 10	-0.168	0.0765	-0.0307	-0.0751
	(0.118)	(0.148)	(0.219)	(0.226)
Math 10	0.0499	0.314*	-0.119	-0.0306
	(0.116)	(0.151)	(0.225)	(0.208)
English 10	-0.428***	0.326*	0.378	-0.236
	(0.110)	(0.139)	(0.209)	(0.210)
Individual Characteristics				
Age	8.608***	14.61***	8.410***	11.96***
	(1.018)	(1.010)	(1.373)	(1.514)
Mean Program Earnings				
Mean Program Earnings	-63.93***	2.145***	50.28**	0.206
	(17.68)	(0.590)	(16.93)	(1.881)
Academic Rankings Grade 12 Cohort(Base - 1st Quintile)				
Second Quintile	-0.233	-1.345***	0.377	-0.109
	(0.257)	(0.395)	(0.458)	(0.442)
Third Quintile	0.0240	-1.810***	-1.489	-2.047
	(0.367)	(0.530)	(0.973)	(1.107)
Fourth Quintile	-0.0621	-1.950**	-1.465	-2.313
	(0.609)	(0.630)	(1.223)	(1.440)
Fifth Quintile	0.334	-2.577***	-1.977	-2.453
	(0.758)	(0.736)	(1.359)	(1.651)
N	3520	4380	1930	1060
pseudo R^2	0.357	0.368	0.366	0.274

Standard errors in parentheses

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

Notes: This table displays the propensity score logit estimates for male students. Coefficient estimates are derived from the logistic regression specified in equation (1). Column (1)-(4) are for male students who began in a major in the fields of LFA, STEM, BHPS or SSE respectively. All students began in a Bachelors program between 2007 and 2012. Nonparametric bootstrapped standard errors are in parentheses. All specifications control for: Grade 10 teacher-assigned and exam grades, specified quadratically; high school cohort and post-secondary field achievement quintiles; science courses taken in Grade 12; age at enrollment, specified quadratically; language spoken at home; ESL status; gifted status in Grade 12; starting year of post-secondary education; mean earnings of initial major, specified cubically; university fixed effects; forward sortation area fixed effects. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

Table 3.4: Logistic Regression Coefficients - Women

	(1) LFA	(2) STEM	(3) BHPS	(4) SSE
Dependent Variable: Switch Majors = 1; Remain in Major = 0				
Grade 12 Science Courses (Base - No Science)				
Physics Only	0.0772	-0.125	-0.213	-0.829
	(0.308)	(0.403)	(0.658)	(0.656)
Biology Only	0.171*	0.242	0.410	-0.333*
	(0.0726)	(0.230)	(0.253)	(0.153)
Chemistry Only	0.330*	0.489	-0.531	0.0147
	(0.145)	(0.258)	(0.450)	(0.314)
Biology & Chemistry	0.612***	0.00907	-0.0129	0.163
	(0.102)	(0.146)	(0.272)	(0.199)
Biology & Physics	0.811*	-0.0121	1.179*	0.578
	(0.395)	(0.293)	(0.592)	(0.676)
Physics & Chemistry	0.416	-0.655**	0.789	-0.0749
	(0.307)	(0.233)	(0.546)	(0.649)
All Three	0.586*	-0.297	0.907*	0.663
	(0.254)	(0.166)	(0.462)	(0.397)
Standardized Exam Grades				
Science 10	-0.103	-0.412***	0.0851	-0.221
	(0.0592)	(0.122)	(0.173)	(0.126)
Math 10	-0.0560	-0.194	0.101	-0.0195
	(0.0573)	(0.100)	(0.162)	(0.120)
English 10	-0.128**	-0.0278	0.0346	-0.0155
	(0.0454)	(0.0848)	(0.144)	(0.0883)
Standardized Teacher Assigned Grades				
Science 10	-0.00479	0.0842	0.426	-0.0544
	(0.0786)	(0.176)	(0.244)	(0.163)
Math 10	0.0616	0.209	-0.196	0.0686
	(0.0762)	(0.162)	(0.235)	(0.152)
English 10	-0.135	0.509**	-0.0697	-0.104
	(0.0711)	(0.160)	(0.208)	(0.141)
Individual Characteristics				
Age	12.48***	16.19***	9.524***	11.69***
	(0.650)	(1.093)	(1.546)	(1.251)
Mean Program Earnings				
Mean Program Earnings	-45.34***	2.401***	82.94***	-0.341
	(8.170)	(0.625)	(22.01)	(0.356)
Academic Rankings Grade 12 Cohort (Base - 1st Quintile)				
Second Quintile	0.0130	-0.368	-0.495	0.635
	(0.197)	(0.641)	(0.573)	(0.406)
Third Quintile	0.193	-0.892	14.34	0.649
	(0.277)	(0.781)	(1177.3)	(0.625)
Fourth Quintile	0.0849	-1.194	15.23	1.045
	(0.397)	(0.887)	(1177.3)	(0.977)
Fifth Quintile	-0.00468	-1.558	14.75	1.283
	(0.476)	(0.963)	(1177.3)	(1.117)
N	7740	3450	2160	1870
pseudo R^2	0.379	0.414	0.334	0.262

Standard errors in parentheses

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

Notes: This table displays the propensity score logit estimates for male students. Coefficient estimates are derived from the logitistic regression specified in equation (1). Column (1)-(4) are for male students who began in a major in the fields of LFA, STEM, BHPS or SSE respectively. All students began in a Bachelor's program between 2007 and 2012. Nonparametric bootstrapped standard errors are in paraentheses. All specifications control for: Grade 10 teacher-assigned and exam grades, specified quadratically; high school cohort and post-secondary field achievement quintiles; science courses taken in Grade 12; age at enrollment, specified quadratically; language spoken at home; ESL status; gifted status in Grade 12; starting year of post-secondary education; mean earnings of initial major, specified cubically; university fixed effects; forward sortation area fixed effects. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

TABLE 3.5: Mean differences in high school marks (Switchers Minus Non-Switchers) - Men

Initial Field	LFA	STEM	BHPS	SSE
Panel A: Unweighted				
Science 10 - Teacher Assigned	-0.16***	-0.30***	-0.30***	0.00
Math 10 - Teacher Assigned	-0.10***	-0.33***	-0.34***	0.07
English 10 - Teacher Assigned	-0.26***	-0.18***	-0.22***	-0.03
Science 10 - Exam	-0.18***	-0.38***	-0.22***	0.03
Math 10 - Exam	-0.18***	-0.36***	-0.32***	0.14***
English 10 - Exam	-0.27***	-0.19***	-0.06	0.03
Panel B: Weighted				
Science 10 - Teacher Assigned	0.05	0.03	-0.04	0.00
Math 10 - Teacher Assigned	0.07	0.05	-0.04	0.00
English 10 - Teacher Assigned	0.03	0.01	-0.05	-0.02
Science 10 - Exam	0.04	0.06	-0.03	-0.01
Math 10 - Exam	0.07	0.09*	-0.04	-0.01
English 10 - Exam	0.01	0.02	0.00	-0.02

Notes: This table displays the difference in mean characteristics between switchers and non-switchers, calculated as switchers minus non-switchers. Column (1) is for those who begin their studies in the field of Liberal and Fine Arts. Column (2) is for those who begin their studies in the field of Science, Technology, Engineering and Math. Column (3) is for those who begin their studies in the field of Business, Health and Professional Services. Column (4) is for those who begin their studies in the field of Social Science and Education. Exam and course marks are standardized within subject and year of high school graduation cohort. Source: BC Ministry of Education and Child Care, 2021; Statistics Canada, 2021.

TABLE 3.6: Mean differences in high school marks (Switchers Minus Non-Switchers) - Women

Initial Field	LFA	STEM	BHPS	SSE
Panel A: Unweighted				
Science 10 - Teacher Assigned	-0.26***	-0.36***	-0.21***	0.02
Math 10 - Teacher Assigned	-0.22***	-0.41***	-0.32***	0.07
English 10 - Teacher Assigned	-0.25***	-0.23***	-0.18***	0.01
Science 10 - Exam	-0.36***	-0.50***	-0.29***	-0.04
Math 10 - Exam	-0.32***	-0.52***	-0.32***	-0.02
English 10 - Exam	-0.31***	-0.30***	-0.13*	0.01
Panel B: Weighted				
Science 10 - Teacher Assigned	0.00	0.05	0.02	-0.02
Math 10 - Teacher Assigned	0.01	0.01	0.02	-0.01
English 10 - Teacher Assigned	-0.01	0.04	-0.01	-0.02
Science 10 - Exam	-0.01	0.07*	-0.01	-0.01
Math 10 - Exam	0.01	0.08*	-0.01	0.01
English 10 - Exam	-0.05	-0.01	-0.01	-0.04

Notes: This table displays the difference in mean characteristics between switchers and non-switchers, calculated as switchers minus non-switchers. Column (1) is for those who begin their studies in the field of Liberal and Fine Arts. Column (2) is for those who begin their studies in the field of Science, Technology, Engineering and Math. Column (3) is for those who begin their studies in the field of Business, Health and Professional Services. Column (4) is for those who begin their studies in the field of Social Science and Education. Exam and course marks are standardized within subject and year of high school graduation cohort. Source: BC Ministry of Education and Child Care, 2021; Statistics Canada, 2021.

TABLE 3.7: Share of Students Who Switch Under Different Definitions

	Overall	LFA	BHPS	STEM	SSE
	(1)	(2)	(3)	(4)	(5)
% Small Switch	42	54	16	41	47
% Large Switch	35	49	12	29	32

Notes: This table displays the share of students who switch programs under the definitions of “Small Switch" and “Large Switch", respectively. A “Large Switch" occurs when a switch in programs results in a change in field of study, while a “Small Switch" allows for any change in program. All students begin in a Bachelors program between 2007 and 2012. Column (1) is for all students. Column (2) is for those who begin their studies in the field of Liberal and Fine Arts. Column (3) is for those who begin their studies in the field of Science, Technology, Engineering and Math. Column (4) is for those who begin their studies in the field of Business, Health and Professional Services. Column (5) is for those who begin their studies in the field of Social Science and Education. Source: BC Ministry of Education and Child Care, 2021; Statistics Canada, 2021.

3.12 Appendix

Table A3.1: Fields of Study and Majors

Field of Study	Majors
Liberal and Fine Arts	Ethnic, Cultural, and Gender Studies; Foreign Languages; General Humanities; English; History, Philosophy and Religion; Visual and Performing Arts
Science, Technology, Engineering and Math	Agriculture and Natural Resources; Architecture; Computer Science; Engineering and Engineering Technology; Biological and Biomedical Sciences; Mathematics and Statistics; Physical Sciences; General Sciences
Business, Health and Professional Services	Parks, Recreation, Leisure and Fitness Studies; Security Services; Public Administration; Business; Health Professions; Personal and Culinary Services
Social Science and Education	Communications; Education; Consumer Sciences; Psychology; Social Sciences

Notes: This table displays the majors assigned to each broad field of study. Majors are determined by the Classification of Instructional Program 2-digit designation. Source: Statistics Canada, 2021.

Table A3.2: Logistic Coefficients (Bachelor's)

Variable Group	Variables
Academic	Standardized Exam and Teacher Assigned Marks for Grade 10 English, Math and Science; High School Cohort and Post-Secondary Field Achievement Quintiles; Science courses taken in Grade 12 (Physics, Biology and Chemistry)
Individual Characteristics	Age at Admission; Language spoken at home; Indigenous identity; ESL status; Student gender; Gifted Status in Grade 12
University	Starting Year; Average Earnings of Initial Major
Fixed Effects	University Fixed Effects; Forward Sortation Area Fixed Effects

Notes: This table displays the variables employed in the first-stage (logistic regression) of the doubly-robust estimator. Exam and teacher-assigned marks, as well as age at admission, are specified quadratically while the average earnings of initial major is given a cubic specification. Source: Statistics Canada, 2021.

Table A3.3: Impact of Switching on Not Working

	(1) LFA	(2) STEM	(3) BHPS	(4) SSE
Panel A: Men				
Switch	-0.0127	-0.0349*	0.00311	0.000381
	(0.0127)	(0.0137)	(0.0200)	(0.0145)
N	3050	4240	1900	1020
adj. R^2	0.027	0.022	0.067	0.014
Panel B: Women				
Switch	-0.00634	-0.0577***	0.0401*	0.00452
	(0.00792)	(0.0166)	(0.0201)	(0.0107)
N	7140	3130	2140	1810
adj. R^2	0.012	0.046	0.091	0.021

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table displays the impact of switching majors on the likelihood of not working eight years after starting post-secondary education. Here, “not working" is defined as reporting labour income of zero on federal tax forms. Panel A focuses on Men while Panel B is for women. Column (1)-(4) are for students who begin in majors in the fields of LFA, STEM, BHPS and SSE, respectively. All specifications control for: Grade 10 teacher-assigned and exam grades, specified quadratically; work experience, measured as the difference between age when earnings are measured and age at graduation, specified linearly; Indigenous status; a binary variable, indicating whether English is spoken at home; year of graduation from post-secondary; a categorical variable indicating post-secondary studies were completed at a Research or Teaching University, a Community College, or at a post-secondary institution out of the province. Source: Authors’ calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

Table A3.4: Trimming Percentages for Each Field of Study and Gender

	Trimming %
Panel A: Men	
Liberal and Fine Arts	25
Science, Technology, Engineering and Math	15
Business, Health and Professional Services	10
Social Science and Education	10
Panel B: Women	
Liberal and Fine Arts	15
Science, Technology, Engineering and Math	20
Business, Health and Professional Services	10
Social Science and Education	10

Notes: This table displays trimming percentages employed for each combination of gender and field of study in the doubly-robust estimation procedure. Trimming removes the specified share of treated observations for which propensity score density of control observations is lowest. Differences in trimming percentages are attributed to differences in switch likelihood across gender and field of study combinations.

TABLE A3.5: Full Logit Results - Men

	(1) LFA	(2) STEM	(3) BHPS	(4) SSE
Dependent Variable: Switch Majors = 1; Remain in Major = 0				
Physics Only	0.651**	-0.173	-0.220	-0.296
	(0.204)	(0.282)	(0.382)	(0.409)
Biology Only	0.311**	0.555*	-0.268	-0.390
	(0.117)	(0.260)	(0.245)	(0.212)
Chemistry Only	0.157	0.558*	-0.309	0.844*
	(0.207)	(0.257)	(0.353)	(0.364)
Biology & Chemistry	0.504**	0.328	-0.215	-0.461
	(0.174)	(0.173)	(0.293)	(0.319)
Biology & Physics	1.433***	0.279	-0.801	0.382
	(0.336)	(0.283)	(0.500)	(0.578)
Physics & Chemistry	0.606**	-0.0257	0.165	0.0948
	(0.210)	(0.160)	(0.326)	(0.354)
All Three	1.020***	0.119	0.316	0.0500
	(0.279)	(0.163)	(0.417)	(0.480)
Standardized Exam Grades				
Science 10	-0.0411	-0.254*	0.102	-0.144
	(0.0839)	(0.107)	(0.165)	(0.157)
(Science 10)^2	-0.0757	-0.0664	0.0489	0.101
	(0.0519)	(0.0617)	(0.108)	(0.0791)
Math 10	0.00410	0.0509	0.0610	0.234
	(0.0794)	(0.107)	(0.157)	(0.150)
(Math 10)^2	-0.00770	-0.0584	-0.0582	-0.163
	(0.0428)	(0.0608)	(0.100)	(0.0908)
English 10	-0.186**	0.119	0.285*	-0.0685
	(0.0636)	(0.0733)	(0.125)	(0.125)
(English 10)^2	-0.0527	0.0346	0.0464	-0.255**
	(0.0366)	(0.0396)	(0.0752)	(0.0858)
Standardized Teacher Assigned Grades				
Science 10	-0.168	0.0765	-0.0307	-0.0751
	(0.118)	(0.148)	(0.219)	(0.226)
(Science 10)^2	-0.141*	-0.113	-0.0668	0.0407
	(0.0589)	(0.0806)	(0.120)	(0.0998)
Math 10	0.0499	0.314*	-0.119	-0.0306
	(0.116)	(0.151)	(0.225)	(0.208)

	(1)	(2)	(3)	(4)
	LFA	STEM	BHPS	SSE
$(\text{Math } 10)^2$	-0.0278	-0.137	0.193	-0.0298
	(0.0538)	(0.0802)	(0.119)	(0.0992)
English 10	-0.428***	0.326*	0.378	-0.236
	(0.110)	(0.139)	(0.209)	(0.210)
$(\text{English } 10)^2$	-0.160**	-0.142*	0.365***	-0.0606
	(0.0496)	(0.0645)	(0.0959)	(0.0898)
Individual Characteristics				
Indigenous Status	0.113	0.376	0.677	0.123
	(0.344)	(0.387)	(0.633)	(0.731)
English At Home	-0.132	-0.311*	0.106	0.0791
	(0.128)	(0.133)	(0.236)	(0.233)
Grade 12 Gifted	-0.0916	-0.0548	-0.0292	0.610
	(0.258)	(0.227)	(0.495)	(0.581)
Age	8.608***	14.61***	8.410***	11.96***
	(1.018)	(1.010)	(1.373)	(1.514)
$(\text{Age})^2$	-0.190***	-0.340***	-0.187***	-0.278***
	(0.0257)	(0.0252)	(0.0340)	(0.0375)
Mean Program Earnings				
Mean Program Earnings	-63.93***	2.145***	50.28**	0.206
	(17.68)	(0.590)	(16.93)	(1.881)
$(\text{Mean Program Earnings})^2$	1.521***	-0.0490***	-0.837**	-0.00170
	(0.422)	(0.0134)	(0.278)	(0.0402)
$(\text{Mean Program Earnings})^3$	-0.0119***	0.000344***	0.00461**	-0.00000443
	(0.00332)	(0.0000942)	(0.00151)	(0.000286)
Academic Rank in Post-Secondary Program				
Second Quintile	0.0593	0.0699	1.198	0.165
	(0.232)	(0.231)	(0.813)	(0.414)
Third Quintile	0.0349	-0.0451	0.631	2.337*
	(0.343)	(0.342)	(1.060)	(1.091)
Fourth Quintile	0.587	0.445	0.806	2.627
	(0.595)	(0.498)	(1.176)	(1.388)
Fifth Quintile	0.648	0.597	0.498	2.978
	(0.724)	(0.626)	(1.352)	(1.583)
Academic Rank in High School Cohort				
Second Quintile	-0.233	-1.345***	0.377	-0.109
	(0.257)	(0.395)	(0.458)	(0.442)
Third Quintile	0.0240	-1.810***	-1.489	-2.047

	(1) LFA	(2) STEM	(3) BHPS	(4) SSE
	(0.367)	(0.530)	(0.973)	(1.107)
Fourth Quintile	-0.0621	-1.950**	-1.465	-2.313
	(0.609)	(0.630)	(1.223)	(1.440)
Fifth Quintile	0.334	-2.577***	-1.977	-2.453
	(0.758)	(0.736)	(1.359)	(1.651)
Starting Year of Post-Secondary Education				
2008	1.074***	1.071***	1.610***	0.482
	(0.176)	(0.180)	(0.413)	(0.360)
2009	1.163***	1.133***	1.726***	0.440
	(0.178)	(0.180)	(0.399)	(0.322)
2010	1.509***	1.208***	1.554***	0.724*
	(0.181)	(0.186)	(0.404)	(0.330)
2011	1.613***	1.088***	2.031***	0.853**
	(0.181)	(0.186)	(0.400)	(0.324)
2012	1.289***	0.949***	1.807***	0.630
	(0.189)	(0.194)	(0.416)	(0.338)
Fixed Effects				
Postal Code	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
N	3520	4380	1930	1060
pseudo R^2	0.357	0.368	0.366	0.274

Standard errors in parentheses

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

Table A3.6: Full Logit Results - Women

	(1) LFA	(2) STEM	(3) BHPS	(4) SSE
Dependent Variable: Switch Majors = 1; Remain in Major = 0				
Physics Only	0.0772	-0.125	-0.213	-0.829
	(0.308)	(0.403)	(0.658)	(0.656)
Biology Only	0.171*	0.242	0.410	-0.333*
	(0.0726)	(0.230)	(0.253)	(0.153)
Chemistry Only	0.330*	0.489	-0.531	0.0147
	(0.145)	(0.258)	(0.450)	(0.314)
Biology & Chemistry	0.612***	0.00907	-0.0129	0.163
	(0.102)	(0.146)	(0.272)	(0.199)
Biology & Physics	0.811*	-0.0121	1.179*	0.578
	(0.395)	(0.293)	(0.592)	(0.676)
Physics & Chemistry	0.416	-0.655**	0.789	-0.0749
	(0.307)	(0.233)	(0.546)	(0.649)
All Three	0.586*	-0.297	0.907*	0.663
	(0.254)	(0.166)	(0.462)	(0.397)
Standardized Exam Grades				
Science 10	-0.103	-0.412***	0.0851	-0.221
	(0.0592)	(0.122)	(0.173)	(0.126)
(Science 10)^2	0.0408	0.208**	0.0696	-0.113
	(0.0218)	(0.0752)	(0.113)	(0.0747)
Math 10	-0.0560	-0.194	0.101	-0.0195
	(0.0573)	(0.100)	(0.162)	(0.120)
(Math 10)^2	0.0683*	0.0304	-0.0362	0.0998
	(0.0318)	(0.0499)	(0.0742)	(0.0749)
English 10	-0.128**	-0.0278	0.0346	-0.0155
	(0.0454)	(0.0848)	(0.144)	(0.0883)
(English 10)^2	-0.0397	0.0863	-0.0668	0.0328
	(0.0284)	(0.0556)	(0.105)	(0.0390)
Standardized Teacher Assigned Grades				
Science 10	-0.00479	0.0842	0.426	-0.0544
	(0.0786)	(0.176)	(0.244)	(0.163)
(Science 10)^2	-0.0509	-0.0573	0.0498	-0.0247
	(0.0398)	(0.0920)	(0.129)	(0.0795)
Math 10	0.0616	0.209	-0.196	0.0686

	(1)	(2)	(3)	(4)
	LFA	STEM	BHPS	SSE
	(0.0762)	(0.162)	(0.235)	(0.152)
$(\text{Math 10})^2$	0.0274	-0.103	-0.0548	-0.0494
	(0.0376)	(0.0725)	(0.117)	(0.0810)
English 10	-0.135	0.509**	-0.0697	-0.104
	(0.0711)	(0.160)	(0.208)	(0.141)
$(\text{English 10})^2$	-0.0508	-0.133	0.00674	0.0421
	(0.0377)	(0.0784)	(0.109)	(0.0715)
Individual Characteristics				
Indigenous Status	-0.231	0.447	-1.076	0.0694
	(0.175)	(0.323)	(0.672)	(0.537)
English At Home	-0.0430	-0.126	0.251	0.149
	(0.0914)	(0.138)	(0.257)	(0.192)
Grade 12 Gifted	-0.0286	-0.0639	-1.988	-0.0782
	(0.178)	(0.242)	(1.098)	(0.342)
Age	12.48***	16.19***	9.524***	11.69***
	(0.650)	(1.093)	(1.546)	(1.251)
$(\text{Age})^2$	-0.285***	-0.373***	-0.212***	-0.274***
	(0.0163)	(0.0273)	(0.0383)	(0.0312)
Mean Program Earnings				
Mean Program Earnings	-45.34***	2.401***	82.94***	-0.341
	(8.170)	(0.625)	(22.01)	(0.356)
$(\text{Mean Program Earnings})^2$	1.084***	-0.0539***	-1.360***	0.0131
	(0.194)	(0.0142)	(0.362)	(0.00914)
$(\text{Mean Program Earnings})^3$	-0.00850***	0.000373***	0.00736***	-0.000140
	(0.00152)	(0.000101)	(0.00196)	(0.0000768)
Academic Rank in Post-Secondary Program				
Second Quintile	-0.0473	0.104	-15.17	-0.0945
	(0.169)	(0.295)	(1177.3)	(0.354)
Third Quintile	-0.189	-0.0943	-16.17	0.0740
	(0.250)	(0.391)	(1177.3)	(0.583)
Fourth Quintile	-0.0123	0.0864	-16.01	-0.199
	(0.376)	(0.499)	(1177.3)	(0.921)
Fifth Quintile	0.104	-0.0304	-16.68	-0.293
	(0.443)	(0.600)	(1177.3)	(1.045)
Academic Rank in High School Cohort				
Second Quintile	0.0130	-0.368	-0.495	0.635

	(1)	(2)	(3)	(4)
	LFA	STEM	BHPS	SSE
	(0.197)	(0.641)	(0.573)	(0.406)
Third Quintile	0.193	-0.892	14.34	0.649
	(0.277)	(0.781)	(1177.3)	(0.625)
Fourth Quintile	0.0849	-1.194	15.23	1.045
	(0.397)	(0.887)	(1177.3)	(0.977)
Fifth Quintile	-0.00468	-1.558	14.75	1.283
	(0.476)	(0.963)	(1177.3)	(1.117)
Starting Year of Post-Secondary Education				
2008	1.162***	1.365***	1.544***	1.219***
	(0.117)	(0.187)	(0.380)	(0.278)
2009	1.325***	1.565***	1.481***	1.060***
	(0.119)	(0.189)	(0.399)	(0.269)
2010	1.553***	1.523***	1.409***	1.320***
	(0.120)	(0.191)	(0.395)	(0.266)
2011	1.657***	1.398***	1.112**	1.289***
	(0.118)	(0.192)	(0.405)	(0.268)
2012	1.391***	1.440***	1.357***	1.120***
	(0.124)	(0.200)	(0.408)	(0.279)
Fixed Effects				
Postal Code	Yes	Yes	Yes	Yes
Institution	Yes	Yes	Yes	Yes
N	7740	3450	2160	1870
pseudo R^2	0.379	0.414	0.334	0.262

Standard errors in parentheses

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

Table A3.7: Full Double-Robust Results - Men

	(1)	(2)	(3)	(4)
	LFA	STEM	BHPS	SSE
Switch	0.237***	0.0736	-0.120	0.106
	(0.0590)	(0.0667)	(0.100)	(0.0999)
Work Experience	0.0936***	0.125***	0.116*	0.184***
	(0.0267)	(0.0310)	(0.0458)	(0.0541)
Standardized Exam Grades				
Science 10	-0.0389	-0.0323	-0.00187	-0.122
	(0.0515)	(0.0678)	(0.114)	(0.0948)
(Science 10)^2	-0.0293	-0.00780	-0.189	0.0110
	(0.0304)	(0.0401)	(0.105)	(0.0650)
Math 10	-0.0732	-0.0241	-0.112	-0.0561
	(0.0517)	(0.0643)	(0.0791)	(0.0879)
(Math 10)^2	-0.0114	0.0243	-0.00579	-0.0233
	(0.0294)	(0.0427)	(0.0633)	(0.0517)
English 10	-0.00501	-0.0132	0.00139	-0.00969
	(0.0380)	(0.0466)	(0.0711)	(0.0676)
(English 10)^2	-0.0137	-0.0352	0.00143	0.0427
	(0.0242)	(0.0269)	(0.0474)	(0.0434)
Standardized Teacher Assigned Grades				
Science 10	0.0695	0.0778	-0.0541	0.220*
	(0.0548)	(0.0693)	(0.0879)	(0.0942)
(Science 10)^2	-0.0219	-0.0517	0.0545	-0.00137
	(0.0318)	(0.0480)	(0.0645)	(0.0591)
Math 10	0.102	0.0485	0.160*	0.0975
	(0.0605)	(0.0680)	(0.0811)	(0.0854)
(Math 10)^2	0.0363	0.00342	0.0152	-0.0173
	(0.0390)	(0.0486)	(0.0756)	(0.0458)
English 10	-0.0113	-0.00565	0.106	-0.0514
	(0.0480)	(0.0510)	(0.0685)	(0.0737)
(English 10)^2	-0.00459	0.00461	-0.0280	-0.0164
	(0.0309)	(0.0403)	(0.0536)	(0.0479)
Graduation Year				
2012	0.135	0.170	0.284	0.243
	(0.226)	(0.263)	(0.448)	(0.411)
2013	0.0372	0.343	0.333	0.337
	(0.229)	(0.243)	(0.460)	(0.389)

2014	0.263	0.460	0.487	0.248
	(0.218)	(0.242)	(0.450)	(0.402)
2015	0.0754	0.501*	0.375	0.411
	(0.232)	(0.249)	(0.454)	(0.396)
2016	0.156	0.402	0.357	0.353
	(0.227)	(0.261)	(0.448)	(0.422)
2017	0.184	0.389	0.277	0.218
	(0.231)	(0.253)	(0.449)	(0.427)
2018	0.128	0.253	0.425	0.541
	(0.241)	(0.267)	(0.473)	(0.420)
2019	0.0921	0.182	0.282	0.308
	(0.251)	(0.294)	(0.484)	(0.454)
2020	-0.617*	-0.262	-0.275	0.245
	(0.287)	(0.310)	(0.545)	(0.476)
2021	-0.0733	-0.135	0.505	0.287
	(0.315)	(0.351)	(0.561)	(0.585)
Indigenous Status	0.0788	-0.197	0.114	-0.169
	(0.151)	(0.224)	(0.227)	(0.370)
English at Home	0.132	0.290***	0.148	0.0306
	(0.0696)	(0.0810)	(0.127)	(0.130)
Final Post-Secondary Institution				
Teaching University	0.202**	-0.0611	0.0691	0.128
	(0.0763)	(0.112)	(0.126)	(0.137)
Community College	0.0759	-0.0339	-0.0267	0.232*
	(0.0679)	(0.0832)	(0.119)	(0.115)
Out of Province School	-0.0109	0.0297	-0.181	0.403
	(0.150)	(0.159)	(0.250)	(0.261)
N	3050	4240	1900	1020
adj. R^2	0.081	0.096	0.113	0.105

Standard errors in parentheses

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

Table A3.8: Full Double-Robust Results - Women

	(1) LFA	(2) STEM	(3) BHPS	(4) SSE
Switch	0.157***	0.410***	-0.483***	0.0644
	(0.0405)	(0.0741)	(0.121)	(0.0732)
Work Experience	0.0546**	0.103**	0.0300	0.0782*
	(0.0176)	(0.0369)	(0.0577)	(0.0351)
Standardized Exam Grades				
Science 10	0.0210	-0.0539	0.0521	-0.0200
	(0.0370)	(0.0782)	(0.0912)	(0.0604)
$(\text{Science 10})^2$	0.00404	0.0300	0.0108	-0.00964
	(0.0139)	(0.0533)	(0.0637)	(0.0385)
Math 10	-0.0470	0.00887	-0.0829	-0.00538
	(0.0369)	(0.0565)	(0.104)	(0.0633)
$(\text{Math 10})^2$	-0.0237	0.0287	-0.0369	0.0459
	(0.0210)	(0.0326)	(0.0590)	(0.0435)
English 10	-0.0128	0.0786	0.143	0.0602
	(0.0251)	(0.0600)	(0.0884)	(0.0459)
$(\text{English 10})^2$	-0.0189	-0.0378	-0.0326	-0.00430
	(0.0161)	(0.0393)	(0.0682)	(0.0264)
Standardized Teacher Assigned Grades				
Science 10	0.0202	-0.0748	-0.0632	0.0472
	(0.0345)	(0.0730)	(0.105)	(0.0701)
$(\text{Science 10})^2$	-0.00669	0.0969*	-0.0414	-0.0175
	(0.0198)	(0.0477)	(0.0736)	(0.0456)
Math 10	0.0378	0.0192	-0.000636	-0.0231
	(0.0322)	(0.0636)	(0.102)	(0.0559)
$(\text{Math 10})^2$	0.0161	-0.00314	-0.00879	0.0315
	(0.0197)	(0.0404)	(0.0610)	(0.0329)
English 10	0.00915	0.00168	0.0111	-0.0277
	(0.0297)	(0.0715)	(0.0886)	(0.0542)
$(\text{English 10})^2$	-0.00174	-0.00479	-0.0114	0.0201
	(0.0194)	(0.0439)	(0.0694)	(0.0389)
Graduation Year				
2012	0.156	-0.0320	0.107	-0.169
	(0.113)	(0.370)	(0.371)	(0.271)
2013	0.0176	0.601	-0.217	-0.272
	(0.107)	(0.337)	(0.397)	(0.263)

2014	0.0703	0.514	-0.108	-0.0253
	(0.108)	(0.343)	(0.394)	(0.252)
2015	0.0701	0.486	-0.119	-0.137
	(0.114)	(0.356)	(0.376)	(0.255)
2016	0.0973	0.284	0.0541	-0.0989
	(0.112)	(0.349)	(0.384)	(0.256)
2017	0.0635	0.461	0.0329	-0.127
	(0.121)	(0.353)	(0.399)	(0.266)
2018	-0.0566	0.178	-0.372	-0.317
	(0.128)	(0.386)	(0.499)	(0.292)
2019	-0.0991	0.238	-0.320	-0.501
	(0.142)	(0.395)	(0.517)	(0.315)
2020	-0.219	0.341	-0.377	-0.599
	(0.154)	(0.391)	(0.491)	(0.321)
2021	-0.584**	0.00829	-0.0000583	-0.782
	(0.211)	(0.421)	(0.609)	(0.473)
Indigenous Status	-0.209*	0.190	0.257	-0.0460
	(0.106)	(0.189)	(0.245)	(0.185)
English at Home	0.179***	0.101	0.144	-0.00460
	(0.0501)	(0.0828)	(0.137)	(0.0889)
Final Post-Secondary Institution				
Teaching University	-0.0102	0.141	0.0781	-0.0129
	(0.0510)	(0.120)	(0.154)	(0.101)
Community College	-0.0180	0.328***	0.116	0.224*
	(0.0525)	(0.0769)	(0.175)	(0.0903)
Out of Province School	-0.0621	0.543***	-0.177	-0.132
	(0.118)	(0.131)	(0.329)	(0.189)
N	7140	3130	2140	1810
adj. R^2	0.052	0.107	0.103	0.075
rmse	0.993	1.111	1.043	0.964

Standard errors in parentheses

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

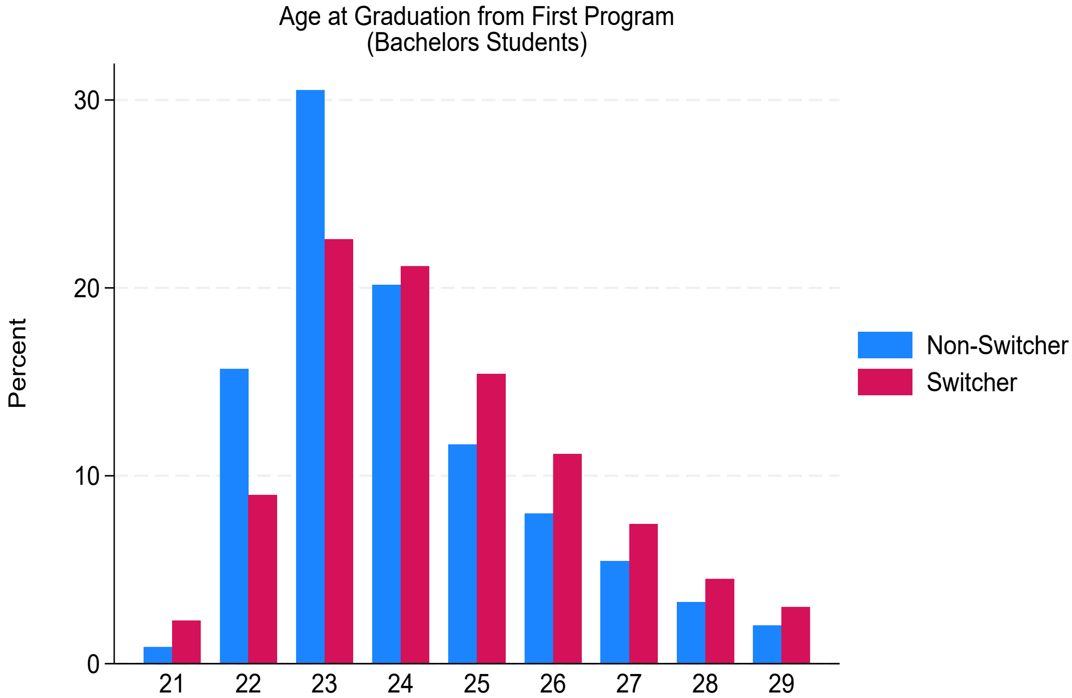

FIGURE A3.1: Age at Graduation - Switchers and Non-Switchers

Notes: This figure displays share of switchers and non-switchers graduating from post-secondary education between the ages of 21 and 29. All students enrolled in a Bachelors degree between 2007 and 2012. All students complete only one degree before entering the labour market post-graduation. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

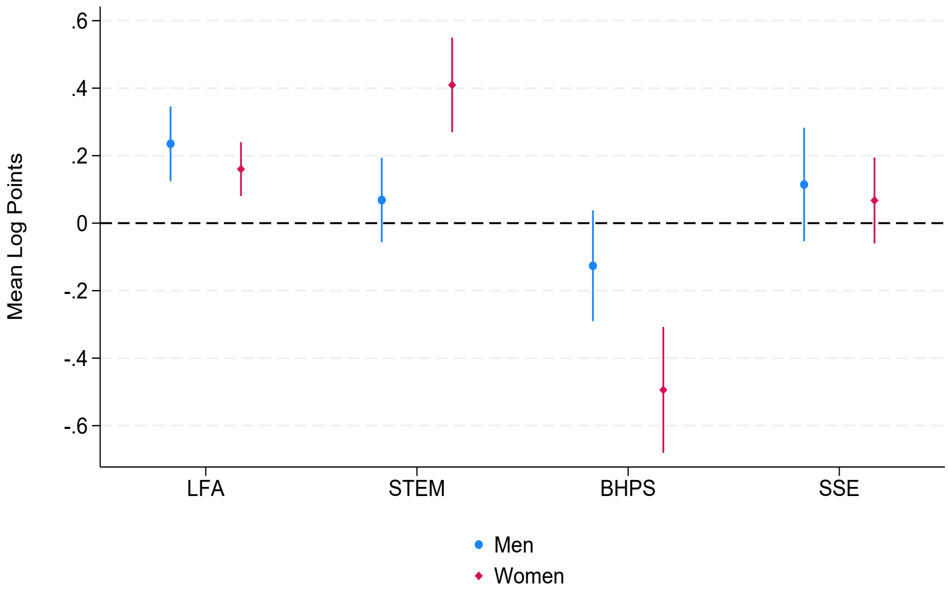

Figure A3.2: Impact of Switching - Bandwidth 0.06

Notes: This figure displays the impact of switching majors on earnings eight years after starting post-secondary education, displayed in mean log points. Here, the bandwidth of the propensity score matching has been changed to 0.06 (relative to the preferred specification of 0.12). The points displayed are the estimated coefficients on the binary variable Switch from equation (2). Point estimates are displayed for each combination of initial field of study and student gender. All specifications control for: Grade 10 teacher-assigned and exam grades, specified quadratically; work experience, measured as the difference between age when earnings are measured and age at graduation, specified linearly; Indigenous status; a binary variable, indicating whether English is spoken at home; year of graduation from post-secondary; a categorical variable indicating post-secondary studies were completed at a Research or Teaching University, a Community College, or at a post-secondary institution out of the province. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

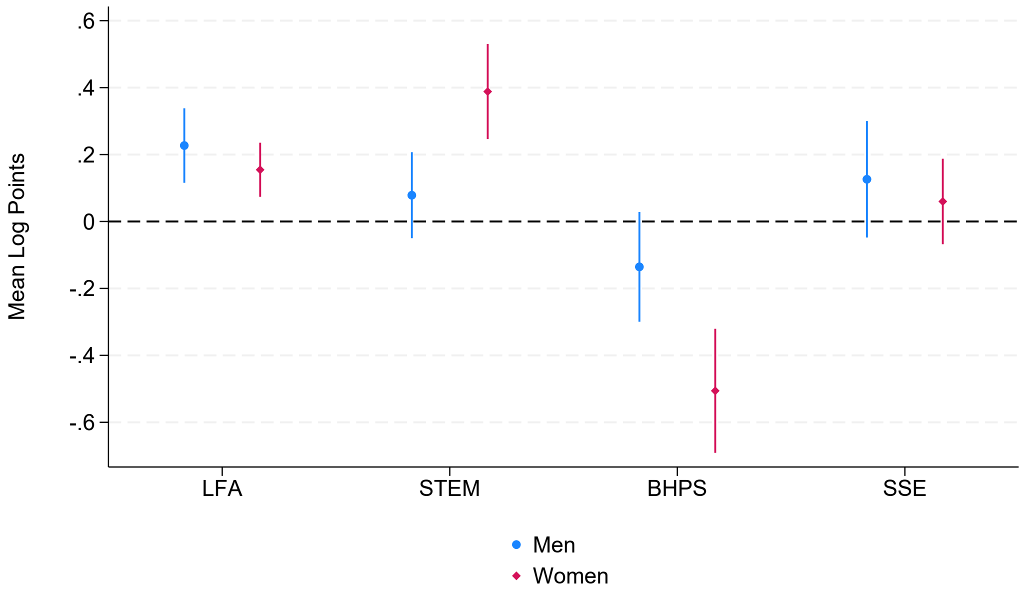

FIGURE A3.3: Impact of Switching - Bandwidth 0.03

Notes: This figure displays the impact of switching majors on earnings eight years after starting post-secondary education, displayed in mean log points. Here, the bandwidth of the propensity score matching has been changed to 0.03 (relative to the preferred specification of 0.12). The points displayed are the estimated coefficients on the binary variable Switch from equation (2) with 95 % confidence intervals. Point estimates are displayed for each combination of initial field of study and student gender. All specifications control for: Grade 10 teacher-assigned and exam grades, specified quadratically; work experience, measured as the difference between age when earnings are measured and age at graduation, specified linearly; Indigenous status; a binary variable, indicating whether English is spoken at home; year of graduation from post-secondary; a categorical variable indicating post-secondary studies were completed at a Research or Teaching University, a Community College, or at a post-secondary institution out of the province. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

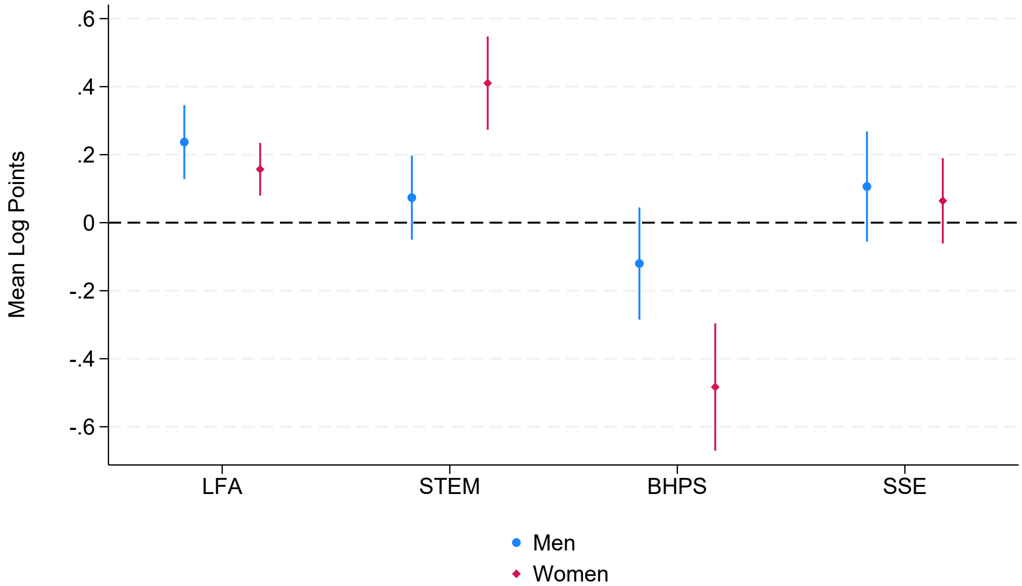

Figure A3.4: Impact of Switching - No Bootstraps

Notes: This figure displays the impact of switching majors on earnings eight years after starting post-secondary education, displayed in mean log points. Here, no bootstraps of the doubly-robust estimator have been completed, relative to the 599 bootstrap replications of the preferred specification. The points displayed are the estimated coefficients on the binary variable Switch from equation (2) with 95 % confidence intervals. Point estimates are displayed for each combination of initial field of study and student gender. All specifications control for: Grade 10 teacher-assigned and exam grades, specified quadratically; work experience, measured as the difference between age when earnings are measured and age at graduation, specified linearly; Indigenous status; a binary variable, indicating whether English is spoken at home; year of graduation from post-secondary; a categorical variable indicating post-secondary studies were completed at a Research or Teaching University, a Community College, or at a post-secondary institution out of the province. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

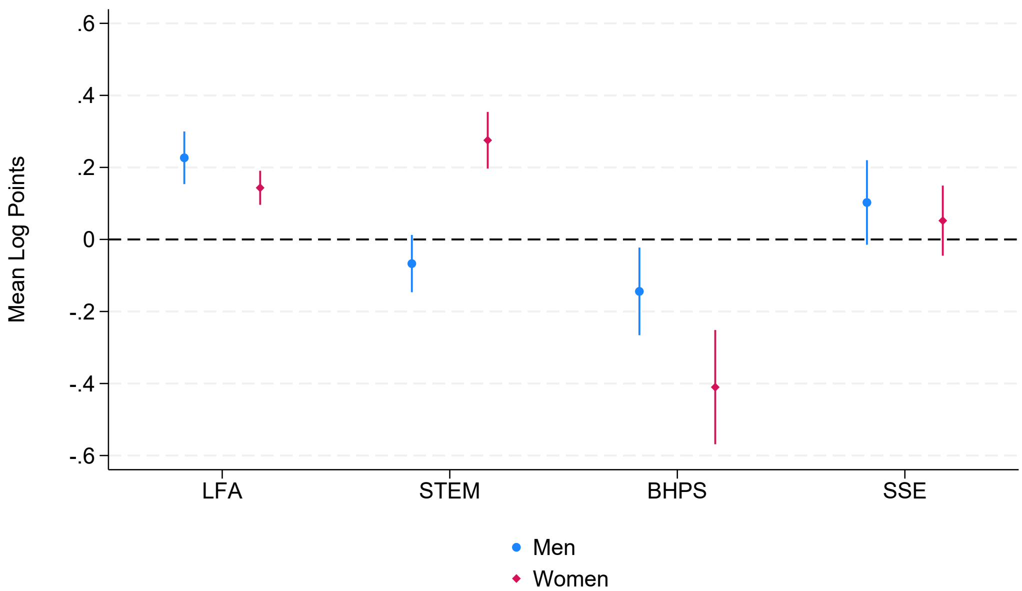

FIGURE A3.5: Impact of Switching - No Matching

Notes: This figure displays the impact of switching majors on earnings eight years after starting post-secondary education, displayed in mean log points. Point estimates displayed here are derived exclusively from equation (2) with no propensity score matching. Point estimates are displayed for each combination of initial field of study and student gender. All specifications control for: Grade 10 teacher-assigned and exam grades, specified quadratically; work experience, measured as the difference between age when earnings are measured and age at graduation, specified linearly; Indigenous status; a binary variable, indicating whether English is spoken at home; year of graduation from post-secondary; a categorical variable indicating post-secondary studies were completed at a Research or Teaching University, a Community College, or at a post-secondary institution out of the province. Source: Authors' calculations based on BC Ministry of Education and Children Care, 2021 and Statistics Canada, 2021.

Chapter 4

Gender Gaps in the Application Process to Engineering and Computer Science Programs

Abstract

Recent literature documents gender gaps in enrollment across Science, Technology, Engineering and Mathematics (STEM) university programs. In particular, while programs such chemistry and mathematics are near gender parity, engineering and computer science programs have much lower shares of female students. This study investigates the gender gap in applications, offers and acceptances to undergraduate engineering and computer science programs. We use unique administrative data on the university application process for all secondary school students in Ontario, Canada, that allows to observe not only student applications, but also the offers they receive and where they ultimately enroll. We find large gender gaps for engineering programs in both applications (11.9 percentage points) and offers (1.9 percentage points) and for computer science programs in applications (8.4 percentage points) and acceptances (9.0 percentage points). Our results suggest that both programs face unique challenges to increase the share of women enrolled.

4.1 Introduction

The under-representation of women in Science, Technology, Engineering and Mathematics (STEM) occupations, and particularly in engineering and computer science ones, has drawn the attention of both researchers and policy makers. Despite women representing half of the labour force, they make-up less than one-third of those employed in STEM occupations in Canada (Chan et al., 2021). This has implications for the gender wage gap as some STEM occupations, especially engineering-related ones, enjoy a pay premium relative to non-STEM occupations (Finnie et al., 2019). To address this, organizations such as the American Association of University Women have advocated for increasing the enrollment of women in university STEM programs (AAUW, 2022). Further, within STEM the share of women in Engineering and Computer Science is much lower than that in Biological and Health Sciences. For example, in 2015, women represented only 20 % (18 %) of graduates from Engineering (Computer Science) undergraduate programs in Canada while they made up 56 % of those from Biology (Wall, 2019). Organizations, such as Engineers Canada, have sought to close this gender gap through advocacy and outreach programs (Engineers Canada, 2020). Closing this gap has implications beyond undergraduate enrollment. The dearth of women in Engineering and Computer Science programs has disproportionate implications for the presence of women in STEM occupations since 70 % of women with a degree in Engineering work in STEM occupations while only 13 % of women with Biology degrees do so (Statistics Canada, 2017).

This paper investigates the gender gap in applications, offers and acceptances to university Engineering and Computer Science programs in Ontario, Canada. These programs have the largest gender gaps among all STEM programs (Wall, 2019) while having somewhat different prerequisites from each other. We employ university application data from 2011 to 2016 provided by the Ontario University Application Center (OUAC). This dataset has three advantages. First, we can observe the complete ranked list of applications submitted by students graduating from Ontario high schools to all Ontario undergraduate programs. Second, we can observe most courses taken and grades from each applicant's final year in high school. This allows us to examine high school academic factors that contribute to the gender gaps in Engineering and Computer Science. Finally, we are able to observe both offers and acceptances, allowing us to observe where these Ontario high school students apply, programs' reactions, and where applicants eventually enroll.

Ontario universities have different prerequisites for admission into relevant programs. Engineering programs typically demand several Grade 12 math and science courses. Completing these courses requires planning since applicants must, in turn, complete the relevant Grade 11 prerequisites (e.g., a student cannot take Grade 12 Physics without having completed Grade 11 Physics). In contrast, Computer Science programs demand fewer prerequisites, and these typically overlap with popular majors including Business and Finance. Accordingly, we are able to study factors that contribute to the wide gender gaps across two high paying STEM programs with different prerequisite demands. Our study, focuses primarily on those applicants who have completed the most common prerequisites for Engineering and/or Computer Science programs at the time of application and we refer to them as "Engineering-Ready" and "Computer Science-Ready". Anyone who is Engineering-Ready must also be Computer Science-Ready.

Our empirical methodology takes into account the academic and demographic characteristics that can both directly and indirectly affect the likelihood of enrolling in an engineering or computer science program. As shown by prior research, both academic achievement (in terms of course marks) and preparedness (in terms of courses completed) play an important role in shaping the gender gap in STEM programs (for examples see). To account for academic preparation, we control for standardized course marks in prerequisite courses as well as the presence of and marks in science courses completed beyond the prerequisites. Moreover, as the likelihood of applying to engineering or computer science programs may vary with background characteristics, we control for neighbourhood-level measures of immigrant status and average household income. Finally, to account for unobserved characteristics associated with an applicant's high school (including teachers, emphasis on STEM courses etc.) we include high school fixed effects. We discuss the empirical methodology in greater detail in Section 4.6.

Our results indicate that there are considerable gender gaps throughout the application process for both fields. To start, there is a wide gender gap in preparedness as, while, 33 % (58 %) of men can be classified as Engineering (Computer Science) ready the same is only true for 15 % (38 %) of women. Card and Payne (2021) document a similar lack of preparation for the broader set of STEM undergraduate programs among female Ontario high school students.

Examining applications to undergraduate engineering (computer science) programs among those who are classified as engineering (computer science) ready we find an unconditional gap in applications to engineering (computer science) programs of 35.3 (11.6) percentage points. Controlling for grade 12 Biology reduces the gap in engineering (computer science) applications by approximately 24 (3) percentage points. As biology is often not a prerequisite for admission into either program, this may suggest that completion of biology is associated with interest in STEM programs outside of engineering and computer science. Further investigation reveals two key points. First, performance in high school Physics and English has sizeable associations with the likelihood of applying to engineering programs. Indeed, a one standard deviation increase in Physics (English) marks increases (decreases) the likelihood of application by nearly 8 (4) percent for both men and women. Second, completing Physics is associated with a large increase in the likelihood of applying to computer science programs for both men and women.

In the next stage of the analysis, we examine the likelihood of having at least one offer to an engineering or a computer science program, conditional on having applied. We find no statistically significant gap in computer science offers However, while women are very slightly more likely to receive an engineering offer than are men overall, they are about 4 percentage points less likely to receive an offer after controlling for marks and other characteristics. Moreover, we find that the program rankings in an applicant's portfolio has implications for the likelihood of receiving an offer from engineering programs. Controlling for our full set of regressors, each rank below first, and especially below the first three, results in a considerable drop in the likelihood of receiving an offer, with a much larger effect for women.

Finally, we investigate gaps in the likelihood of accepting an offer to either an engineering or computer science program, both over all and conditional on having at least one offer. We find an unconditional gender gap of 6.6 (12.6) percentage points for engineering (computer science) programs; women are less likely to accept offers. Similar to the application stage, having taken Biology explains a sizeable portion of the engineering acceptance gap, reducing it to 1.8 percentage points. Women who complete Biology are less likely to enroll in engineering, even if they apply and receive an offer. After including all controls, we find no statistically significant gap in the likelihood of accepting an offer to an engineering program. In contrast, out control variables do little to reduce the gap in computer science acceptances, leaving an unexplained gender gap of 13.0 percentage points. That statistically and economically significant gaps exist for engineering in the offer stage and for computer science in the acceptance stage suggests that both programs face different problems in attempting to address gender parity.

Selection into the engineering/computer science-ready samples is a potential problem for the interpretation of some results. Since a much smaller share of women than men meet either "ready" definition, there may be differences in average ability, with only the highest academically able women choosing to become engineering or computer science ready. This would be in line with the work of Cimpian et al. (2020) who find that while men and women of the highest academic ability intend to major in engineering and computer science at near equal rates, the share of men who intend to major in either program is much greater throughout the remainder of the ability distribution.

These findings have policy implications for closing the gender gap in undergraduate engineering and computer science programs. Specifically, they highlight that not only do gender gaps exist in high school course choices, with men being more likely to take relevant engineering and computer science prerequisites, but they are reinforced throughout the application process. Closing the gender gap in engineering and computer science enrollment will require efforts that recognize the entire process.

4.2 Literature Review

There is a growing literature that employs administrative data to investigate the gender gap in students' outcomes within university STEM programs. Card and Payne (2021) use the same data we do to investigate aspects of the broader gender gap in STEM in Ontario. They find that it is largely explained by the disproportionate share of women who are not "STEM-Ready" by the conclusion of high school (that is, have not completed the prerequisites for admission into a STEM undergraduate program). There are two key distinctions between this work and that of Card and Payne (2021). First, we examine the entirety of the application process, including both offers and acceptances. This provides a more complete view of the enrollment gap in engineering and computer science programs are able to document gaps in offers and their acceptance. Second, we have a narrower focus, examining the gender gap in Engineering and Computer Science programs which, historically, have exhibited the lowest share of female students out of all STEM programs. Indeed, the higher-level STEM analysis combines fields in which women are over- and under-represented.

Employing application data from Ireland, Delaney and Devereux (2019) find an unadjusted gender gap of 22 percentage points in ranking a STEM program first during university applications. Like Card and Payne (2021), they find that this gap is largely explained by differential course selection in high school, with women less likely to complete STEM pre-requisites compared to men. A key contribution of our work, which builds on the analysis of Delaney and Devereux (2019), is our investigation of offers given by engineering and computer science programs. University enrollment is, ultimately, a two-sided matching problem in each one side (applicants) must choose where to apply based on preferences and qualifications, while the other side (university programs) must choose who to admit based on prerequisite criteria and available spaces. While much of the existing literature has focused on the gender gap in applications to undergraduate STEM programs, we expand the discussion by incorporating information on offers made by programs.

Other work has sought to employ a wider array of both academic and personal characteristics to explain the gender gap in undergraduate STEM programs. For example, Bordon et al. (2020) employ Chilean university application data to investigate the gender gap in applications to various university programs. They show that females' likelihood of applying to STEM programs is influenced by both academic preparation and parental occupation. Of course, as Finnie et al. (2004) point out, beyond their direct effects, characteristics such as parental occupation, household income, and workplace preferences that are chronologically early in the education process can indirectly influence university program enrollment through their effect on academic outcomes/choices. With this in mind, we incorporate several personal and neighbourhood-level characteristics into our regression framework given their potential indirect effect on application decisions.

In research similar to that here, Shi (2018) employs administrative and survey data from North Carolina to investigate the gender gap in engineering undergraduate programs. Shi (2018) finds that both differences in academic preparation in high school and workplace preferences explain a significant portion of the gender gap in engineering program enrollment. There are three key differences between our work and Shi's. First, we make use of end of high school grades and courses, while Shi (2018) employs a less directly relevant measure: credit accumulation during the first two years of high school. This allows us to measure preparation more precisely and examine gaps among applicants that have met the prerequisites for engineering and computer science undergraduate programs. Second, and more important, we examine the full application process. We see applications to all program-university combinations in the province from an applicant's ranked list in an institutional context where applications to two different programs (say physics and chemical engineering at the same university) would usually be considered as separate applications, as would applications to the same program at different universities (say electrical engineering at alternative institutions). Moreover, unlike Shi (2018), we are able to determine whether an applicant has an interest in Engineering or Computer Science at the application stage, rather than only observing those who ultimately enroll in a program. We can assess whether men and women prioritize engineering (or computer science) programs (e.g. ranking in the portfolio) or differ in the total number of applications submitted to either program type. We also observe all offers an applicant receives in the province and, observe which offer is accepted. Observing the full process provides greater insight.

Although only indirectly relevant to our analysis, there is an extensive literature that examines additional factors that contribute to the gender gap in STEM programs. Given that representation can play a role in shaping an individual's sense of belonging (Cheryan et al., 2016), the association between exposure to female peers and persistence in STEM programs has begun to receive attention. For example, Bostwick and Weinberg (2022) study the effect of female peers on female perseverance in STEM doctoral programs.

They find that an increase in the percentage of female students in a STEM doctoral program increases the likelihood of female students remaining enrolled beyond their first year. At the high school level, Mougaine and Wang (2020) find that exposure to high performing female peers in mathematics increases the chance that women will choose a science track during high school.

Some studies suggest that differences in psychological beliefs and attitudes may play a role in STEM gender gaps. For instance, Saltiel (2019) finds that self-confidence in math ability is a strong predictor for STEM enrollment. This has implications for our work as Kurtz-Costes, Rowley, Harris-Britt and Woods (2008) suggest that girls have a lower self-perception of their math ability compared to boys. Moreover, gendered attitudes towards competition may play a role in widening the gender gap in STEM university program enrollment given the highly competitive nature of certain STEM programs (Riegle-Crumb et al., 2019). Finally, preferences for non-pecuniary elements of STEM workplaces (e.g. flexibility and work-life balance), and perceptions of workplace characteristics, may drive gender gaps in STEM programs (Wiswall and Zafar, 2017).

4.3 Institutional Setting

Applications to all undergraduate programs in all 23 provincial universities go through the Ontario Universities' Application Centre (OUAC), which is a centralized agency that also records offer decisions sent to applicants. Applicants are subdivided into two categories. Those applying directly from an Ontario high school are referred to as 101 applicants, while mature applicants, high school students from other Canadian provinces, and international applicants are designated as 105 applicants.

OUAC (2023) indicates that, in general, applicants from Ontario high schools must have an Secondary School Diploma and at least six Grade 12 courses from one of two streams: pre-university (called 4U), or pre-university/pre-community college (called mixed). Universities may require specific courses and minimum grades for their programs above this minimum and requirements for the same program (e.g., civil engineering) can sometimes vary across universities. Programs determine admissions based on a combination of grades in required prerequisites and the grades in other courses (OUAC, 2023).

The most common prerequisites for Engineering programs are the following five 4U-level courses: English, Physics, Chemistry, Advanced Functions, and Calculus and Vectors. We refer to applicants who have completed these courses as "Engineering-Ready". While Engineering programs are usually demanding in their high school course requirements, Computer Science programs typically require only three 4U-level courses: English, Advanced Functions, and Calculus and Vectors. Accordingly, applicants who are "Engineering-Ready" are also, by definition, "Computer Science-Ready". In choosing to focus on "ready" students, however, we exclude a select share of individuals who do not meet our definitions of "readiness" and still choose to apply to (and often receive offers from) these programs. As shown in Appendix Table A.3, approximately 15 % of applicants to both engineering and computer science do not meet the typical prerequisites for either program. However, as seen in Appendix Table A.4, a much smaller of individuals outside the "ready" classification receive offers to either program.

Applicants submit a ranked list of undergraduate programs (where program is a field-of-study and university combination) to OUAC which then provides the applications to each institution. Programs may or may not make use of the ranking information. At present, each is supposed to provide information on this issue to students (on a university website) and OUAC advises applicants that, for the most part, ranking is not usually a factor in a program's decision (OUAC, 2023). It should be noted however, that admissions offices often use the ordering of choices to project the number of applicants that are likely to accept offers in the future application cycles (OUAC, 2023). Applicants pay a flat fee for their first three choices and an additional fee for each subsequent choice. Along with their choices, OUAC also provides each selected university with an applicant's Grade 12 grades, their high school's identity, and certain demographic information. Applicants are notified of each program's decision regarding their application and are free to accept any offer. They are not restricted to their top ranked offer. Offers need not be revealed to applicants simultaneously as some programs may take longer to make decisions than others. There is no coordination of offers across universities; whether or not there is coordination across programs within a university is unclear. It should also be noted that programs may employ automated decision making based on high school grades for Ontario high school applicants. These decisions making processes are, therefore, blind to the gender and personal characteristics of the applicant.

4.4 Data

Data are provided by OUAC and include information on all applicants to undergraduate programs from Ontario high schools (101 applicants) between 2011 and 2016. For these applicants we observe their Grade 12 course marks, high school, ranked choices, offers received, and responses to offers. We standardize all Grade 12 course marks within each year and course to mean zero and standard deviation one among all of those who apply to an Ontario university (not only those who apply to engineering/computer science). The OUAC data also contain the following demographic information for each applicant: age, gender, immigration status at the time of application (Canadian Citizen, Permanent Resident, or Study Visa), years spent in the Canadian education system, mother tongue, and marital status. We combine these individual data with dissemination area (DA) statistics from the 2011 Canadian Census, which allows us to determine the following information about each applicant's home neighbourhood: mean household income, as well as the shares of immigrants and visible minorities.

We remove those applicants with fewer than six courses on their transcript (the minimum number needed to be considered for university admissions). We also remove all applicants aged over 20 or below 17 at the time of application, anyone listed as graduating under an outdated provincial curriculum, missing Grade 12 English on their transcript, or with missing average neighbourhood household income. Additionally, as we employ high school fixed effects, we remove high schools with fewer than 10 university applicants across our entire time period. We are left with a final sample of 440,648 applicants.

4.5 Descriptive Statistics

We begin by presenting application and academic profiles of males and females. In addition to Engineering and Computer Science programs we also record applications to “Other STEM” which consists of the following: Biology and Life Sciences, Health Professions (e.g., Nursing and Kinesiology, but not Medicine as it is typically a second degree in Ontario), Mathematics and Statistics, Physics, Chemistry, and Earth and Environmental Sciences. Classification for programs within each category is determined by the Classification for Instructional Program Primary Grouping (CIPPG), an internationally employed classification of post-secondary programs. Finally, the determination for which programs are considered STEM follows Beede et al. (2011, esp. Table A.2).

For ease of exposition, we present selected summary statistics in the order of the application process: pre-application characteristics, specifically the academic preparedness (and performance) of both men and women; applications, offers received, and offers accepted.

4.5.1 Academic Characteristics

As is well known, there is a wide gender gap in preparation for Engineering and Computer Science programs. Table 4.1 Panel A shows the share of women and men who have completed each Grade 12 Science and Math course. There is a considerable difference in completion rates for Physics, Calculus and Advanced Functions, and to a lesser extent Biology between men and women. For example, while 42 % of men complete Physics only 19 % of women do so. Similarly, while over half of all men completed Calculus only 38 % of women did so. This wide gap in the completion of prerequisites for both engineering and computer science suggests a lack of "readiness" to apply to either program type among women.

Further to this point, Table 4.1 Panel B shows a near 20 percentage point gap in "readiness" for both engineering and computer science programs; only 16 % (38 %) of women can be classified as engineering (computer science) ready compared to 34 % (58 %) of men. This sizeable gap corroborates the findings of Card and Payne (2021) and suggests that prior to the application process many women do not meet the prerequisites for admission into either engineering or computer science.

Focusing on those who do meet our definition of "readiness," there is a noticeable difference in both course completion and the academic performance of men and women. While "ready" students must complete certain courses to meet prerequisite demands, they are also able to complete science courses outside of these prerequisites. Table 4.2 Panel A (Panel B) shows the share of engineering-ready (computer science ready) men and women who complete each science class that is outside of their prerequisites. Focusing first on Panel A, 81 % of engineering-ready women complete Biology (in addition to their prerequisites) while only 46 % of engineering-ready men do the same; this is the only science course that is not an engineering prerequisite. Panel B (computer science-ready) further highlights the gendered preferences for science courses. While equal percentages of computer science ready men and women complete Chemistry, relatively more women (resp. men) complete Biology (resp. Physics) in addition to their required courses.

Table 4.3 shows the means of standardized marks for both women and men and various subgroups of students. In Column 1 and 2 marks are standardized across all students while for Columns 3 and 4 they are standardized only among students who are engineering-ready (Panel A) or computer science-ready (Panel B). Columns 1 and 2 allow us to see how engineering- (and computer science) ready students have high grades, on average, than other applications. This is true for most genders and especially for women. Furthermore, Columns 3 and 4 show that engineering and computer science ready women have higher grades, on average, than men who are ready for these subjects.

As mentioned previously, men are more likely to be either engineering-ready or computer science-ready compared with women. If high-achieving students are more likely to become, for example, engineering-ready, then the average marks displayed in Table 4.3 Columns 1 and 2 consider the highest-achieving 16.5 % of women and 34 % of men. To visualize this, Figure 4.1 and 4.2 display kernel density plots for engineering-ready and computer science-ready students, respectively. For both Figures, the x-axis displays the average mark in prerequisite classes, standardized among students who meet each "ready" classification. We show density plots for four categories of applicants; all men who met the "ready" classification; all women who met the "ready" classification; "ready" men who apply to engineering (or computer science); "ready" women who apply to engineering (or computer science). For both Figures, the sum under the areas under all four curves is equal to one.

It is clear from both Figures that the share of women who are "ready" is smaller when compared to share of men who are "ready". Moreover, the share of students who are both "ready" and choose to apply to either program is much smaller than the share of students who meet either "ready" classification. However, for both engineering- and computer science-ready students, the mode of prerequisite grades is further right for women relative to men, indicating a higher average level of performance. This remains true when looking at female relative to male applicants.

4.5.2 Applications

Applicants choose how many applications to submit. Figure 4.3 displays the share of men and women who submit between 1 and 10 or more applications, across all applicants. Almost 70 % of all applicants submit at most 5 applications with 40 % submitting just 3 applications. While the share of men and women remains roughly equivalent at each point along Figure 4.1, a slightly greater share of men submit more than 5 applications.

Beyond its size, applicants also choose the composition of their portfolios, varying the share of applications submitted to each program category. For marginal applicants, a smaller number of applications submitted to, say, engineering programs will limit the number of offers received from that category and the likelihood of at least one such offer. To this end, Figure 4.4 displays the average portfolio share for each program category (engineering, computer science, Other STEM and Non-STEM) for engineering-ready men and women. The "average share of applications" was determined by calculating the share of each program category in each individuals' portfolio, and then averaging these shares across engineering-ready men and women. There are two key takeaways from Figure 4. First, engineering-ready men devote a larger share of their applications to engineering programs, than to engineering-ready women. Indeed, men devote almost 50 % of portfolio space to engineering programs, on average. To contrast, female engineering-ready applicants devote less than 20 % of their portfolios to engineering programs. Second, approximately 70 % of applications submitted by engineering-ready women go to STEM programs outside of engineering and computer science. Combined, these two observations demonstrate that engineering-ready men more likely to apply to multiple engineering programs and engineering-ready women are more likely to have a portfolio with larger shares on non-Engineering STEM programs. Both are about equally likely to apply to non-STEM programs.

Figure 4.5 displays the average portfolio composition for all computer science-ready men and women. Recall that all applicants who are engineering ready are also computer science ready. To contrast, Figure 4.6 shows the average portfolio composition for men and women who are computer-science ready but not engineering-ready (they have not completed both Physics and Chemistry). Examining Figure 4.6 it is evident that those who are computer science-ready but not engineering-ready are a much different group of applicants. Indeed, relative to the average computer science-ready applicant in Figure 4.5, those who are not engineering-ready have a much greater interest in Non-STEM courses. Moreover, while the portfolio-share of computer science applications remains roughly stable between the two groups (for both men and women) there is a noticeable reduction in the average portfolio share devoted to engineering applications. This difference in portfolio composition will be important to consider when discussing regression results in Section 6.

Table 4.4 Panel A provides insight into the share of applicants that include engineering (computer science) applications in their portfolio. The sample in Table 4.4 is restricted to those who are either engineering-ready (Panel A) or computer science-ready (Panel B). Looking first at Panel A, there is a large difference in the share of engineering-ready men who have at least one engineering application in their portfolio (69 %) compared to engineering-ready women (34 %). A gap of near equal magnitude exists among those who have multiple engineering applications, with 58 % of engineering-ready men submitting at least two engineering applications compared to 25 % of engineering-ready women.

As mentioned previously students are also able to rank the applications within their portfolios. Accordingly, rows 3 and 4 of Panel A show the share of engineering-ready applicants who rank engineering first among those who submit three (Row 3) or more than three (Row 4) applications (among those who have applied to engineering). For those who submit only three applications, 79 % of men and 71 % of women rank engineering first. Among those who submit more than three applications, however, 63 % of men and only 49 % of women rank engineering first. Accordingly, it would appear that not only are engineering-ready men more likely to apply to an engineering program, they are also more likely to rank said application first (assuming they have more than one application).

Panel B shows similar information for computer science applications among computer science-ready applicants. As expected from the outcomes presented in Figure 4.3, there is a considerable smaller share of both men and women that apply to computer science as only 17 % (5 %) of computer science-ready men (women) have a computer science application in their portfolio. Moreover, computer science appears to be a lower priority application, relative to engineering, as only 59 % (48 %) of computer science-ready men (women) rank their computer science application first.

4.5.3 Offers and Acceptances

Table 4.5 Panel A shows, by gender, the share of applicants to engineering programs (among engineering-ready students) who received offers, split into three categories: those who received at least one offer from an engineering program; those who received multiple engineering offers; those who received offers from both engineering and other STEM programs. We also display the share of students who receive offers conditional on ranking within one's portfolio: those who rank engineering first; those who rank engineering beyond the top three choices. Panel B displays the same information for those who applied to computer science programs (among computer science ready students). Recall, we focus on those applicants who are either "engineering-ready" or "computer science-ready".

Looking at Table 4.5 Panel A, we can see that a near equivalent share of male and female applicants to engineering-programs receive at least one offer at 87 % and 88 %, respectively. However, a greater share of male applicants receive multiple engineering offers (63 %) than female applicants (56 %). This is somewhat unsurprising given the greater share of applications submitted to engineering programs by men. In Section 4.8.2, we condition on the likelihood of receiving an offer among those who submit the same of applications to engineering programs. Women are more likely to receive both an offer from an engineering program and another STEM program than men (53 % versus 38 %). Again, this is line with application patterns observed above, as engineering-ready women are more likely to submit applications to a diverse array of STEM programs. A similar pattern emerges when examining offers to computer science programs (Panel B).

Table 4.5 also examines the share of applicants who receive an offer to a program given its ranking in their portfolio. Row 4 of Panel A displays the share of engineering-ready applicants who receive an offer to a first-ranked engineering program. There is a large difference in the offer share between men and women, as nearly 71 % of women who rank an engineering program first receive an offer compared to only 59 % of men. As we show below, this difference can largely be attributed to difference in marks because the GPA of the average male engineering applicant is lower than the GPA of the average female engineering applicant. There is limited difference in offer reception for applications ranked below the top three (Row 5).

Table 4.6 Panel A (Panel B) displays the share of applicants accepting offers to engineering (computer science) programs. Looking first at Panel A, the share of men (69 %) who accept an offer to an engineering program is slightly larger than the share of woman (62 %) who do the same. Looking at Panel B, there is a much larger difference in the share of men (47 %) who accept an offer from a computer science program when compared to women (34 %). As applicants can have offers to several different programs, understanding how having multiple inter-disciplinary offers impacts the likelihood of enrolling in engineering (or computer science) is of high importance. To that end, Table 4.6 also shows the share of applicants who accept an offer to engineering despite also having offers to other STEM programs (outside of engineering). For both engineering (Panel A) and computer science (Panel B) there is a stark decline in acceptance rates, suggesting that applicants with diverse portfolios may be less inclined to study engineering (or computer science). Finally, we also investigate if there is a gendered difference in the likelihood of acceptance given an applications ranking in one's portfolio. For both engineering (Panel A) and computer science (Panel B) programs there is limited difference in the likelihood of accepting an offer on a first-ranked, or outside-of-top-three ranked, application between women and men.

4.6 Regression Methodology

We use a linear probability model to determine the influence of various factors on key outcomes throughout the application process. Specifically, we estimate the following,

$$\begin{aligned} y_i = \beta_0 + \beta_1 female_i + \beta_2 courses_i + \beta_3 marks_i + \\ \beta_4 female_i \text{x} courses_i + \beta_5 female_i \text{x} marks_i + X_i\beta_6 + \varepsilon_i \end{aligned} \tag{1}$$

where y_i is the binary dependent variable of interest (either application, offer or acceptance). We estimate this equation separately for applicants who are engineering-ready and computer science-ready. The unit of analysis is the individual, meaning that y_i records whether an individual has at least one application (or one offer or one acceptance). In section 4.7.2.1, we change the unit of analysis to the application to focus on the association between choice rank and the likelihood of receiving an offer.

The coefficient of interest is β_1 on the binary variable $female_i$, which is equal to 1 if individual i is female and 0 otherwise. Given the interaction terms and the fact that marks are normalized to mean zero in the population of applicants, this coefficient can be interpreted as the average gap in the dependent variable between females and male students whose marks are equal to the average and who did not take any science courses other than the ones needed to be engineering or computer-science ready. The variable $courses_i$ is a vector of indicator variables for having taken each potential Grade 12 science course beyond the mandatory prerequisites, which differs by “ready” classification. For computer science-ready applicants, $courses_i$ is a vector of 7 indicator variables that represent each possible combination of Chemistry, Biology and Physics. In contrast, for engineering-ready applicants, $courses_i$ is a single binary variable equal to 1 if i has taken Biology and 0 otherwise. The variable $marks_i$ is a vector containing each individual’s i standardized marks on mandatory prerequisites depending on i’s “ready” classification. For example, for Engineering-Ready applicants the variable $marks_i$ records i’s performance in English, Physics, Chemistry, Calculus and Vectors, and Advanced Functions. All marks are standardized across students in each ready-classification in our sample in each year. Following a series of Wald tests, all standardized course marks are specified as linear. As a robustness exercise we display the regression results using quadratic marks. We interact both $marks_i$ and $courses_i$ with $female_i$ to examine the differential effect of academic characteristics on men and women.

The vector X_i contains variables for individual and neighbourhood-level demographic characteristics. For individual demographics we include the following: mother tongue; a binary variable that equals 1 if an individual is a permanent resident and 0 if they are a Canadian citizen; years in the Canadian education system for persons with fewer than 12 years; a dummy variable equal to 1 if a person has 12 or more years in the Canadian education system, zero otherwise; application year and high school fixed effects. For neighbourhood demographics, we include average household income (inflation-adjusted to 2016 Canadian dollars) as well as the population share of immigrants and visible minorities in the neighbourhood. All continuous variables are mean deviated. Finally, standard errors are heteroscedasticity-consistent when the unit of observation is the individual and clustered at the individual-level when the unit of observation is the application. Tables 4.7 and 4.8 show the mean and standard deviations for all variables included in the regression for engineering and computer science-ready students, respectively, prior to any mean-deviation or standardization.

4.7 Results

Our regression results, summarized in Tables 4.9 through 4.14 and with full results in the appendix, are ordered to align with the application process and focus on students who are engineering- or computer science-ready thereby comparing men and women of similar academic profiles at the end of high school.

4.7.1 Engineering Application

Table 4.9 addresses the likelihood of applying to an engineering program among engineering-ready students. The outcome variable is equal to 1 if there is a recorded application to an engineering program in individual i's portfolio, zero otherwise. Column (1) presents results with only a binary control variable for gender. The results suggest that: engineering-ready women are 35.4 % less likely to make at least one engineering application than engineering-ready men. Column (2) adds a binary variable for whether i has taken Biology, which is the only Grade 12 science course often not required by engineering programs. The incorporation of Biology produces two key results. First, the application gap between men and women who have not taken Biology stands at 11.5 percentage points, much smaller than the gap presented in Column (1). Second, those who have completed Biology are much less likely to apply to engineering, with a larger effect among women. Indeed, engineering-ready women (men) who have completed Biology are approximately 50 percentage points (36.8 percentage points) less likely to apply to engineering, compared with women (men) who have not. Given the large share of applications that are submitted to STEM programs outside of engineering by engineering-ready women (which include biology and life sciences), it is unsurprising that including Grade 12 Biology explains such a sizeable portion of the gap in engineering program applications. Column (3) incorporates standardized marks in prerequisite courses. Physics appears to have a large effect (relative to other prerequisites) on the likelihood of applying to an engineering program; a one standard deviation increase in physics marks increases the likelihood that a student applies by more than 5 percentage points (for both men and women). Apart from chemistry and advanced functions, marks received in most Grade 12 courses have a negligible gap on the relative likelihoods that men and women apply to at least one engineering program. Finally, Columns (4) and (5) incorporate individual and neighbourhood demographics characteristics and school and year fixed effects, respectively. Adding these controls does not affect the coefficient estimates on the $female_i$ or $biology_i$ variables (or their interactions). In Column (5) we are left with an unexplained gender gap of 11.9 percentage points in applications to engineering programs.

4.7.1.1 Computer Science Application

Table 4.10 presents the results from equation (1) describing the likelihood of applying to a Computer Science program among Computer Science-Ready applicants. Column (1) displays results with only a binary control variable for gender. The estimate suggests that female computer-science ready students are 11.6 % less likely to make at least one computer science application than male computer science-ready students. Column (2) adds a vector of binary variables representing each combination of science courses that can be taken in Grade 12 (here, “no science courses” acts as the base category). The application gap between computer-science ready men and women who do not taken any science courses stands at 8.76 percentage points. Completing a physics course (either alone or in combination with other science courses) increases the likelihood of applying to at least one computer science program more for men than women. Column (3) incorporates the standardized marks in perquisite courses. Similar to Table 4.9, better performance in Grade 12 English reduces the likelihood of applying to a computer science program for both men and women. Finally, Columns (4) and (5) incorporate individual and neighbourhood demographics and school and year fixed effects, respectively. Much like with engineering applicants, controls beyond science course completion have little to no independent effects on the probability of apply to computer science. Following the incorporation of all controls, we are left with an unexplained gender gap of 8.42 percentage points in applications to computer science programs.

4.7.2 Offers

Table 4.11 (Table 4.12) presents estimates from equation (1) when the dependent variables is equal to 1 if i receives at least one offer to an engineering (computer science) program anywhere in their portfolio conditional on having applied. Columns (1)-(5) add the same variables as in Table 4.9 (Table 4.10). For these tables, the sample is restricted to those who are engineering-ready (resp. computer science-ready) and who have applied to at least one engineering (resp. computer science) program.

It should be noted that, here, we do not focus on the number of offers received (or, by extension, the number of applications submitted). Rather, the following examines the likelihood of receiving an offer conditional on having applied to at least one engineering (computer science) program. However, as shown in section 4.5.2, engineering-ready (computer science ready) men are more likely to submit multiple applications to engineering (computer science) programs, increasing the chance they will receive at least one offer. In section 4.8.2 we examine the likelihood of offer reception between men and women who submit an identical number of applications to engineering (and computer science) programs.

The estimate in Table 4.11, Column 1 indicates that women are approximately one percentage point more likely to receive an engineering offer than men. Including biology (Column 2) increases this gap to 2 percentage points suggesting that engineering-ready women are slightly more likely to receive an offer relative to engineering-ready men (if neither has taken biology). However, incorporating standardized marks in prerequisite courses (Column 3) reverses this gap, to over 2 percentage points in favour of men. This suggests that women with average marks in prerequisite courses (relative to other engineering-ready students) are slightly less likely to receive an offer when compared to engineering-ready men with average marks. There may be two factors driving these results. First, as discussed above, men with average marks may be submitting slightly more applications to engineering programs relative to women with average marks, thus increasing the chance of receiving an offer. Second, as discussed in Section 4.5.1, it may be the case that only the highest-achieving women are choosing to become "engineering-ready" while both high and medium-achieving men choose to do so. Accordingly, even if the likelihood of receiving an offer is the same across the achievement distribution for both men and women, a greater share of medium-achieving men will decrease the likelihood of women receiving an offer when conditioning on marks. In Section 4.8.3 we examine how the likelihood of receiving an offer (along with the likelihood of application and offer acceptance) differs throughout the achievement distribution. Finally, the inclusion of demographics (Column 4) and fixed effects (Column 5) explain little of this gender gap in the likelihood of receiving an offer.

Turning to Table 4.12 we observe an unconditional gender gap in the likelihood of receiving a computer science offer of nearly 3 percentage points, in favour of men (Column 1). However, upon controlling for science courses completed (Column 2) the gap changes in to nearly 5 percentage points, in favour of women. Similar to the estimates in Table 4.8, the completion of physics is associated with a modest increase in the likelihood of receiving an offer. Indeed, the completion of "Physics Only" is associated with a 7 percentage point increase in the likelihood of receiving an offer for both men and women. After controlling for marks in prerequisite courses, the gender gap in the likelihood of receiving a computer science offer disappears.

4.7.2.1 Program Ranking and Offers

Programs may take their ranking in the applicant's application portfolio into consideration when making offers. We test whether ranking has an effect on offers by estimating the following,

$$\begin{aligned}&y_{ij} = \beta_0 + \beta_1 female_{ij} + \beta_2 rank_{ij} + \beta_3 courses_{ij} + \beta_4 marks_{ij} + \\ &\beta_5 female_{ij}\text{x}courses_{ij} + \beta_6 female_{ij}\text{x}marks_{ij} + \beta_7 female_{ij}\text{x}rank_{ij} + X_{ij}\beta_8 + \varepsilon_{ij}\end{aligned} \tag{2}$$

where y_{ij} equals 1 if application j from individual i receives an offer and 0 otherwise. Crucially, in order to estimate the association between program rank and offer reception we change the unit of observation from the individual, i, to the individual application, ij. Accordingly, $female_{ij}$ equals 1 if individual i submitting application, j, is a women and zero otherwise. Importantly, $rank_{ij}$ is a set of categorical variables for the ranking of application j submitted by i within the portfolio (from rankings 2 through 10 with 1 as the base category). The variables $marks_{ij}$ and $courses_{ij}$ include the same measures of academic achievement and binary course variables as discussed in section 4.6. X_{ij} includes all demographic and school fixed effects discussed in section 4.6. Standard errors are clustered at the level of the individual.

Figure 4.7 presents the average predicted probability of receiving an offer to an engineering program given portfolio ranking, separated by student gender, from the full specification of equation (2). The results are striking. Not only does the likelihood of receiving an offer fall considerably for each ranking below first, but the gap in likelihood between men and women widens as the ranking decreases. Moreover, while the likelihood of receiving an offer hovers around 45 % for men between rankings 1 and 3, it falls by 5 percent points for women (from 45 % to 40 %). This suggests that engineering programs may take ranking into account when distributing offers and, in particular, may place considerable weight on being ranked first among female applicants. Figure 4.8 tells a similar story for the likelihood of receiving an offer from computer science, albeit with a less steep gradient.

4.7.3 Acceptances

Table 4.13 (Table 4.14) presents coefficient estimates from equation (1), where the outcome of variable is equal to 1 if i accepts an offer to an engineering (computer science) program. The specifications in columns (1)-(5) sequentially add independent variables in the same order in Table 4.9. The sample is restricted to engineering- (computer science-) ready applicants who have received an offer. Looking first at Table 4.13, we observe an unconditional gender gap of accepting an offer to an engineering program of 6.61 percentage points (Column 1). The incorporation of biology (Column 2) yields interesting results. Men who complete Grade 12 biology are nearly 10 percentage points less likely to accept an offer relative to men who have not. As in Table 4.9 and 4.11, the completion of biology is associated with a larger negative effect on outcomes for engineering-ready women. With the exception of marks in Grade 12 chemistry, higher marks in the other subjects differentially affect the likelihood of accepting an engineering offer (column 3). For instance, a one standard deviation increase in the course grade for Grade 12 physics is associated with an approximate 4.5-5 percentage point increase in the likelihood of accepting an engineering offer for both men and women. Similar to Table 4.9 and 11, the inclusion of individual demographic characteristics and neighbourhood characteristics does not change the results (columns 4 and 5).

The estimates in Table 4.14 suggest that female students are 9-12 percentage points less likely to accept an offer in computer science than men. Adding covariates to the model in equation (1) does little to explain the gender gap (columns 2-5). This suggests that unobserved variables (such as academic or social preferences) may be driving the gap in offer acceptance for computer science programs.

4.7.3.1 Acceptances - Other Offers

Students may have offers from other programs as well as those from engineering or computer science programs. As shown in Table 4.3 this may reduce the likelihood of accepting an offer. To estimate the association between accepting an offer to engineering (or computer science) and having multiple (and diverse) offers, we estimate the following:

$$\begin{aligned} y_i = \beta_0 + \beta_1 female_i + \beta_2 offers_i + \beta_3 courses_i + \beta_4 marks_i + \\ \beta_5 female_i \text{x} courses_i + \beta_6 female_i \text{x} marks_i + \beta_7 female_i \text{x} offers_i + X_i\beta_8 + \varepsilon_i \end{aligned} \tag{3}$$

where y_i is equal to 1 if the applicant accepts an offer to an engineering (computer science) program, zero otherwise. Equation (3) adds the categorical variable $offers_i$ to equation (1), which records the other types of offers individual i may have, in addition to an offer (or offers) to an engineering or computer science programs. Specifically, $offers_i$ is composed of the following four categories (for engineering-ready students): only engineering offers; engineering and other science offers; engineering and non-STEM offers; engineering, other science, and non-STEM offers. For computer science-ready student the categories of $offers_i$ are: only computer science offers; computer science and other science offers; computer science and non-STEM offers; computer science, other science, and non-STEM offers. For both programs "only engineering (computer science) offers" are the base category. X_i includes all demographic, academic characteristics (including standardized marks and courses) and fixed effects discussed in section 4.6. Standard errors are clustered at the level of the individual. We estimate equation (3) separately for men and women.

Figure 4.8 (4.9) presents the estimated coefficients for $offers_i$ from the fully-specified version of equation (3) for engineering (computer science) ready applicants. The omitted category is only having offers from engineering (computer science) programs. The results suggest that holding offers from a variety of programs dramatically reduces the likelihood of accepting both engineering and computer science offers. For example, having an offer from another science program is associated with a reduction in the likelihood of accepting an offer to an engineering program (Figure 4.9) by nearly 30 percentage points for both men and women. Combined with the descriptive statistics presented in Figure 4.2 which suggest that engineering-ready women are more likely to have a more diverse portfolio (relative to engineering-ready men), the estimates presented in Figure 4.9 suggests that engineering programs may be competing with other science programs for female enrollees.

4.7.4 Discussion

The results presented in Section 4.7 provide further evidence that the gender gap in undergraduate engineering and computer science programs is not solely a product of a gap in applications. While both programs exhibit large gender gap in the likelihood of applying, the gender gap differs for offers and acceptances differs between the programs. For engineering programs there exists a gender gap in the likelihood of receiving an offer (conditional on applying), while the gender gap in computer science is relatively larger for acceptances. These results suggest that reducing the gender gap will require policy interventions that both increase in interest in both programs among applicants while also addressing potential biases in admission decisions.

4.8 Robustness Exercises

4.8.1 Top Three Application

A potential critique of our original application estimates is that they do not account for the relative importance of an application to the applicant. Indeed, the results presented in Table 4.9 account for the likelihood of an individual including an engineering or computer Science application anywhere on their ranked listed. However, as shown in in section 4.7.2.1, there is a potential cost in ranking engineering (or computer science) programs outside of one's top three. Moreover, the flat price associated with the first three options may place a degree of importance on the top three choices for each applicant.

Accordingly, in Table 4.15 (Table 4.16) we present estimates for the likelihood that an engineering (computer science) applicant includes an engineering (computer science) program in their top three choices. To do so, we estimate equation (1) where the outcome is a binary variable equal to 1 if individual i places an engineering or computer science program in their top three. Here, we condition both on being engineering (computer science) ready and on having applied to an engineering (computer science) program. Columns (1)-(5) introduce the same covariates as those seen in Table 4.9. First, there is an unconditional gender gap of 6.93 percentage points in the likelihood of placing an engineering program in the top three (Column 1 Table 4.15). The estimates in column (2) suggest that women who have not taken Grade 12 biology are 2.14 percentage points less likely than men to rank their engineering in the top three. Having taken Grade 12 biology reduces the likelihood than men rank engineering in their top three by 8 percentage points and reduces the likelihood that women rank engineering in their top 3 by 13 percentage points. This suggests that those who complete biology may not view engineering as a "priority" application and, hence, relegate it to a ranked position outside of the top three. The incorporation of the remaining covariates (Column 3-5) provide limited independent effects, leaving an unexplained gender gap of 1.71 percentage points.

Looking at computer science applicants (Table 4.16), there is a much larger gap in top three placement likelihood at 13.7 percentage points (Column 1). In line with results presented above this suggests that computer science is a much lower priority program for women than it is for men. Controlling for science courses (Column 2) reduces the effect of gender to 8.66 percentage points with no statistical difference in the effect of science classes between men and women. Incorporating the remaining covariates (Columns 3-5) leaves an unexplained effect of gender of nearly 7.39 percentage points. In addition to the results presented above, this provides further evidence that computer science programs face unique issues in the retention of female students as women are both more unlikely to accept offers and unlikely to prioritize computer science applications within their portfolios.

4.8.2 Offers with Equivalent Number of Applications

As shown in Table 4.4, men are more likely to submit multiple applications to both engineering and computer science programs relative to women. This may influence the likelihood of having at least one offer as discussed in Section 4.7.2. To account for this, we apply to equation (1) to two groups of applicants: those who have 1 application to an engineering (computer science) program and those who have 3 or more applications to these programs. Here, the outcome variable is equal to 1 if individual i has at least one offer to an engineering (computer science program). Table 4.17 (Table 4.18) shows the results of this estimation for engineering (computer science) applicants. Column (1) shows the gender gap from the full specification of equation (1) for those with only 1 application while Column (2) are for those with 3 or more applications. Again, we focus on those who are engineering-ready (Table 4.17) or computer science-ready (Table 4.18).

Looking first at Table 4.17 there is no difference in the effect of gender between the two applicant groups. This is surprising and suggests that the gap found in offer reception that there is limited evidence to suggest that offer reception differs between men and women if they submit the same number of applications. It is interesting to note that, between the two groups, a one standard deviation increase in prerequisite marks is associated with a greater increase in the likelihood of receiving an offer among those with only one engineering application.

Results for applicants to computer science are presented in Table 4.18. Looking first at Column (1) we can see that, among those with 1 application, women are 7.85 percentage points more likely to receive an offer relative to men. In contrast, among those with 3 or more applications, there is no statistically significant effect of gender in the likelihood of receiving an offer. This is a surprising result and reaffirms the findings presented in Section 4.7. Namely, that the primary drivers of gender gaps in enrollment for computer science programs may be both applications and offer acceptances.

4.8.3 Achievement Distribution

To account for this, we examine how gender gaps in all three application process outcomes (applications, offers and acceptances) differs across the achievement distribution for engineering-ready and computer science-ready students. To do so, we first determine each student's average across all prerequisite courses for both "ready" classifications. We then rank students in percentiles, based on these averages, separately for engineering-ready and computer science ready students. Recall, that marks are standardized within ready-classifications.

To see how the outcomes of the application process differ across the achievement distribution we apply the fully-specified equation (1) to three different groups of applicants. Table 4.19-4.21 (4.22-4.24) display these results for engineering-ready (computer science-ready) applicants for applications, offers and acceptances, respectively. Outcomes are measured in a similar way to those presented in Section 4.7, namely, the likelihood of having an application, offer or acceptance any where in your portfolio. Across all tables, Columns (1)-(3) are for those in the bottom 25 percent, middle 50 percent and top 25 percent in the achievement distribution of engineering-ready students.

Looking first at Table 4.19 (applications), the independent effect of gender differs in magnitude throughout the achievement distribution. Indeed, while engineering-ready women are altogether less likely to apply to engineering programs, relative to men, the gender gap is largest in the top 25 percent of engineering-ready students where the average women is 15.9 percentage points less likely to apply. Interestingly, as we move from Column (1)-(3) (i.e. as we move up the achievement distribution), the positive (negative) effect of physics (English) increases, suggesting that an incremental is more meaningful to high-achieving students.

Turning to Table 4.20 (offers) we can see that the gender gap in offer reception is largest among students in the bottom 25 percent of achievers (Column 1). Here, the average engineering-ready women is 9.83 percentage points less likely to receive an engineering-offer when compared to an engineering-ready man. As suggested above, this may be a product of an increase number of applications submitted to engineering programs submitted by men throughout the achievement distribution. Among students in the middle 50 percent (Column 2), this gender gap in receiving an offer shrinks to 3.11 percentage points and among those in the top 25 percent (Column 3) the independent effect of gender is no longer statistically significant. For acceptances (Table 4.21), the gender gap in the likelihood of accepting an offer is no longer significant across the entire achievement distribution.

Table 4.22-4.24 displays the result of applying the fully-specified equation (1) to each outcome of the application process for computer science applicants. Columns are ordered identically to Tables 4.19-4.21. The results shown in Tables 4.22-4.24 reaffirm the results shown in Section 4.7. Namely, that while there are limited gender gaps in the likelihood of receiving an offer (Table 4.22), there are significant gaps in both application (Table 4.23) and offer acceptance (Table 4.24). Accordingly, computer science programs are faced with the challenge of increasing interest in their programs from women across the achievement distribution.

4.9 Conclusion

This paper studied the gender gaps throughout the application process to engineering and computer science undergraduate programs, two traditionally male-dominated fields of study. Prior to the application phase we found that women are much less prepared for engineering (computer science) programs as only 16 % (38 %) can be classified as engineering- (computer science) ready compared to 34 % (58 %) of men. We find an unexplained gender gap in applications of 14 (8) percentage points to Engineering (Computer Science) programs. Much like in Card and Payne (2021), we find that performance (and exposure to) high school science courses explains a significant portion of the application gap to both programs. Specifically, Grade 12 Physics plays an important role in the determination of application likelihood among women. Investigating gaps in offers we find a statistically significant of 4 percentage points in the likelihood of offer reception to engineering programs in favour of men. Moreover, the likelihood of offer reception decreases considerably when engineering applications are ranked outside of the first spot in a portfolio. Finally, we find a statistically significant gap in the likelihood of offer acceptance for computer science programs of approximately 13 percentage points. Our results suggest that closing the gender gap in undergraduate Engineering and Computer Science programs will require interventions both at the high school level (to improve science course take-up and interest in engineering/computer science) as well as among admissions offices to correct for any potential biases in offer provision.

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4.11 Tables and Figures

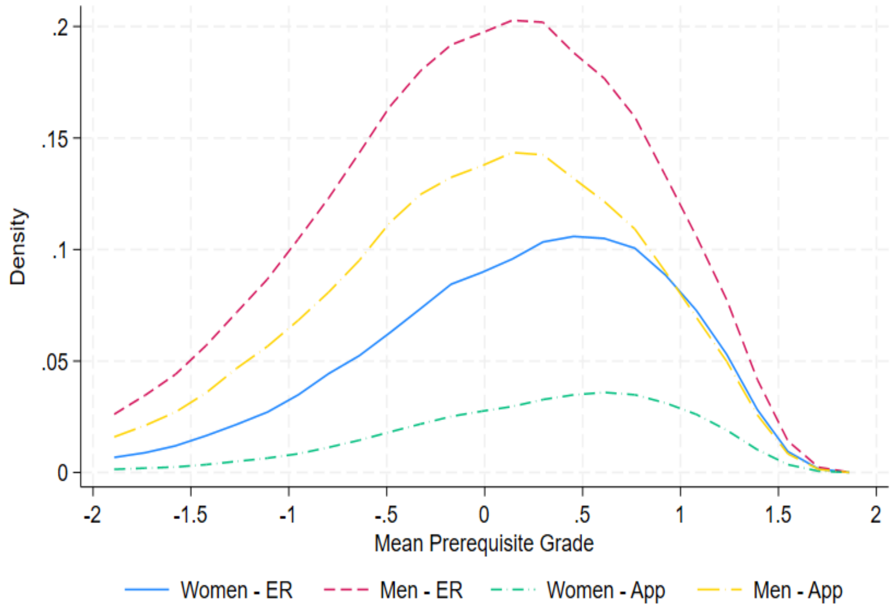

FIGURE 4.1: Kernel Density of Mean Prerequisite Grades - Engineering Ready

Notes: This figure displays the distribution of mean prerequisite grades for male and female engineering-ready students across two categories: all engineering-ready students and those who apply to engineering programs. Each kernel density curve represents the approximate share of each category to the total amount of engineering-ready students. The sum of the area under all curves equals one. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

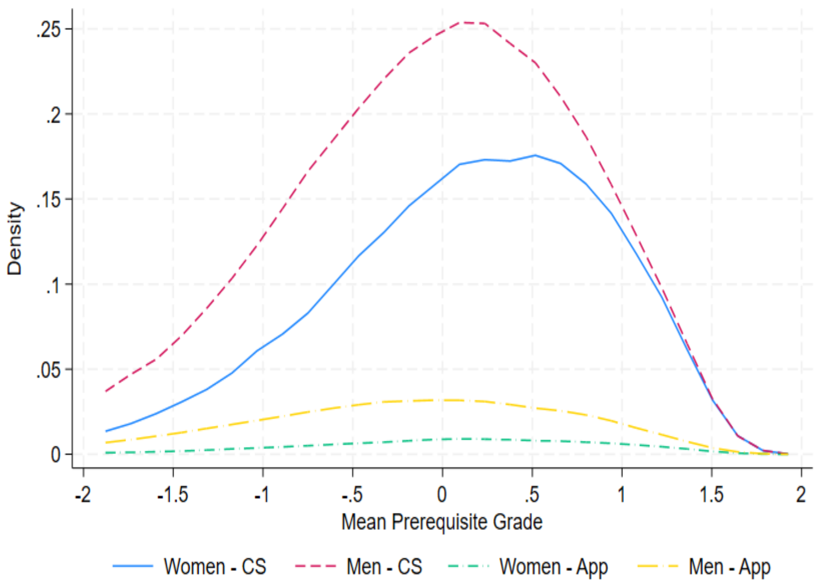

FIGURE 4.2: Kernel Density of Mean Prerequisite Grades - Computer Science Ready

Notes: This figure displays the distribution of mean prerequisite grades for male and female computer science-ready students across two categories: all computer science-ready students and those who apply to computer science programs. Each kernel density curve represents the approximate share of each category to the total amount of computer science-ready students. The sum of the area under all curves equals one. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

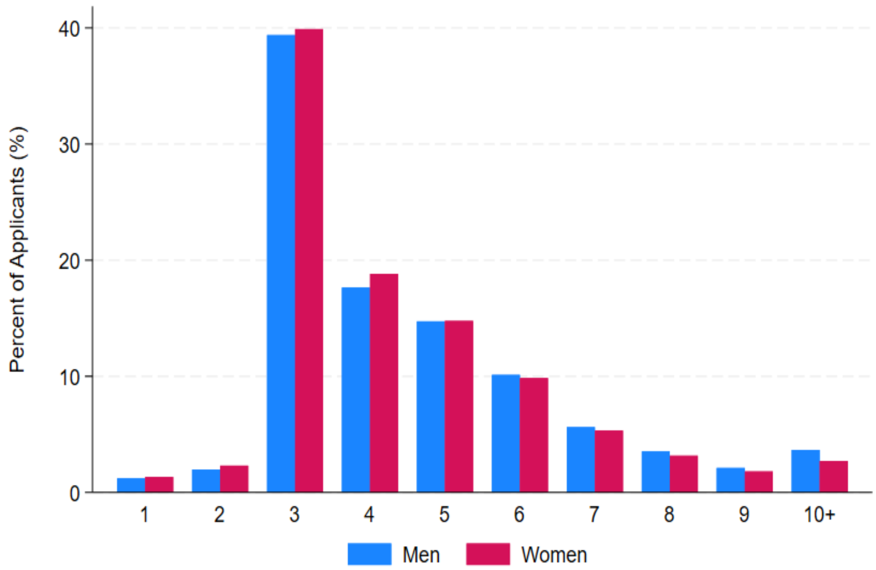

FIGURE 4.3: Share of Applicants Submitting X Number of Applications

Notes: This figure displays the distribution of men and women (across all applicants) given the number of applications submitted. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

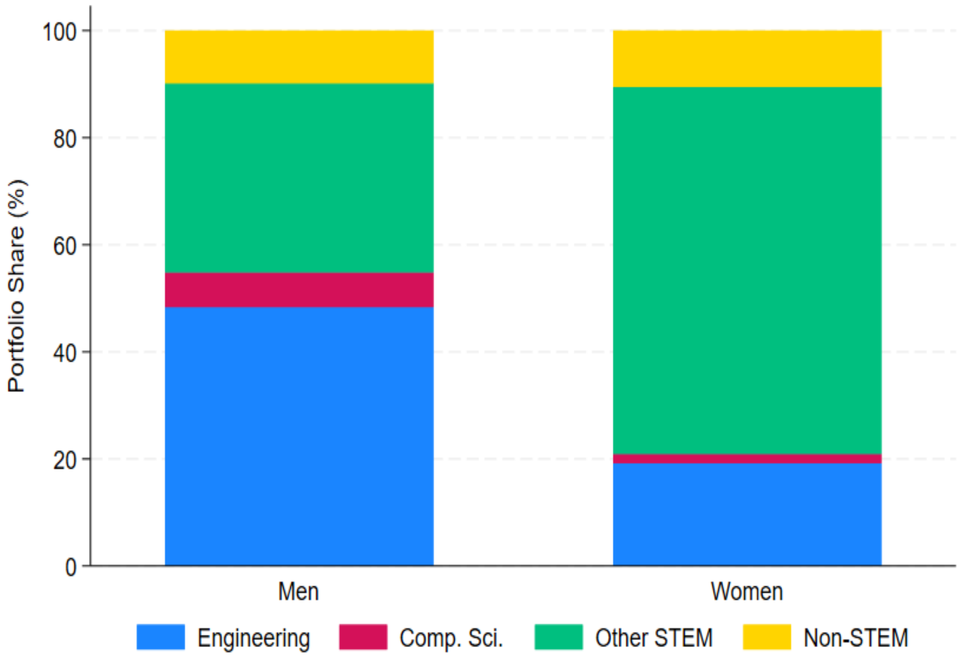

FIGURE 4.4: Portfolio Share for Engineering-Ready Applicants

Notes: This figure displays the average portfolio composition of engineering-ready men and women. Average portfolio composition is determined by summing the total number of applications to Engineering, Computer Science, Other STEM and non-STEM programs and dividing by the total number of applications submitted (by either engineering-ready men or women) Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

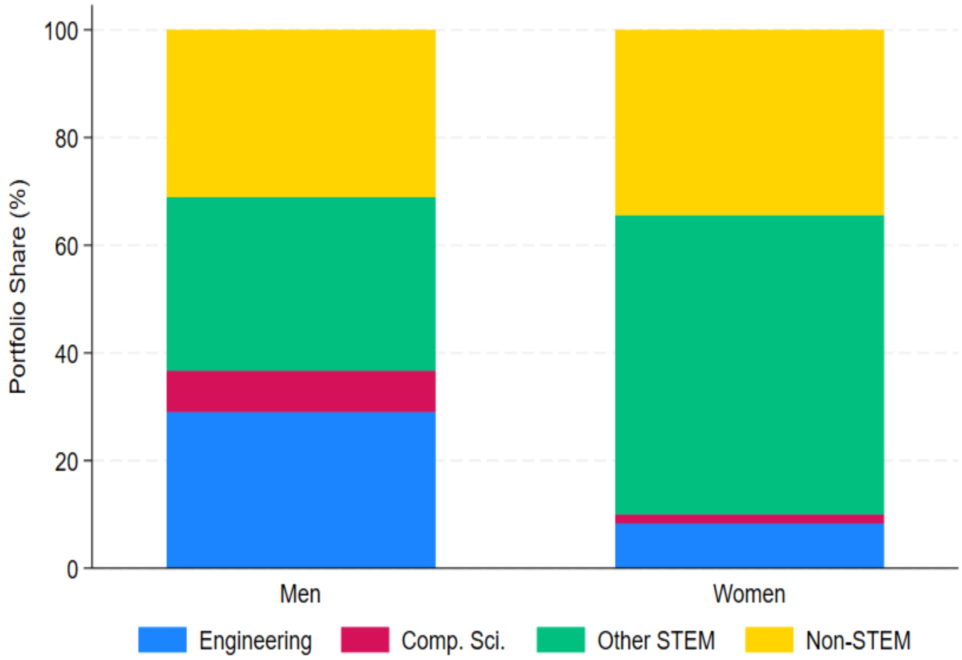

FIGURE 4.5: Portfolio Share for Computer Science-Ready Applicants

Notes: This figure displays the average portfolio composition of computer science-ready men and women. Average portfolio composition is determined by summing the total number of applications to Engineering, Computer Science, Other STEM and non-STEM programs and dividing by the total number of applications submitted (by either computer science-ready men or women) Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

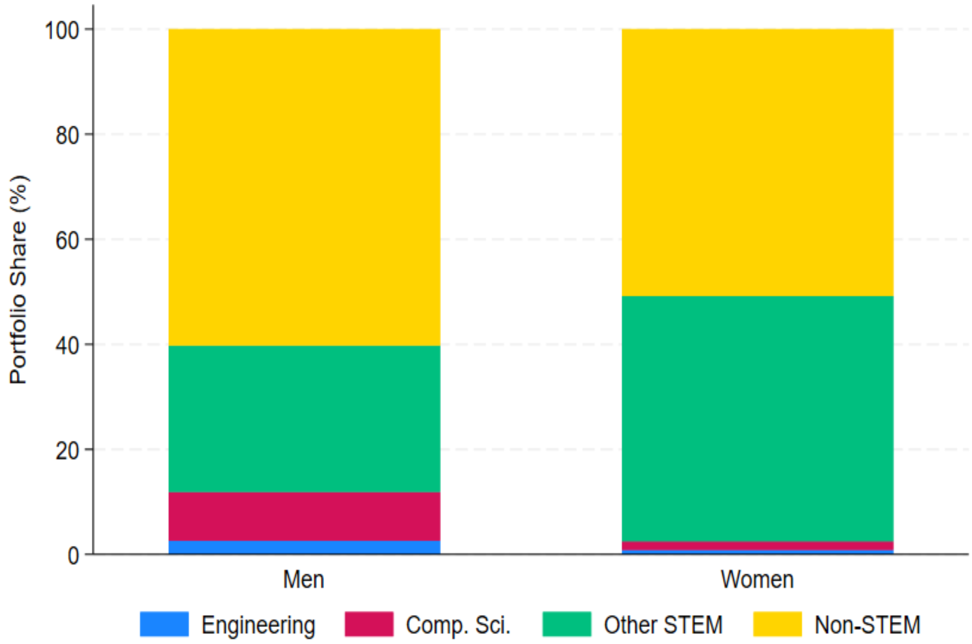

FIGURE 4.6: Portfolio Share for Computer Science Ready Applicants who are not Engineering-Ready

Notes: This figure displays the average portfolio composition of computer science-ready men and women, for those who are not engineering-ready. Average portfolio composition is determined by summing the total number of applications to Engineering, Computer Science, Other STEM and non-STEM programs and dividing by the total number of applications submitted (by either computer science-ready men or women) Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

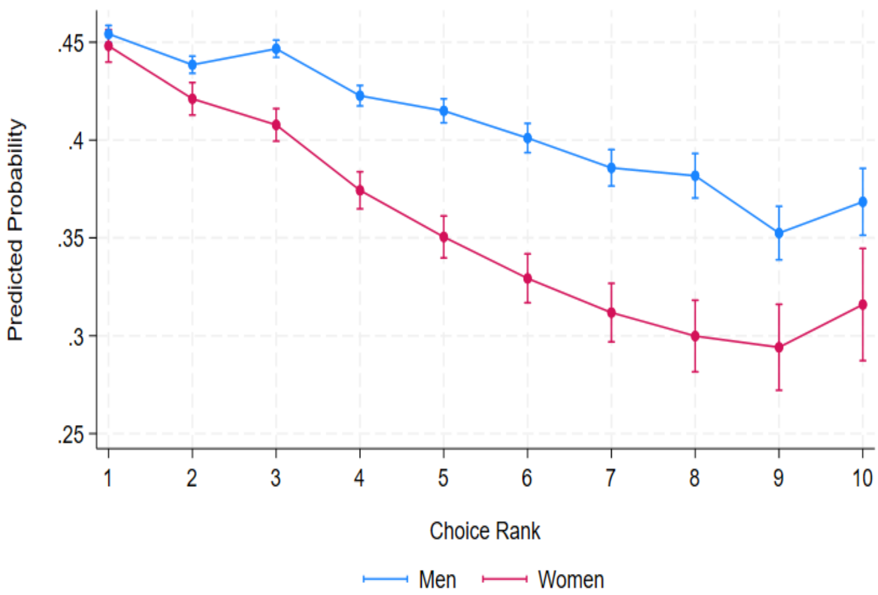

FIGURE 4.7: Predicted Probability of Engineering Offer Reception given Portfolio Ranking

Notes: This figure displays the predicted probability of receiving an engineering offer (conditional on having applied) for engineering-ready men and women, given the portfolio ranking of an engineering application. Estimates derived from a fully-specified equation (2) where the dependent variable equals 1 if individual i receives an engineering offer, zero otherwise. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

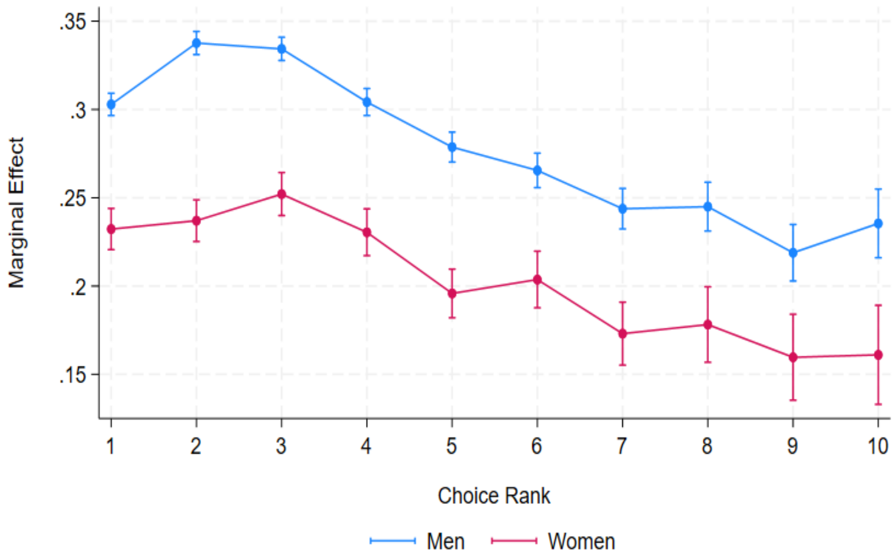

Figure 4.8: Predicted Probability of Computer Science Offer Reception given Portfolio Ranking

Notes: This figure displays the predicted probability of receiving a computer science offer (conditional on having applied) for computer science-ready men and women, given the portfolio ranking of a computer science application. Estimates derived from a fully-specified equation (2) where the dependent variable equals 1 if individual i receives a computer science offer, zero otherwise. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

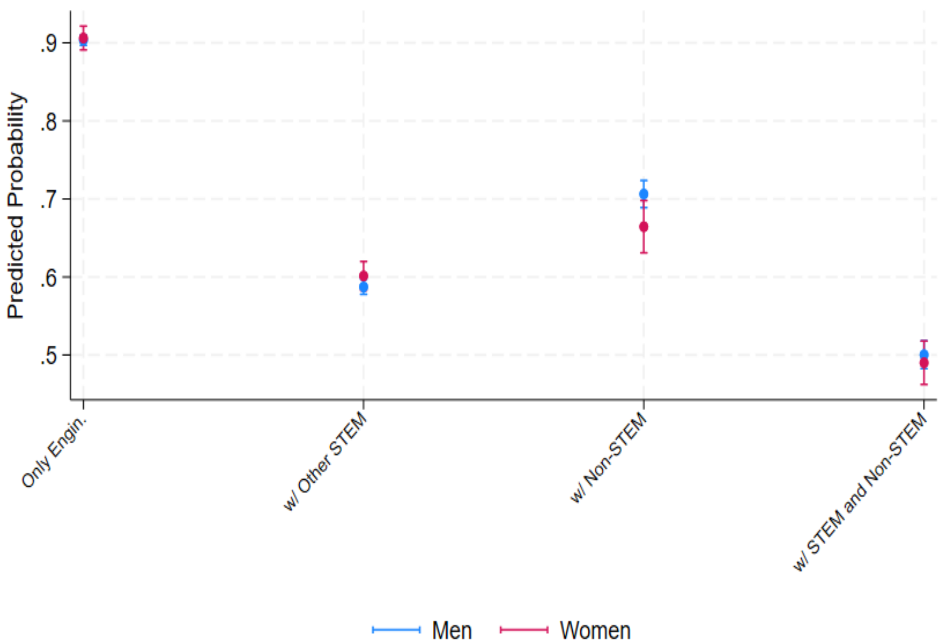

FIGURE 4.9: Predicted Probability of Accepting Engineering Offer Conditional on Other Offers Received

Notes: This figure displays the predicted probability of accepting an engineering offer conditional on various program offer combinations. Estimates derived from a fully-specified equation (3) where the dependent variable equals 1 if individual I accepts an engineering offer, zero otherwise. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

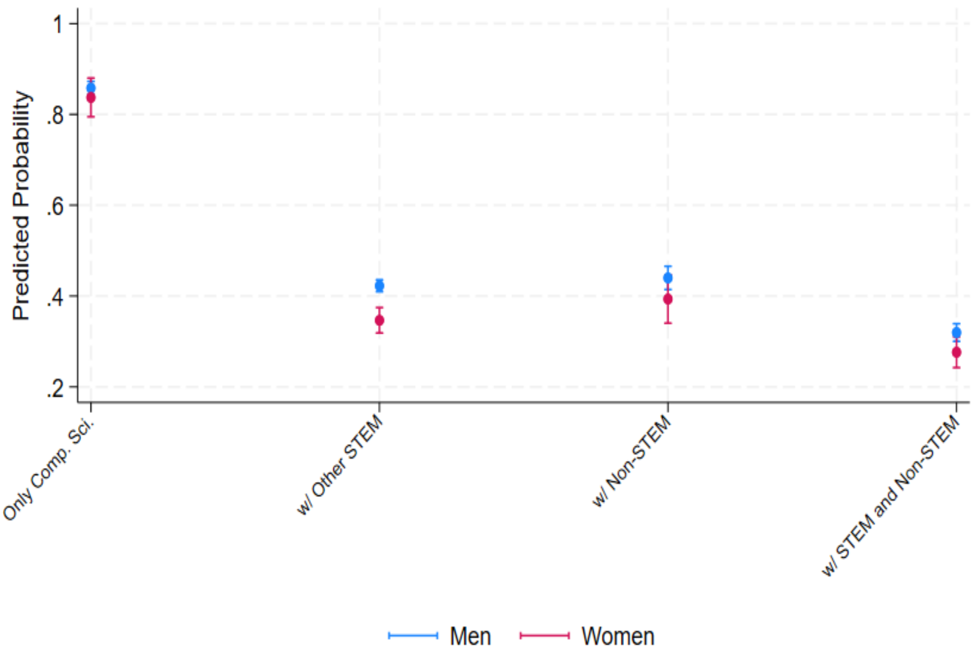

FIGURE 4.10: Predicted Probability of Accepting Computer Science Offer Conditional on Other Offers Received

Notes: This figure displays the predicted probability of accepting a computer science offer conditional on various program offer combinations. Estimates derived from a fully-specified equation (3) where the dependent variable equals 1 if individual I accepts an engineering offer, zero otherwise. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

Table 4.1: Course Completion and Ready Status

	(1) Women (%)	(2) Men (%)
Panel A: Grade 12 Course Completion		
Physics	19	42
Chemistry	44	49
Biology	47	34
Calculus	38	58
Advanced Functions	57	75
Panel B: Ready-Status		
Engineering-Ready	16	34
Computer Science-Ready	38	58

Notes: Panel A displays the share of men and women, across all students in our sample who complete each Grade 12 Science course. Panel B shows the share of men and women who are engineering- or computer science-ready. Engineering-ready is defined as completing Advanced Functions, Calculus, Physics, Chemistry and English. Computer Science-ready is defined as completed Advanced Functions, Calculus and English. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

Table 4.2: Share of Students Taking Science Courses by Ready Classification

	(1) Women (%)	(2) Men (%)
Panel A: Engineering-Ready		
Biology	81	46
Panel B: Computer Science Ready		
Biology	68	40
Chemistry	74	71
Physics	45	65

Notes: Panel A displays the share of engineering-ready men and women who have completed Biology. Panel B displays the share of computer science-ready men and women who have completed Biology, Physics or Chemistry. Engineering-ready is defined as completing Advanced Functions, Calculus, Physics, Chemistry and English. Computer Science-ready is defined as completed Advanced Functions, Calculus and English. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

Table 4.3: Share of Students Taking Science Courses by Ready Classification

	(1)	(2)	(3)	(4)
Panel A: Engineering-Ready	Women - All Students	Men - All Students	Women - ER Only	Men - ER Only
English	0.65	0.17	0.34	-0.19
Physics	0.19	0.15	0.03	-0.02
Chemistry	0.46	0.22	0.17	-0.10
Biology	0.55	0.41	0.09	-0.09
Calculus	0.30	0.18	0.08	-0.05
Advanced Functions	0.52	0.41	0.09	-0.05
Panel B: Computer Science Ready	Women - All Students	Men - All Students	Women - CS Only	Men - CS Only
English	0.53	0.11	0.26	-0.21
Physics	0.16	0.08	0.06	-0.03
Chemistry	0.30	0.16	0.09	-0.07
Biology	0.40	0.29	0.06	-0.08
Calculus	0.04	-0.03	0.04	-0.03
Advanced Functions	0.31	0.25	0.04	-0.03

Notes: Panel A displays the mean normalized grade in Grade 12 English, Science and Math classes among men and women who are engineering ready. Panel B displays the mean normalized grade in Grade 12 English, Science and Math classes among men and women who are computer science ready. Grades are normalized within year and high school cohort. Engineering-ready is defined as completed Physics, Chemistry, Biology, Advanced Functions, Calculus and English. Computer Science-ready is defined as completed Advanced Functions, Calculus and English. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

Table 4.4: Share of Applicants who Apply by Ready Classification

	(1) Women (%)	(2) Men (%)
Panel A: Engineering-Ready		
Have at Least One Engineering Application	34	69
Have More Than One Engineering Application	25	58
Rank Engineering First with Only Three Applications	71	79
Rank Engineering First with more than Three Applications	49	63
Panel B: Computer Science Ready		
Have At Least One Computer Science Application	5	17
Have More Than One Computer Science Application	2	10
Rank Computer Science First With Only Three Applications	48	59
Rank Computer Science First with More Than Three Applications	24	36

Notes: Panel A displays key application statistics for engineering-ready men and women. Panel B displays key application statistics for computer science-ready men and women. Engineering-ready is defined as completed Physics, Chemistry, Biology, Advanced Functions, Calculus and English. Computer Science-ready is defined as completed Advanced Functions, Calculus and English. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

Table 4.5: Offer Shares for Engineering- and Computer Science-Ready Students

	(1) Women (%)	(2) Men (%)
Panel A: Engineering-Ready Applicants		
At Least One Engineering	88	87
With Multiple Engineering Offers	56	63
With Engineering and Other STEM Offers	53	38
Receive Offer on Engineering Application that is Ranked First	71	59
Receive Offer on Applications Beyond Top Three	79	78
Panel B: Computer Science Ready Applicants		
At Least one Computer Science Offer	83	86
With Multiple Computer Science Offers	26	45
With Computer Science and Other STEM Offers	66	58
Receive Offer on Computer Science Application that is Ranked First	75	71
Receive Offer on Applications Beyond Top Three	76	80

Notes: Panel A displays key offer statistics for engineering-ready men and women who have applied to an engineering program. Panel B displays key offer statistics for computer science-ready men and women who have applied to a computer science program. Engineering-ready is defined as completed Physics, Chemistry, Biology, Advanced Functions, Calculus and English. Computer Science-ready is defined as completed Advanced Functions, Calculus and English. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

Table 4.6: Share who Accept Engineering and Computer Science Offers

	(1) Women (%)	(2) Men (%)
Panel A: Engineering-Ready Applicants		
Accepting Engineering Offer	62	69
Accept Engineering with Other STEM Offers	31	23
Accept Offer on Engineering Application that is Ranked First	64	62
Accept Offer on Applications Ranked Outside Top Three	10	12
Panel B: Computer Science Ready Applicants		
Accept Computer Science Offer	34	47
Accept Computer Science with Other STEM Offers	22	24
Accept Offer on Computer Science Application that is Ranked First	55	54
Accept Offer on Applications Ranked Outside Top Three	9	11

Notes: Panel A displays key offer statistics for engineering-ready men and women who have received an offer to an engineering program. Panel B displays key offer statistics for computer science-ready men and women who have received an offer to a computer science program. Engineering-ready is defined as completed Physics, Chemistry, Biology, Advanced Functions, Calculus and English. Computer Science-ready is defined as completed Advanced Functions, Calculus and English. Source: Author's own calculations from data provided by the Ontario University Applications Centre (OUAC).

Table 4.7: Descriptive Statistics - Engineering-Ready

	Women		Men	
	Mean	Std. Dev.	Mean	Std. Dev.
Courses Taken				
Biology	0.81	0.40	0.46	0.50
Course Marks (%)				
English	86.33	6.76	82.16	7.65
Physics	82.28	10.06	81.77	10.42
Chemistry	84.32	9.26	81.63	10.34
Calculus	84.29	10.82	82.83	9.56
Advanced Functions	86.48	9.10	85.21	9.56
Individual Characteristics				
Share English at Home	0.80	0.40	0.81	0.39
Share French at Home	0.00	0.07	0.00	0.06
Share Other Language at Home	0.20	0.40	0.18	0.39
Permanent Residents	0.09	0.28	0.09	0.28
Yrs. in Cdn. Educ.	1.53	3.17	1.59	3.22
Share 12 years Cdn. Educ.	0.77	0.42	0.77	0.42
Neighbourhood Characteristics				
Mean Household Income (1000s)	120.77	83.60	118.67	73.33
Immigrants(%)	38.63	23.33	39.35	23.13
Visible Minorities(%)	29.98	27.20	30.75	27.12
N	37637		66071	

Notes: This table presents the mean and standard deviations for all variables included in each regression for engineering-ready students. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table 4.8: Descriptive Statistics - Computer Science Ready

	Women		Men	
	Mean	Std. Dev.	Mean	Std. Dev.
Courses Taken				
Biology Only	0.03	0.18	0.02	0.13
Chemistry Only	0.03	0.16	0.03	0.17
Physics Only	0.03	0.17	0.06	0.25
Biology and Chemistry	0.31	0.46	0.11	0.31
Biology and Physics	0.01	0.09	0.01	0.10
Physics and Chemistry	0.08	0.27	0.31	0.46
All Three	0.33	0.47	0.26	0.44
Course Marks (%)				
English	85.30	7.03	81.66	8.01
Calculus	81.13	11.80	80.25	12.29
Advanced Functions	84.08	9.08	83.34	10.16
Individual Characteristics				
Share English at Home	0.81	0.40	0.83	0.38
Share French at Home	0.01	0.07	0.00	0.06
Share Other Language at Home	0.19	0.39	0.17	0.38
Permanent Residents	0.08	0.27	0.08	0.27
Yrs. in Cdn. Educ.	1.42	3.08	1.48	3.13
Share 12 years Cdn. Educ.	0.79	0.41	0.78	0.41
Neighbourhood Characteristics				
Mean Household Income (1000s)	125.22	92.60	123.80	87.68
Immigrants(%)	39.42	23.00	39.87	22.83
Visible Minorities(%)	30.73	27.23	31.12	27.12
N	92203		114143	

Notes: This table presents the mean and standard deviations for all variables included in each regression for computer science-ready students. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table 4.9: Application Results – Engineering Ready

	(1)	(2)	(3)	(4)	(5)
Female	-0.354***	-0.115***	-0.112***	-0.117***	-0.119***
	(0.00303)	(0.00545)	(0.00549)	(0.00546)	(0.00551)
Courses Taken					
Biology		-0.368***	-0.370***	-0.367***	-0.363***
		(0.00342)	(0.00345)	(0.00346)	(0.00350)
Female*(Biology)		-0.135***	-0.123***	-0.121***	-0.117***
		(0.00664)	(0.00673)	(0.00669)	(0.00669)
Course Marks					
English			-0.0327***	-0.0305***	-0.0353***
			(0.00199)	(0.00200)	(0.00206)
Physics			0.0563***	0.0582***	0.0682***
			(0.00245)	(0.00244)	(0.00254)
Chemistry			0.00210	0.00450	0.00412
			(0.00245)	(0.00245)	(0.00252)
Calculus			0.00728**	0.00513	0.00246
			(0.00266)	(0.00265)	(0.00272)
Functions			0.0107***	0.00759**	0.00558*
			(0.00254)	(0.00254)	(0.00258)
Female*(English)			-0.000216	0.00272	0.0000901
			(0.00361)	(0.00360)	(0.00359)
Female*(Physics)			-0.00952*	-0.00934*	-0.00871*
			(0.00394)	(0.00392)	(0.00395)
Female*(Chemistry)			-0.0125**	-0.0129**	-0.0130**
			(0.00432)	(0.00430)	(0.00431)
Female*(Calculus)			0.00952*	0.00824	0.00846
			(0.00446)	(0.00444)	(0.00444)
Female*(Functions)			0.0185***	0.0198***	0.0190***
			(0.00427)	(0.00425)	(0.00425)
Constant	0.691***	0.859***	0.856***	0.907***	0.972***
	(0.00180)	(0.00184)	(0.00194)	(0.00851)	(0.0256)
N	103708	103708	103708	103708	103708
R^2	0.117	0.262	0.278	0.282	0.299
ll	-67967.8	-58665.7	-57571.5	-57250.1	-56022.4

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. *Source: Ontario University Applications Centre (OUAC) and Statistics Canada.*

Table 4.10: Application Results – Computer Science

	(1)	(2)	(3)	(4)	(5)
Female	-0.116***	-0.0876***	-0.0802***	-0.0826***	-0.0842***
	(0.00133)	(0.00260)	(0.00261)	(0.00262)	(0.00267)
Courses Taken					
Biology Only		0.0149	0.0169*	0.0214**	0.0262***
		(0.00790)	(0.00784)	(0.00783)	(0.00782)
Chemistry Only		0.171***	0.169***	0.170***	0.168***
		(0.00829)	(0.00823)	(0.00818)	(0.00813)
Physics Only		0.294***	0.287***	0.289***	0.289***
		(0.00615)	(0.00613)	(0.00611)	(0.00607)
Biology and Chemistry		-0.0370***	-0.0328***	-0.0309***	-0.0281***
		(0.00335)	(0.00334)	(0.00334)	(0.00337)
Biology and Physics		0.140***	0.137***	0.144***	0.144***
		(0.0131)	(0.0131)	(0.0130)	(0.0129)
Physics and Chemistry		0.103***	0.100***	0.101***	0.101***
		(0.00311)	(0.00315)	(0.00315)	(0.00317)
All Three		-0.0261***	-0.0196***	-0.0179***	-0.0178***
		(0.00278)	(0.00282)	(0.00284)	(0.00288)
Female*(Biology Only)		-0.00919	-0.00860	-0.00766	-0.0115
		(0.00875)	(0.00870)	(0.00868)	(0.00868)
Female*(Chemistry Only)		-0.106***	-0.103***	-0.101***	-0.0979***
		(0.0104)	(0.0104)	(0.0103)	(0.0103)
Female*(Physics Only)		-0.185***	-0.180***	-0.179***	-0.178***
		(0.00919)	(0.00916)	(0.00910)	(0.00905)
Female*(Biology and Chemistry)		0.0479***	0.0460***	0.0481***	0.0462***
		(0.00383)	(0.00382)	(0.00383)	(0.00385)
Female*(Biology and Physics)		-0.0578***	-0.0537**	-0.0535**	-0.0534**
		(0.0174)	(0.0174)	(0.0173)	(0.0172)
Female*(Physics and Chemistry)		-0.0127*	-0.00896	-0.00805	-0.00838
		(0.00516)	(0.00519)	(0.00516)	(0.00516)
Female*(All Three)		0.0342***	0.0314***	0.0324***	0.0340***
		(0.00331)	(0.00338)	(0.00338)	(0.00341)
Course Marks					
English			-0.0266***	-0.0245***	-0.0255***
			(0.00125)	(0.00126)	(0.00128)
Calculus			0.00813***	0.00765***	0.00906***
			(0.00151)	(0.00151)	(0.00152)
Functions			-0.00386*	-0.00415**	-0.00559***
			(0.00153)	(0.00152)	(0.00153)
Female*(English)			0.0138***	0.0147***	0.0137***
			(0.00161)	(0.00161)	(0.00162)
Female*(Calculus)			-0.00788***	-0.00787***	-0.00802***
			(0.00187)	(0.00187)	(0.00187)
Female*(Functions)			0.00614**	0.00701***	0.00664***
			(0.00188)	(0.00187)	(0.00187)
Constant	0.169***	0.122***	0.116***	0.0898***	0.0350**
	(0.00111)	(0.00220)	(0.00219)	(0.00519)	(0.0128)
N	206346	206346	206346	206346	206346
R^2	0.0320	0.0787	0.0827	0.0880	0.103
ll	-55301.9	-50202.3	-49751.2	-49156.1	-47487.8

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to a computer science program, zero otherwise. All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. *Source: Ontario University Applications Centre (OUAC) and Statistics Canada.*

TABLE 4.11: Offer Results – Engineering Ready

	(1)	(2)	(3)	(4)	(5)
Female	0.00682*	0.0181***	-0.0216***	-0.0198***	-0.0191***
	(0.00328)	(0.00461)	(0.00453)	(0.00454)	(0.00461)
Courses Taken					
Biology		-0.00842*	-0.0570***	-0.0578***	-0.0592***
		(0.00337)	(0.00323)	(0.00324)	(0.00331)
Female*(Biology)		-0.0160*	0.000318	0.000660	-0.000807
		(0.00667)	(0.00638)	(0.00638)	(0.00644)
Course Marks					
English			0.0184***	0.0175***	0.0185***
			(0.00199)	(0.00201)	(0.00208)
Physics			0.0429***	0.0422***	0.0454***
			(0.00270)	(0.00270)	(0.00283)
Chemistry			0.0382***	0.0370***	0.0407***
			(0.00262)	(0.00262)	(0.00273)
Calculus			0.0232***	0.0240***	0.0203***
			(0.00295)	(0.00294)	(0.00304)
Functions			0.0263***	0.0278***	0.0298***
			(0.00277)	(0.00277)	(0.00282)
Female*(English)			0.00315	0.00156	0.00172
			(0.00467)	(0.00466)	(0.00468)
Female*(Physics)			0.00805	0.00828	0.00893
			(0.00619)	(0.00618)	(0.00619)
Female*(Chemistry)			-0.00389	-0.00403	-0.00344
			(0.00622)	(0.00621)	(0.00621)
Female*(Calculus)			0.00390	0.00407	0.00257
			(0.00710)	(0.00707)	(0.00706)
Female*(Functions)			-0.00543	-0.00531	-0.00341
			(0.00669)	(0.00667)	(0.00666)
Constant	0.873***	0.875***	0.899***	0.904***	0.904***
	(0.00156)	(0.00188)	(0.00172)	(0.00841)	(0.0245)
N	58361	58361	58361	58361	58361
R^2	0.0000719	0.000469	0.130	0.131	0.157
ll	-18389.6	-18378.0	-14327.9	-14282.2	-13400.9

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i received an offer to an engineering program, zero otherwise (conditional on having applied). All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.12: Offer Results – Computer Science

	(1)	(2)	(3)	(4)	(5)
Female	-0.0258***	0.0497**	-0.0104	-0.00902	-0.00851
	(0.00591)	(0.0164)	(0.0156)	(0.0157)	(0.0161)
Courses Taken					
Biology Only		-0.0445	-0.0223	-0.0233	-0.0139
		(0.0266)	(0.0251)	(0.0251)	(0.0257)
Chemistry Only		0.0507***	0.0469***	0.0450***	0.0406**
		(0.0137)	(0.0130)	(0.0130)	(0.0133)
Physics Only		0.0656***	0.0548***	0.0544***	0.0512***
		(0.00975)	(0.00916)	(0.00916)	(0.00945)
Biology and Chemistry		-0.0458**	-0.0790***	-0.0799***	-0.0772***
		(0.0153)	(0.0144)	(0.0144)	(0.0146)
Biology and Physics		-0.00388	-0.0136	-0.0132	-0.0171
		(0.0242)	(0.0223)	(0.0223)	(0.0226)
Physics and Chemistry		0.0783***	0.00584	0.00560	0.00308
		(0.00843)	(0.00819)	(0.00820)	(0.00846)
All Three		0.0646***	-0.0408***	-0.0420***	-0.0470***
		(0.00988)	(0.00969)	(0.00969)	(0.00999)
Female*(Biology Only)		0.0215	0.00851	0.00746	0.000938
		(0.0452)	(0.0445)	(0.0446)	(0.0452)
Female*(Chemistry Only)		-0.0652*	-0.0559	-0.0537	-0.0548
		(0.0313)	(0.0297)	(0.0297)	(0.0304)
Female*(Physics Only)		-0.0178	-0.0156	-0.0133	-0.00997
		(0.0231)	(0.0220)	(0.0220)	(0.0225)
Female*(Biology and Chemistry)		-0.0508*	-0.0172	-0.0157	-0.0109
		(0.0243)	(0.0232)	(0.0232)	(0.0236)
Female*(Biology and Physics)		-0.101	-0.0844	-0.0833	-0.0844
		(0.0533)	(0.0493)	(0.0492)	(0.0497)
Female*(Physics and Chemistry)		-0.0124	0.00502	0.00716	0.00719
		(0.0191)	(0.0186)	(0.0185)	(0.0190)
Female*(All Three)		-0.105***	-0.0482*	-0.0471*	-0.0449*
		(0.0207)	(0.0201)	(0.0201)	(0.0204)
Course Marks					
English			0.0428***	0.0418***	0.0399***
			(0.00291)	(0.00292)	(0.00306)
Calculus			0.0501***	0.0505***	0.0508***
			(0.00397)	(0.00396)	(0.00406)
Functions			0.0500***	0.0509***	0.0530***
			(0.00384)	(0.00385)	(0.00396)
Female*(English)			-0.0116	-0.0129	-0.0135
			(0.00716)	(0.00716)	(0.00734)
Female*(Calculus)			-0.0114	-0.0106	-0.00829
			(0.00938)	(0.00938)	(0.00952)
Female*(Functions)			0.00835	0.00848	0.00626
			(0.00931)	(0.00931)	(0.00941)
Constant	0.857***	0.805***	0.884***	0.840***	0.857***
	(0.00252)	(0.00764)	(0.00724)	(0.0155)	(0.0554)
N	24162	24162	24162	24162	24162
R^2	0.000853	0.0155	0.126	0.128	0.167
ll	-9246.7	-9068.0	-7630.0	-7604.2	-7042.9

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to a computer science program, zero otherwise. All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table 4.13: Acceptance Results – Engineering Ready

	(1)	(2)	(3)	(4)	(5)
Female	-0.0661***	-0.0180*	-0.0234**	-0.0200**	-0.0179*
	(0.00514)	(0.00713)	(0.00736)	(0.00737)	(0.00750)
Courses Taken					
Biology		-0.0990***	-0.129***	-0.132***	-0.133***
		(0.00508)	(0.00510)	(0.00509)	(0.00520)
Female*(Biology)		-0.0412***	-0.0209*	-0.0202	-0.0218*
		(0.0104)	(0.0105)	(0.0105)	(0.0105)
Course Marks					
English			-0.0139***	-0.0149***	-0.0109***
			(0.00287)	(0.00289)	(0.00303)
Physics			0.0469***	0.0459***	0.0504***
			(0.00384)	(0.00383)	(0.00405)
Chemistry			0.0460***	0.0436***	0.0468***
			(0.00373)	(0.00372)	(0.00391)
Calculus			0.0283***	0.0297***	0.0277***
			(0.00410)	(0.00410)	(0.00426)
Functions			-0.0146***	-0.0107**	-0.00822*
			(0.00388)	(0.00389)	(0.00400)
Female*(English)			-0.00101	-0.00420	-0.00638
			(0.00706)	(0.00707)	(0.00711)
Female*(Physics)			0.00206	0.00256	0.00315
			(0.00892)	(0.00889)	(0.00897)
Female*(Chemistry)			-0.0297**	-0.0294**	-0.0276**
			(0.00905)	(0.00901)	(0.00910)
Female*(Calculus)			-0.0160	-0.0147	-0.0130
			(0.0101)	(0.0101)	(0.0102)
Female*(Functions)			-0.000909	-0.00133	-0.00148
			(0.00944)	(0.00942)	(0.00952)
Constant	0.690***	0.721***	0.720***	0.741***	0.792***
	(0.00232)	(0.00273)	(0.00282)	(0.0131)	(0.0378)
N	51020	51020	51020	51020	51020
R^2	0.00341	0.0158	0.0405	0.0443	0.0709
ll	-33607.3	-33286.9	-32638.6	-32537.8	-31817.8

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to an engineering program, zero otherwise (conditional on having received an offer). All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.14: Acceptance Results – Computer Science

	(1)	(2)	(3)	(4)	(5)
Female	-0.126***	-0.111***	-0.0937***	-0.0892***	-0.0904***
	(0.00839)	(0.0244)	(0.0245)	(0.0245)	(0.0250)
Courses Taken					
Biology Only		-0.0631	-0.0662	-0.0686	-0.0800*
		(0.0358)	(0.0357)	(0.0356)	(0.0357)
Chemistry Only		0.0586**	0.0585**	0.0558**	0.0508*
		(0.0204)	(0.0204)	(0.0204)	(0.0207)
Physics Only		0.103***	0.103***	0.102***	0.102***
		(0.0143)	(0.0143)	(0.0143)	(0.0145)
Biology and Chemistry		-0.168***	-0.155***	-0.160***	-0.163***
		(0.0201)	(0.0201)	(0.0201)	(0.0206)
Biology and Physics		-0.0510	-0.0458	-0.0517	-0.0492
		(0.0338)	(0.0338)	(0.0337)	(0.0338)
Physics and Chemistry		-0.0708***	-0.0550***	-0.0529***	-0.0521***
		(0.0123)	(0.0125)	(0.0125)	(0.0128)
All Three		-0.158***	-0.131***	-0.135***	-0.138***
		(0.0144)	(0.0148)	(0.0148)	(0.0152)
Female*(Biology Only)		0.0157	0.0190	0.0183	0.0201
		(0.0630)	(0.0626)	(0.0628)	(0.0642)
Female*(Chemistry Only)		-0.000286	-0.000121	-0.00182	-0.00164
		(0.0466)	(0.0467)	(0.0466)	(0.0471)
Female*(Physics Only)		-0.0159	-0.0178	-0.0136	-0.0120
		(0.0373)	(0.0375)	(0.0375)	(0.0381)
Female*(Biology and Chemistry)		0.0339	0.0275	0.0237	0.0363
		(0.0330)	(0.0331)	(0.0331)	(0.0339)
Female*(Biology and Physics)		0.0681	0.0717	0.0675	0.0484
		(0.0718)	(0.0720)	(0.0713)	(0.0713)
Female*(Physics and Chemistry)		0.0441	0.0370	0.0398	0.0386
		(0.0303)	(0.0307)	(0.0306)	(0.0310)
Female*(All Three)		0.0327	0.0185	0.0138	0.0166
		(0.0296)	(0.0302)	(0.0302)	(0.0309)
Course Marks					
English			-0.0240***	-0.0246***	-0.0242***
			(0.00430)	(0.00433)	(0.00457)
Calculus			-0.00125	0.000376	0.00256
			(0.00574)	(0.00573)	(0.00593)
Functions			-0.0152**	-0.0132*	-0.0140*
			(0.00558)	(0.00559)	(0.00577)
Female*(English)			-0.00141	-0.00442	-0.00424
			(0.0101)	(0.0101)	(0.0104)
Female*(Calculus)			0.00756	0.00820	0.00507
			(0.0130)	(0.0130)	(0.0134)
Female*(Functions)			0.00445	0.00463	0.0102
			(0.0129)	(0.0128)	(0.0132)
Constant	0.469***	0.514***	0.495***	0.421***	0.288***
	(0.00388)	(0.0107)	(0.0110)	(0.0238)	(0.0760)
N	20590	20590	20590	20590	20590
R^2	0.0102	0.0385	0.0426	0.0464	0.101
ll	-14708.9	-14411.2	-14367.2	-14325.7	-13717.4

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to a computer science program, zero otherwise (conditional on having received an offer). All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.15: Top Three Placement – Engineering Ready

	(1)	(2)	(3)	(4)	(5)
Female	-0.0693***	-0.0214***	-0.0197***	-0.0170***	-0.0171***
	(0.00327)	(0.00349)	(0.00356)	(0.00357)	(0.00367)
Courses Taken					
Biology		-0.0829***	-0.0867***	-0.0887***	-0.0908***
		(0.00294)	(0.00297)	(0.00296)	(0.00304)
Female*(Biology)		-0.0468***	-0.0468***	-0.0455***	-0.0451***
		(0.00638)	(0.00649)	(0.00645)	(0.00649)
Course Marks					
English			-0.00985***	-0.00999***	-0.00879***
			(0.00135)	(0.00135)	(0.00144)
Physics			0.0213***	0.0197***	0.0222***
			(0.00203)	(0.00202)	(0.00215)
Chemistry			0.0114***	0.00820***	0.00828***
			(0.00195)	(0.00194)	(0.00206)
Calculus			-0.00409*	-0.00251	-0.00384
			(0.00206)	(0.00205)	(0.00215)
Functions			-0.00945***	-0.00642***	-0.00562**
			(0.00191)	(0.00190)	(0.00197)
Female*(English)			-0.00244	-0.00480	-0.00554
			(0.00425)	(0.00422)	(0.00425)
Female*(Physics)			0.00331	0.00386	0.00329
			(0.00592)	(0.00588)	(0.00592)
Female*(Chemistry)			-0.000543	-0.000597	-0.000620
			(0.00585)	(0.00582)	(0.00584)
Female*(Calculus)			0.0113	0.0120	0.0120
			(0.00648)	(0.00643)	(0.00645)
Female*(Functions)			-0.00445	-0.00503	-0.00396
			(0.00601)	(0.00596)	(0.00595)
Constant	0.932***	0.959***	0.958***	0.969***	1.007***
	(0.00118)	(0.00113)	(0.00122)	(0.00719)	(0.0184)
N	58361	58361	58361	58361	58361
R^2	0.0107	0.0379	0.0435	0.0530	0.0699
ll	-7361.4	-6547.8	-6378.9	-6087.7	-5562.9

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has placed an engineering program in their top three choices, zero otherwise (conditional on having applied). All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.16: Top Three Results – Computer Science

	(1)	(2)	(3)	(4)	(5)
Female	-0.137***	-0.0866***	-0.0820***	-0.0721***	-0.0739***
	(0.00729)	(0.0191)	(0.0193)	(0.0190)	(0.0195)
Courses Taken					
Biology Only		0.0127	0.0123	0.00596	-0.00399
		(0.0223)	(0.0223)	(0.0220)	(0.0228)
Chemistry Only		0.0813***	0.0813***	0.0768***	0.0717***
		(0.0112)	(0.0112)	(0.0111)	(0.0116)
Physics Only		0.0898***	0.0889***	0.0867***	0.0872***
		(0.00842)	(0.00844)	(0.00837)	(0.00876)
Biology and Chemistry		-0.186***	-0.183***	-0.194***	-0.190***
		(0.0164)	(0.0164)	(0.0163)	(0.0164)
Biology and Physics		0.0101	0.0110	-0.00451	-0.0133
		(0.0217)	(0.0217)	(0.0216)	(0.0221)
Physics and Chemistry		-0.0463***	-0.0445***	-0.0404***	-0.0439***
		(0.00837)	(0.00864)	(0.00855)	(0.00886)
All Three		-0.144***	-0.140***	-0.145***	-0.154***
		(0.0111)	(0.0114)	(0.0113)	(0.0116)
Female*(Biology Only)		-0.0709	-0.0726	-0.0746	-0.0765
		(0.0501)	(0.0500)	(0.0495)	(0.0505)
Female*(Chemistry Only)		0.00496	0.00400	-0.00187	0.00471
		(0.0319)	(0.0320)	(0.0320)	(0.0328)
Female*(Physics Only)		-0.0180	-0.0156	-0.00821	-0.0150
		(0.0275)	(0.0276)	(0.0273)	(0.0279)
Female*(Biology and Chemistry)		0.00677	0.000909	-0.0113	-0.00746
		(0.0278)	(0.0279)	(0.0276)	(0.0280)
Female*(Biology and Physics)		-0.0687	-0.0726	-0.0819	-0.0753
		(0.0556)	(0.0556)	(0.0555)	(0.0562)
Female*(Physics and Chemistry)		0.0334	0.0349	0.0399	0.0425
		(0.0245)	(0.0248)	(0.0246)	(0.0251)
Female*(All Three)		-0.0112	-0.0152	-0.0274	-0.0303
		(0.0250)	(0.0254)	(0.0251)	(0.0256)
Course Marks					
English			-0.00764**	-0.00998***	-0.00779*
			(0.00294)	(0.00294)	(0.00311)
Calculus			0.00630	0.00959*	0.0100*
			(0.00396)	(0.00393)	(0.00406)
Functions			-0.00592	-0.00300	-0.00194
			(0.00375)	(0.00372)	(0.00388)
Female*(English)			0.0163*	0.0115	0.0102
			(0.00830)	(0.00823)	(0.00843)
Female*(Calculus)			-0.0151	-0.0141	-0.0124
			(0.0107)	(0.0105)	(0.0106)
Female*(Functions)			0.00266	0.00232	0.00437
			(0.0104)	(0.0103)	(0.0104)
Constant	0.809***	0.841***	0.836***	0.780***	0.754***
	(0.00283)	(0.00705)	(0.00738)	(0.0187)	(0.0663)
N	24162	24162	24162	24162	24162
R^2	0.0178	0.0581	0.0586	0.0741	0.118
ll	-12743.6	-12236.8	-12230.1	-12030.2	-11440.2

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has placed a computer science program in their top three choices, zero otherwise (conditional on having applied). All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table 4.17: Likelihood of Offer Given Number of Applications - Engineering Ready

	(1) 1 Engineering Application	(2) 3+ Engineering Application
Female	0.0194	0.000521
	(0.0173)	(0.00370)
Courses Taken		
Biology	0.00231	-0.0154***
	(0.0114)	(0.00264)
Female*(Biology)	0.00978	-0.00164
	(0.0210)	(0.00510)
Course Marks		
English	0.0360***	0.0179***
	(0.00675)	(0.00195)
Physics	0.0603***	0.0226***
	(0.00859)	(0.00265)
Chemistry	0.0543***	0.0252***
	(0.00824)	(0.00261)
Calculus	0.0167	0.0248***
	(0.00923)	(0.00295)
Functions	0.0457***	0.0209***
	(0.00866)	(0.00273)
Female*(English)	0.00134	-0.00494
	(0.0127)	(0.00426)
Female*(Physics)	0.0188	0.00263
	(0.0151)	(0.00583)
Female*(Chemistry)	0.00476	-0.00274
	(0.0152)	(0.00582)
Female*(Calculus)	0.00711	-0.0192**
	(0.0169)	(0.00673)
Female*(Functions)	0.00939	0.000430
	(0.0159)	(0.00675)
Constant	0.687***	0.966***
	(0.0640)	(0.0191)
N	10490	37732
R^2	0.269	0.163
ll	-5559.7	7340.2

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has received an offer to an engineering program, zero otherwise (conditional on having applied). All students are Engineering-ready. Column (1) includes students who have applied to only one engineering program. Column (2) includes students who have applied to three or more engineering programs. Both columns include all controls. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.18: Top Three Placement – Computer Science Ready

	(1) 1 Comp. Sci. Application	(2) 3+ Comp. Sci. Application
Female	0.0785**	-0.0145
	(0.0275)	(0.0176)
Courses Taken		
Biology Only	-0.0255	-0.0123
	(0.0498)	(0.0258)
Chemistry Only	-0.00250	0.00620
	(0.0346)	(0.0130)
Physics Only	0.0603**	0.00287
	(0.0227)	(0.00956)
Biology and Chemistry	0.0195	0.00525
	(0.0227)	(0.0192)
Biology and Physics	-0.00150	0.0207
	(0.0413)	(0.0187)
Physics and Chemistry	0.0632***	-0.00571
	(0.0173)	(0.00860)
All Three	0.0331	-0.00110
	(0.0188)	(0.00996)
Female*(Biology Only)	-0.0188	0.0765
	(0.0735)	(0.0394)
Female*(Chemistry Only)	-0.0678	0.0139
	(0.0581)	(0.0251)
Female*(Physics Only)	-0.0300	-0.00153
	(0.0447)	(0.0239)
Female*(Biology and Chemistry)	-0.0578	0.0192
	(0.0347)	(0.0297)
Female*(Biology and Physics)	-0.144*	0.0174
	(0.0727)	(0.0306)
Female*(Physics and Chemistry)	-0.0440	0.00921
	(0.0329)	(0.0213)
Female*(All Three)	-0.101**	0.0180
	(0.0321)	(0.0194)
Course Marks		
English	0.0542***	0.0292***
	(0.00560)	(0.00364)
Calculus	0.0601***	0.0288***
	(0.00758)	(0.00463)
Functions	0.0863***	0.0329***
	(0.00739)	(0.00450)
Female*(English)	-0.0238*	-0.0149
	(0.0109)	(0.0101)
Female*(Calculus)	-0.0146	0.00268
	(0.0142)	(0.0123)
Female*(Functions)	-0.00689	-0.0311**
	(0.0138)	(0.0114)
Constant	0.719***	0.910***
	(0.0911)	(0.107)
N	11156	7359
R^2	0.233	0.210
ll	-4973.8	2201.0

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has received an offer to a computer science program, zero otherwise (conditional on having applied). All students are Engineering-ready. Column (1) includes students who have applied to only one computer science program. Column (2) includes students who have applied to three or more computer science programs. Both columns include all controls. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.19: Application Results (Distribution) - Engineering Ready

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.132***	-0.107***	-0.159***
	(0.0177)	(0.00748)	(0.0261)
Courses Taken			
Biology	-0.394***	-0.367***	-0.305***
	(0.00713)	(0.00486)	(0.00740)
Female*(Biology)	-0.106***	-0.138***	-0.106***
	(0.0148)	(0.00919)	(0.0133)
Course Marks			
English	-0.0235***	-0.0332***	-0.0749***
	(0.00345)	(0.00324)	(0.00675)
Physics	0.0624***	0.0713***	0.0958***
	(0.00392)	(0.00395)	(0.0104)
Chemistry	0.0134***	-0.00207	-0.0261*
	(0.00387)	(0.00393)	(0.0111)
Calculus	-0.00174	0.00527	-0.00708
	(0.00394)	(0.00439)	(0.0144)
Functions	0.00698	0.00355	0.00731
	(0.00378)	(0.00406)	(0.0128)
Female*(English)	0.000653	-0.00860	0.0144
	(0.00626)	(0.00559)	(0.0108)
Female*(Physics)	-0.0240***	-0.0117	-0.00141
	(0.00667)	(0.00602)	(0.0144)
Female*(Chemistry)	-0.00626	-0.0167*	-0.0188
	(0.00680)	(0.00659)	(0.0167)
Female*(Calculus)	0.0102	0.000959	0.0280
	(0.00686)	(0.00683)	(0.0207)
Female*(Functions)	0.0156*	0.0119	0.0326
	(0.00653)	(0.00658)	(0.0187)
Constant	0.973***	1.010***	0.899***
	(0.0650)	(0.0326)	(0.0571)
N	26047	52095	25566
R^2	0.340	0.332	0.255
ll	-13352.1	-26686.9	-14674.1

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) are for those in the bottom 25 % of achievement among engineering-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in engineering prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.20: Offer Results (Distribution) - Engineering Ready

	(1)	(2)	(3)
	Bottom 25 %	Middle 50 %	Top 25 %
Female	-0.0983***	-0.0311***	-0.00390
	(0.0154)	(0.00596)	(0.0246)
Courses Taken			
Biology	-0.0973***	-0.124***	-0.159***
	(0.00523)	(0.00401)	(0.00623)
Female*(Biology)	-0.0158	-0.0193*	-0.0111
	(0.0116)	(0.00809)	(0.0116)
Course Marks			
English	0.0253***	0.0330***	-0.00598
	(0.00241)	(0.00261)	(0.00559)
Physics	0.0552***	0.0703***	0.0628***
	(0.00283)	(0.00327)	(0.00892)
Chemistry	0.0533***	0.0605***	0.0249**
	(0.00268)	(0.00311)	(0.00933)
Calculus	0.0250***	0.0324***	-0.00768
	(0.00278)	(0.00354)	(0.0122)
Functions	0.0370***	0.0340***	-0.0181
	(0.00262)	(0.00325)	(0.0107)
Female*(English)	-0.0107	-0.000456	-0.00148
	(0.00604)	(0.00558)	(0.0105)
Female*(Physics)	-0.0141*	0.00318	-0.00732
	(0.00668)	(0.00642)	(0.0148)
Female*(Chemistry)	-0.0137*	-0.00279	-0.00649
	(0.00659)	(0.00642)	(0.0163)
Female*(Calculus)	-0.00830	0.00266	-0.0121
	(0.00675)	(0.00722)	(0.0210)
Female*(Functions)	-0.00505	0.00283	-0.00973
	(0.00614)	(0.00687)	(0.0189)
Constant	0.441***	0.513***	0.655***
	(0.0444)	(0.0243)	(0.0406)
N	14344	29988	14029
R^2	0.257	0.171	0.188
ll	545.3	-3310.2	-1976.9

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i received an offer to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) are for those in the bottom 25 % of achievement among engineering-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in engineering prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table 4.21: Acceptance Results (Distribution) - Engineering Ready

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	0.0549	0.00661	0.00493
	(0.505)	(0.0244)	(0.0509)
Courses Taken			
Biology	-0.0257	-0.0112	-0.0169
	(0.101)	(0.0159)	(0.0116)
Female*(Biology)	0.237	0.0619*	-0.00878
	(0.351)	(0.0307)	(0.0249)
Course Marks			
English	0.0409	0.00456	-0.00991
	(0.0479)	(0.0102)	(0.00954)
Physics	0.0324	-0.00142	0.00540
	(0.0598)	(0.0132)	(0.0186)
Chemistry	0.0862	0.0338*	0.0133
	(0.0715)	(0.0131)	(0.0167)
Calculus	0.00620	-0.000543	-0.00339
	(0.0516)	(0.0145)	(0.0206)
Functions	0.0796	0.0229	0.0222
	(0.0625)	(0.0131)	(0.0190)
Female*(English)	0.0255	-0.0151	0.0175
	(0.125)	(0.0235)	(0.0228)
Female*(Physics)	0.0889	0.00110	-0.0160
	(0.333)	(0.0319)	(0.0360)
Female*(Chemistry)	-0.176	-0.0147	0.0145
	(0.178)	(0.0292)	(0.0354)
Female*(Calculus)	0.0808	0.00752	-0.00557
	(0.202)	(0.0331)	(0.0507)
Female*(Functions)	0.0875	-0.00462	-0.0309
	(0.272)	(0.0338)	(0.0395)
Constant	0.784*	0.835***	0.946***
	(0.356)	(0.153)	(0.0467)
N	511	3392	3812
R^2	0.560	0.241	0.235
ll	-24.56	-179.0	120.2

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) are for those in the bottom 25 % of achievement among engineering-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in engineering prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.22: Application Results (Distribution) - Computer Science Ready

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.0891***	-0.0743***	-0.0444***
	(0.00838)	(0.00352)	(0.0114)
Courses Taken			
Biology Only	0.0381**	0.0174	0.0214
	(0.0138)	(0.0104)	(0.0177)
Chemistry Only	0.207***	0.160***	0.0886***
	(0.0139)	(0.0116)	(0.0180)
Physics Only	0.287***	0.302***	0.226***
	(0.00977)	(0.00890)	(0.0159)
Biology and Chemistry	-0.0549***	-0.0125**	-0.00984
	(0.00622)	(0.00467)	(0.00761)
Biology and Physics	0.114***	0.154***	0.203***
	(0.0201)	(0.0187)	(0.0379)
Physics and Chemistry	0.0729***	0.104***	0.147***
	(0.00615)	(0.00426)	(0.00735)
All Three	-0.0532***	-0.0152***	0.0171**
	(0.00603)	(0.00385)	(0.00634)
Female*(Biology Only)	-0.0238	0.00536	-0.0224
	(0.0157)	(0.0118)	(0.0190)
Female*(Chemistry Only)	-0.0996***	-0.0876***	-0.0545**
	(0.0209)	(0.0147)	(0.0206)
Female*(Physics Only)	-0.173***	-0.187***	-0.135***
	(0.0167)	(0.0129)	(0.0210)
Female*(Biology and Chemistry)	0.0756***	0.0340***	0.0181*
	(0.00747)	(0.00528)	(0.00854)
Female*(Biology and Physics)	0.00461	-0.0753**	-0.120**
	(0.0320)	(0.0240)	(0.0444)
Female*(Physics and Chemistry)	0.0133	-0.00650	-0.0620***
	(0.0128)	(0.00718)	(0.0101)
Female*(All Three)	0.0740***	0.0338***	-0.0111
	(0.00760)	(0.00456)	(0.00730)
Course Marks			
English	-0.0276***	-0.0282***	-0.0258***
	(0.00241)	(0.00230)	(0.00433)
Calculus	0.0126***	0.00211	0.0221**
	(0.00272)	(0.00253)	(0.00711)
Functions	-0.0134***	-0.00260	0.0180**
	(0.00255)	(0.00264)	(0.00662)
Female*(English)	0.0173***	0.0158***	0.0197***
	(0.00316)	(0.00283)	(0.00514)
Female*(Calculus)	-0.00615	-0.00427	-0.00918
	(0.00359)	(0.00305)	(0.00810)
Female*(Functions)	0.0169***	0.00310	-0.0132
	(0.00334)	(0.00317)	(0.00762)
Constant	0.0846*	0.0184	-0.0325
	(0.0346)	(0.0172)	(0.0231)
N	51845	103692	50809
R^2	0.124	0.0996	0.111
ll	-17066.0	-21266.3	-6840.2

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to a computer science program, zero otherwise. All students are computer science-ready. Column (1) are for those in the bottom 25 % of achievement among computer science-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in computer science prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.23: Offer Results (Distribution) - Computer Science Ready

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.0984*	0.0101	-0.0602
	(0.0493)	(0.0231)	(0.0387)
Courses Taken			
Biology Only	-0.0442	0.0109	0.0240
	(0.0397)	(0.0360)	(0.0178)
Chemistry Only	0.0411	0.0407*	0.00914
	(0.0222)	(0.0180)	(0.0228)
Physics Only	0.0300	0.0755***	0.0416*
	(0.0165)	(0.0122)	(0.0176)
Biology and Chemistry	-0.169***	-0.0228	-0.0199
	(0.0272)	(0.0194)	(0.0275)
Biology and Physics	-0.0524	0.0234	-0.00951
	(0.0420)	(0.0282)	(0.0431)
Physics and Chemistry	-0.0265	0.0411***	0.0215
	(0.0158)	(0.0113)	(0.0151)
All Three	-0.108***	-0.0100	0.00956
	(0.0235)	(0.0141)	(0.0160)
Female*(Biology Only)	0.162*	-0.111	-0.0658
	(0.0723)	(0.0654)	(0.0551)
Female*(Chemistry Only)	-0.146*	-0.00852	-0.00962
	(0.0687)	(0.0387)	(0.0356)
Female*(Physics Only)	0.00640	-0.00485	-0.0436
	(0.0536)	(0.0293)	(0.0334)
Female*(Biology and Chemistry)	-0.0253	-0.0117	-0.0700
	(0.0502)	(0.0321)	(0.0370)
Female*(Biology and Physics)	-0.214*	-0.0806	0.0759
	(0.105)	(0.0680)	(0.0527)
Female*(Physics and Chemistry)	-0.0299	0.00386	-0.0237
	(0.0544)	(0.0265)	(0.0226)
Female*(All Three)	-0.0358	-0.0562	-0.0849***
	(0.0521)	(0.0293)	(0.0256)
Course Marks			
English	0.0858***	0.0296***	0.0000618
	(0.00618)	(0.00515)	(0.00517)
Calculus	0.0997***	0.0344***	0.0158
	(0.00710)	(0.00630)	(0.0116)
Functions	0.103***	0.0409***	0.0146
	(0.00675)	(0.00598)	(0.0107)
Female*(English)	-0.0422*	0.00807	-0.0107
	(0.0172)	(0.0122)	(0.0158)
Female*(Calculus)	-0.0262	-0.00904	0.0447
	(0.0193)	(0.0144)	(0.0271)
Female*(Functions)	-0.0199	0.00762	0.0385
	(0.0186)	(0.0141)	(0.0263)
Constant	1.064***	0.772***	0.957***
	(0.117)	(0.0781)	(0.0261)
N	7900	11419	4843
R^2	0.217	0.112	0.257
ll	-3928.6	-1901.6	1949.8

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i received an offer to a computer science program, zero otherwise. All students are computer science-ready. Column (1) are for those in the bottom 25 % of achievement among computer science-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in computer science prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE 4.24: Acceptance Results (Distribution) - Computer Science Ready

	(1)	(2)	(3)
Female	-0.159*	-0.0863*	-0.0517
	(0.0717)	(0.0361)	(0.0958)
Courses Taken			
Biology Only	-0.0500	-0.0519	-0.0294
	(0.0557)	(0.0574)	(0.137)
Chemistry Only	0.0405	0.0822**	0.0990
	(0.0327)	(0.0312)	(0.0735)
Physics Only	0.0846***	0.106***	0.205***
	(0.0237)	(0.0214)	(0.0520)
Biology and Chemistry	-0.150***	-0.185***	-0.116
	(0.0388)	(0.0291)	(0.0621)
Biology and Physics	-0.0108	-0.0671	-0.0222
	(0.0592)	(0.0489)	(0.105)
Physics and Chemistry	-0.0263	-0.0501**	-0.0620
	(0.0225)	(0.0187)	(0.0428)
All Three	-0.0674*	-0.145***	-0.139**
	(0.0321)	(0.0226)	(0.0444)
Female*(Biology Only)	0.265*	-0.186*	0.112
	(0.114)	(0.0865)	(0.202)
Female*(Chemistry Only)	0.0328	-0.0725	0.0492
	(0.0922)	(0.0658)	(0.132)
Female*(Physics Only)	-0.0571	-0.0245	-0.00807
	(0.0754)	(0.0536)	(0.0983)
Female*(Biology and Chemistry)	0.126	0.000522	0.00360
	(0.0692)	(0.0477)	(0.0889)
Female*(Biology and Physics)	0.218	0.0330	-0.0360
	(0.156)	(0.111)	(0.156)
Female*(Physics and Chemistry)	0.0894	0.0183	0.0607
	(0.0699)	(0.0443)	(0.0749)
Female*(All Three)	0.0257	-0.00874	0.0386
	(0.0710)	(0.0446)	(0.0732)
Course Marks			
English	0.00484	-0.0278**	-0.0416*
	(0.00894)	(0.00882)	(0.0170)
Calculus	0.0498***	-0.0207	-0.0159
	(0.0102)	(0.0106)	(0.0321)
Functions	0.0198*	-0.0216*	-0.0426
	(0.00992)	(0.0102)	(0.0326)
Female*(English)	-0.0320	-0.00408	-0.0186
	(0.0238)	(0.0192)	(0.0346)
Female*(Calculus)	-0.0370	0.0232	0.0609
	(0.0273)	(0.0219)	(0.0589)
Female*(Functions)	0.0380	0.00347	-0.0533
	(0.0256)	(0.0218)	(0.0579)
Constant	0.446**	0.240*	0.430*
	(0.168)	(0.0946)	(0.198)
N	5676	10248	4666
R^2	0.169	0.144	0.192
ll	-3591.7	-6578.9	-2708.4

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to a computer science program, zero otherwise. All students are computer science-ready. Column (1) are for those in the bottom 25 % of achievement among computer science-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in computer science prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

4.12 Appendix

TABLE A4.1: Full Engineering Application Results

	(1)	(2)	(3)	(4)	(5)
Female	-0.354***	-0.115***	-0.112***	-0.117***	-0.119***
	(0.00303)	(0.00545)	(0.00549)	(0.00546)	(0.00551)
Courses Taken					
Biology		-0.368***	-0.370***	-0.367***	-0.363***
		(0.00342)	(0.00345)	(0.00346)	(0.00350)
Female*(Biology)		-0.135***	-0.123***	-0.121***	-0.117***
		(0.00664)	(0.00673)	(0.00669)	(0.00669)
Course Marks					
English			-0.0327***	-0.0305***	-0.0353***
			(0.00199)	(0.00200)	(0.00206)
Physics			0.0563***	0.0582***	0.0682***
			(0.00245)	(0.00244)	(0.00254)
Chemistry			0.00210	0.00450	0.00412
			(0.00245)	(0.00245)	(0.00252)
Calculus			0.00728**	0.00513	0.00246
			(0.00266)	(0.00265)	(0.00272)
Functions			0.0107***	0.00759**	0.00558*
			(0.00254)	(0.00254)	(0.00258)
Female*(English)			-0.000216	0.00272	0.0000901
			(0.00361)	(0.00360)	(0.00359)
Female*(Physics)			-0.00952*	-0.00934*	-0.00871*
			(0.00394)	(0.00392)	(0.00395)
Female*(Chemistry)			-0.0125**	-0.0129**	-0.0130**
			(0.00432)	(0.00430)	(0.00431)
Female*(Calculus)			0.00952*	0.00824	0.00846
			(0.00446)	(0.00444)	(0.00444)
Female*(Functions)			0.0185***	0.0198***	0.0190***
			(0.00427)	(0.00425)	(0.00425)
Language Spoken at Home					
French				-0.0398	-0.0380
				(0.0205)	(0.0206)
Other				-0.00467	0.00369
				(0.00389)	(0.00402)
Years in Canadian Education					
Yrs. Cdn. Educ				-0.00422***	-0.00399***
				(0.00109)	(0.00110)
>12 Years in Cdn. Educ.				-0.0687***	-0.0631***
				(0.00958)	(0.00976)
Permanent Resident Status					
Permanent Resident				0.00798	0.00711
				(0.00656)	(0.00658)
Neighbourhood Demographics					
Household Income ($ 1000s)				0.000140***	0.0000787***
				(0.0000186)	(0.0000218)
Share Immigrants				-0.0133	-0.00456
				(0.0119)	(0.0167)
Share Visible Minority				0.0976***	0.0330**
				(0.00977)	(0.0127)
Constant	0.691***	0.859***	0.856***	0.907***	0.972***
	(0.00180)	(0.00184)	(0.00194)	(0.00851)	(0.0256)
N	103708	103708	103708	103708	103708
R^2	0.117	0.262	0.278	0.282	0.299
ll	-67967.8	-58665.7	-57571.5	-57250.1	-56022.4

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. *Source: Ontario University Applications Centre (OUAC) and Statistics Canada.*

TABLE A4.2: Full Computer Science Application Results

	(1)	(2)	(3)	(4)	(5)
Female	-0.116***	-0.0876***	-0.0802***	-0.0826***	-0.0842***
	(0.00133)	(0.00260)	(0.00261)	(0.00262)	(0.00267)
Courses Taken					
Biology Only		0.0149	0.0169*	0.0214**	0.0262***
		(0.00790)	(0.00784)	(0.00783)	(0.00782)
Chemistry Only		0.171***	0.169***	0.170***	0.168***
		(0.00829)	(0.00823)	(0.00818)	(0.00813)
Physics Only		0.294***	0.287***	0.289***	0.289***
		(0.00615)	(0.00613)	(0.00611)	(0.00607)
Biology and Chemistry		-0.0370***	-0.0328***	-0.0309***	-0.0281***
		(0.00335)	(0.00334)	(0.00334)	(0.00337)
Biology and Physics		0.140***	0.137***	0.144***	0.144***
		(0.0131)	(0.0131)	(0.0130)	(0.0129)
Physics and Chemistry		0.103***	0.100***	0.101***	0.101***
		(0.00311)	(0.00315)	(0.00315)	(0.00317)
All Three		-0.0261***	-0.0196***	-0.0179***	-0.0178***
		(0.00278)	(0.00282)	(0.00284)	(0.00288)
Female*(Biology Only)		-0.00919	-0.00860	-0.00766	-0.0115
		(0.00875)	(0.00870)	(0.00868)	(0.00868)
Female*(Chemistry Only)		-0.106***	-0.103***	-0.101***	-0.0979***
		(0.0104)	(0.0104)	(0.0103)	(0.0103)
Female*(Physics Only)		-0.185***	-0.180***	-0.179***	-0.178***
		(0.00919)	(0.00916)	(0.00910)	(0.00905)
Female*(Biology and Chemistry)		0.0479***	0.0460***	0.0481***	0.0462***
		(0.00383)	(0.00382)	(0.00383)	(0.00385)
Female*(Biology and Physics)		-0.0578***	-0.0537**	-0.0535**	-0.0534**
		(0.0174)	(0.0174)	(0.0173)	(0.0172)
Female*(Physics and Chemistry)		-0.0127*	-0.00896	-0.00805	-0.00838
		(0.00516)	(0.00519)	(0.00516)	(0.00516)
Female*(All Three)		0.0342***	0.0314***	0.0324***	0.0340***
		(0.00331)	(0.00338)	(0.00338)	(0.00341)
Course Marks					
English			-0.0266***	-0.0245***	-0.0255***
			(0.00125)	(0.00126)	(0.00128)
Calculus			0.00813***	0.00765***	0.00906***
			(0.00151)	(0.00151)	(0.00152)
Advanced Functions			-0.00386*	-0.00415**	-0.00559***
			(0.00153)	(0.00152)	(0.00153)
Female*(English)			0.0138***	0.0147***	0.0137***
			(0.00161)	(0.00161)	(0.00162)
Female*(Calculus)			-0.00788***	-0.00787***	-0.00802***
			(0.00187)	(0.00187)	(0.00187)
Female*(Advanced Functions)			0.00614**	0.00701***	0.00664***
			(0.00188)	(0.00187)	(0.00187)
Language Spoken at Home					
French				-0.0303***	-0.0287**
				(0.00901)	(0.00914)
Other				0.00429*	0.00618**
				(0.00213)	(0.00219)
Years in Canadian Education					
Yrs. Cdn. Educ.				0.00389***	0.00359***
				(0.000618)	(0.000626)
>12 Years in Cdn. Educ.				0.0246***	0.0233***
				(0.00539)	(0.00550)
Permanent Resident Status					
Permanent Resident				0.0156***	0.0139***
				(0.00384)	(0.00384)
Neighbourhood Demographics					
Household Income ($ 1000s)				-0.0000151*	-0.0000101
				(0.00000691)	(0.00000844)
Immigrant Share				-0.0232***	0.00116
				(0.00616)	(0.00845)
Visible Minority Share				0.0961***	0.0414***
				(0.00529)	(0.00678)
Constant	0.169***	0.122***	0.116***	0.0898***	0.0350**
	(0.00111)	(0.00220)	(0.00219)	(0.00519)	(0.0128)
N	206346	206346	206346	206346	206346
R^2	0.0320	0.0787	0.0827	0.0880	0.103
ll	-55301.9	-50202.3	-49751.2	-49156.1	-47487.8

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to a computer science program, zero otherwise. All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. *Source: Ontario University Applications Centre (OUAC) and Statistics Canada.*

TABLE A4.3: Full Engineering Offer Results

	(1)	(2)	(3)	(4)	(5)
Female	0.00682*	0.0181***	-0.0216***	-0.0198***	-0.0191***
	(0.00328)	(0.00461)	(0.00453)	(0.00454)	(0.00461)
Courses Taken					
Biology		-0.00842*	-0.0570***	-0.0578***	-0.0592***
		(0.00337)	(0.00323)	(0.00324)	(0.00331)
Female*(Biology)		-0.0160*	0.000318	0.000660	-0.000807
		(0.00667)	(0.00638)	(0.00638)	(0.00644)
Course Marks					
English			0.0184***	0.0175***	0.0185***
			(0.00199)	(0.00201)	(0.00208)
Physics			0.0429***	0.0422***	0.0454***
			(0.00270)	(0.00270)	(0.00283)
Chemistry			0.0382***	0.0370***	0.0407***
			(0.00262)	(0.00262)	(0.00273)
Calculus			0.0232***	0.0240***	0.0203***
			(0.00295)	(0.00294)	(0.00304)
Functions			0.0263***	0.0278***	0.0298***
			(0.00277)	(0.00277)	(0.00282)
Female*(English)			0.00315	0.00156	0.00172
			(0.00467)	(0.00466)	(0.00468)
Female*(Physics)			0.00805	0.00828	0.00893
			(0.00619)	(0.00618)	(0.00619)
Female*(Chemistry)			-0.00389	-0.00403	-0.00344
			(0.00622)	(0.00621)	(0.00621)
Female*(Calculus)			0.00390	0.00407	0.00257
			(0.00710)	(0.00707)	(0.00706)
Female*(Functions)			-0.00543	-0.00531	-0.00341
			(0.00669)	(0.00667)	(0.00666)
Language Spoken at Home					
French				0.0263	0.0196
				(0.0189)	(0.0195)
Other				-0.0118**	-0.0164***
				(0.00399)	(0.00411)
Years in Canadian Education					
Yrs. Cdn. Educ.				0.0000391	0.0000495
				(0.00108)	(0.00110)
>12 Years in Cdn. Educ				-0.000599	-0.000977
				(0.00948)	(0.00975)
Permanent Resident Status					
Permanent Resident				-0.0134*	-0.00945
				(0.00663)	(0.00667)
Neighbourhood Demographics					
Household Income ($ 1000s)				-0.0000178	0.00000989
				(0.0000137)	(0.0000169)
Share Immigrants				-0.0369**	-0.0463**
				(0.0119)	(0.0167)
Share Visible Minority				0.000709	0.00513
				(0.00997)	(0.0130)
Constant	0.873***	0.875***	0.899***	0.904***	0.904***
	(0.00156)	(0.00188)	(0.00172)	(0.00841)	(0.0245)
N	58361	58361	58361	58361	58361
R^2	0.0000719	0.000469	0.130	0.131	0.157
ll	-18389.6	-18378.0	-14327.9	-14282.2	-13400.9

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i received an offer to an engineering program, zero otherwise (conditional on having applied). All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.4: Full Computer Science Offer Results

	(1)	(2)	(3)	(4)	(5)
Female	-0.0258***	0.0497**	-0.0104	-0.00902	-0.00851
	(0.00591)	(0.0164)	(0.0156)	(0.0157)	(0.0161)
Courses Taken					
Biology Only		-0.0445	-0.0223	-0.0233	-0.0139
		(0.0266)	(0.0251)	(0.0251)	(0.0257)
Chemistry Only		0.0507***	0.0469***	0.0450***	0.0406**
		(0.0137)	(0.0130)	(0.0130)	(0.0133)
Physics Only		0.0656***	0.0548***	0.0544***	0.0512***
		(0.00975)	(0.00916)	(0.00916)	(0.00945)
Biology and Chemistry		-0.0458**	-0.0790***	-0.0799***	-0.0772***
		(0.0153)	(0.0144)	(0.0144)	(0.0146)
Biology and Physics		-0.00388	-0.0136	-0.0132	-0.0171
		(0.0242)	(0.0223)	(0.0223)	(0.0226)
Physics and Chemistry		0.0783***	0.00584	0.00560	0.00308
		(0.00843)	(0.00819)	(0.00820)	(0.00846)
All Three		0.0646***	-0.0408***	-0.0420***	-0.0470***
		(0.00988)	(0.00969)	(0.00969)	(0.00999)
Female*(Biology Only)		0.0215	0.00851	0.00746	0.000938
		(0.0452)	(0.0445)	(0.0446)	(0.0452)
Female*(Chemistry Only)		-0.0652*	-0.0559	-0.0537	-0.0548
		(0.0313)	(0.0297)	(0.0297)	(0.0304)
Female*(Physics Only)		-0.0178	-0.0156	-0.0133	-0.00997
		(0.0231)	(0.0220)	(0.0220)	(0.0225)
Female*(Biology and Chemistry)		-0.0508*	-0.0172	-0.0157	-0.0109
		(0.0243)	(0.0232)	(0.0232)	(0.0236)
Female*(Biology and Physics)		-0.101	-0.0844	-0.0833	-0.0844
		(0.0533)	(0.0493)	(0.0492)	(0.0497)
Female*(Physics and Chemistry)		-0.0124	0.00502	0.00716	0.00719
		(0.0191)	(0.0186)	(0.0185)	(0.0190)
Female*(All Three)		-0.105***	-0.0482*	-0.0471*	-0.0449*
		(0.0207)	(0.0201)	(0.0201)	(0.0204)
Course Marks					
English			0.0428***	0.0418***	0.0399***
			(0.00291)	(0.00292)	(0.00306)
Calculus			0.0501***	0.0505***	0.0508***
			(0.00397)	(0.00396)	(0.00406)
Functions			0.0500***	0.0509***	0.0530***
			(0.00384)	(0.00385)	(0.00396)
Female*(English)			-0.0116	-0.0129	-0.0135
			(0.00716)	(0.00716)	(0.00734)
Female*(Calculus)			-0.0114	-0.0106	-0.00829
			(0.00938)	(0.00938)	(0.00952)
Female*(Functions)			0.00835	0.00848	0.00626
			(0.00931)	(0.00931)	(0.00941)
Language Spoken at Home					
French				0.0541	0.0536
				(0.0383)	(0.0376)
Other				-0.00412	-0.00984
				(0.00597)	(0.00622)
Years in Canadian Education					
Yrs. Cdn. Educ.				0.00619***	0.00566**
				(0.00174)	(0.00178)
>12 Years in Cdn. Educ.				0.0540***	0.0479**
				(0.0155)	(0.0159)
Permanent Resident Status					
Permanent Resident				-0.00877	-0.00938
				(0.00983)	(0.0100)
Neighbourhood Demographics					
Household Income ($ 1000s)				-0.0000842**	-0.0000548
				(0.0000271)	(0.0000312)
Share Immigrants				0.0373*	0.00144
				(0.0189)	(0.0272)
Share Visible Minority				-0.00761	-0.0176
				(0.0144)	(0.0199)
Constant	0.857***	0.805***	0.884***	0.840***	0.857***
	(0.00252)	(0.00764)	(0.00724)	(0.0155)	(0.0554)
N	24162	24162	24162	24162	24162
R^2	0.000853	0.0155	0.126	0.128	0.167
ll	-9246.7	-9068.0	-7630.0	-7604.2	-7042.9

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to a computer science program, zero otherwise. All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.5: Full Computer Science Offer Results with Ranking

	(1)	(2)	(3)	(4)	(5)
Female	-0.0846***	-0.0764***	-0.0670***	-0.0605***	-0.0608***
	(0.00335)	(0.0105)	(0.0119)	(0.0118)	(0.0118)
Courses Taken					
Biology Only		-0.0153	-0.0153	-0.0198	-0.0211
		(0.0156)	(0.0151)	(0.0149)	(0.0149)
Chemistry Only		0.0848***	0.0825***	0.0801***	0.0766***
		(0.0106)	(0.0103)	(0.0102)	(0.0100)
Physics Only		0.111***	0.107***	0.106***	0.104***
		(0.00726)	(0.00702)	(0.00695)	(0.00692)
Biology and Chemistry		-0.127***	-0.122***	-0.129***	-0.126***
		(0.00792)	(0.00758)	(0.00761)	(0.00765)
Biology and Physics		-0.0176	-0.0189	-0.0247	-0.0247
		(0.0145)	(0.0140)	(0.0140)	(0.0137)
Physics and Chemistry		-0.0435***	-0.0402***	-0.0383***	-0.0398***
		(0.00582)	(0.00561)	(0.00557)	(0.00557)
All Three		-0.113***	-0.109***	-0.112***	-0.117***
		(0.00646)	(0.00622)	(0.00619)	(0.00625)
Female*(Biology Only)		0.000119	0.000519	0.000404	0.00548
		(0.0279)	(0.0269)	(0.0268)	(0.0264)
Female*(Chemistry Only)		-0.0385	-0.0366	-0.0368	-0.0336
		(0.0221)	(0.0213)	(0.0212)	(0.0212)
Female*(Physics Only)		-0.0239	-0.0225	-0.0191	-0.0194
		(0.0174)	(0.0168)	(0.0166)	(0.0166)
Female*(Biology and Chemistry)		0.0201	0.0191	0.0131	0.0171
		(0.0128)	(0.0122)	(0.0122)	(0.0124)
Female*(Biology and Physics)		-0.00799	-0.0111	-0.0159	-0.0183
		(0.0282)	(0.0274)	(0.0271)	(0.0275)
Female*(Physics and Chemistry)		0.0531***	0.0519***	0.0548***	0.0557***
		(0.0129)	(0.0124)	(0.0123)	(0.0123)
Female*(All Three)		0.0173	0.0160	0.0111	0.0140
		(0.0121)	(0.0116)	(0.0116)	(0.0116)
Course Marks					
English		0.0191***	0.0196***	0.0172***	0.0173***
		(0.00179)	(0.00173)	(0.00173)	(0.00177)
Calculus		0.0290***	0.0287***	0.0305***	0.0314***
		(0.00231)	(0.00223)	(0.00221)	(0.00223)

Functions	0.0186***	0.0194***	0.0214***	0.0242***
	(0.00228)	(0.00220)	(0.00219)	(0.00223)
Female*(English)	-0.000424	-0.00185	-0.00465	-0.00274
	(0.00364)	(0.00350)	(0.00350)	(0.00358)
Female*(Calculus)	-0.0167***	-0.0162***	-0.0153***	-0.0144**
	(0.00459)	(0.00443)	(0.00442)	(0.00450)
Female*(Functions)	-0.00235	-0.00350	-0.00335	-0.00529
	(0.00452)	(0.00437)	(0.00435)	(0.00447)
Ranking of Computer Science Program				
Second		0.0345***	0.0345***	0.0345***
		(0.00449)	(0.00449)	(0.00451)
Third		0.0311***	0.0312***	0.0314***
		(0.00452)	(0.00452)	(0.00453)
Fourth		-0.00715	-0.00304	0.00128
		(0.00496)	(0.00496)	(0.00497)
Fifth		-0.0367***	-0.0307***	-0.0244***
		(0.00534)	(0.00534)	(0.00535)
Sixth		-0.0537***	-0.0459***	-0.0377***
		(0.00584)	(0.00584)	(0.00585)
Seventh		-0.0785***	-0.0694***	-0.0594***
		(0.00657)	(0.00657)	(0.00659)
Eighth		-0.0801***	-0.0698***	-0.0579***
		(0.00768)	(0.00768)	(0.00769)
Ninth		-0.108***	-0.0968***	-0.0834***
		(0.00868)	(0.00871)	(0.00876)
Tenth		-0.0938***	-0.0814***	-0.0670***
		(0.0104)	(0.0104)	(0.0104)
Female*(Second)		-0.0295**	-0.0295**	-0.0295**
		(0.00934)	(0.00934)	(0.00937)
Female*(Third)		-0.0117	-0.0117	-0.0117
		(0.00959)	(0.00959)	(0.00962)
Female*(Fourth)		-0.000287	-0.00140	-0.00295
		(0.0101)	(0.0101)	(0.0102)
Female*(Fifth)		-0.00906	-0.0102	-0.0119
		(0.0104)	(0.0104)	(0.0104)
Female*(Sixth)		0.0116	0.0104	0.00872
		(0.0113)	(0.0113)	(0.0113)
Female*(Seventh)		0.00238	0.00188	0.000330
		(0.0125)	(0.0125)	(0.0125)

Female*(Eighth)			0.00538	0.00477	0.00458
			(0.0144)	(0.0144)	(0.0144)
Female*(Ninth)			0.0110	0.00994	0.0113
			(0.0162)	(0.0162)	(0.0162)
Female*(Tenth)			-0.00526	-0.00563	-0.00338
			(0.0184)	(0.0184)	(0.0185)
Language Spoken at Home					
‘ French				0.0161	0.0154
				(0.0284)	(0.0279)
Other				-0.00397	-0.00772
				(0.00399)	(0.00410)
Years in Canadian Education					
Yrs. Cdn. Educ.				0.00698***	0.00607***
				(0.00104)	(0.00106)
>12 Years in Cdn. Educ.				0.0789***	0.0658***
				(0.00908)	(0.00930)
Permanent Resident Status					
Permanent Resident				-0.00439	-0.00806
				(0.00604)	(0.00606)
Neighbourhood Demographics					
Household Income ($ 1000s)				-0.000157***	-0.0000762***
				(0.0000188)	(0.0000194)
Share Immigrants				-0.0141	0.0219
				(0.0128)	(0.0174)
Share Visible Minority				-0.0347***	-0.0593***
				(0.00971)	(0.0129)
Constant	0.303***	0.340***	0.345***	0.287***	0.243***
	(0.00175)	(0.00534)	(0.00588)	(0.00988)	(0.0325)
N	129489	129489	129489	129489	129489
R^2	0.00593	0.0376	0.0451	0.0484	0.0613
ll	-80345.2	-78250.7	-77739.8	-77519.4	-76635.8

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i received an offer to an engineering program, zero otherwise (conditional on having received an offer). All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (3) also adds binary variables for the ranking of each engineering application within i's portfolio, with interactions for gender. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.6: Full Engineering Acceptance Results

	(1)	(2)	(3)	(4)	(5)
Female	-0.0661***	-0.0180*	-0.0234**	-0.0200**	-0.0179*
	(0.00514)	(0.00713)	(0.00736)	(0.00737)	(0.00750)
Biology		-0.0990***	-0.129***	-0.132***	-0.133***
		(0.00508)	(0.00510)	(0.00509)	(0.00520)
Female*(Biology)		-0.0412***	-0.0209*	-0.0202	-0.0218*
		(0.0104)	(0.0105)	(0.0105)	(0.0105)
English			-0.0139***	-0.0149***	-0.0109***
			(0.00287)	(0.00289)	(0.00303)
Physics		0.0469***	0.0459***	0.0504***	
			(0.00384)	(0.00383)	(0.00405)
Chemistry			0.0460***	0.0436***	0.0468***
			(0.00373)	(0.00372)	(0.00391)
Calculus			0.0283***	0.0297***	0.0277***
			(0.00410)	(0.00410)	(0.00426)
Functions			-0.0146***	-0.0107**	-0.00822*
			(0.00388)	(0.00389)	(0.00400)
Female*(English)			-0.00101	-0.00420	-0.00638
			(0.00706)	(0.00707)	(0.00711)
Female*(Physics)			0.00206	0.00256	0.00315
			(0.00892)	(0.00889)	(0.00897)
Female*(Chemistry)			-0.0297**	-0.0294**	-0.0276**
			(0.00905)	(0.00901)	(0.00910)
Female*(Calculus)			-0.0160	-0.0147	-0.0130
			(0.0101)	(0.0101)	(0.0102)
Female*(Functions)			-0.000909	-0.00133	-0.00148
			(0.00944)	(0.00942)	(0.00952)
French				-0.0729*	-0.0558
				(0.0339)	(0.0343)
Other				-0.0264***	-0.0225***
				(0.00625)	(0.00647)
Yrs. Cdn. Educ.				-0.00459**	-0.00474**
				(0.00168)	(0.00171)
Household Income ($ 1000s)				-0.000145***	-0.0000215
				(0.0000264)	(0.0000311)
Share Immigrants				-0.0984***	-0.0451
				(0.0189)	(0.0264)
Share Visible Minority				0.0315*	-0.0149
				(0.0155)	(0.0201)
Permanent Resident				-0.0178	-0.0189
				(0.0102)	(0.0103)
>12 Years in Cdn. Educ.				-0.0133	-0.0187
				(0.0147)	(0.0151)
Constant	0.690***	0.721***	0.720***	0.741***	0.792***
	(0.00232)	(0.00273)	(0.00282)	(0.0131)	(0.0378)
N	51020	51020	51020	51020	51020
R^2	0.00341	0.0158	0.0405	0.0443	0.0709
ll	-33607.3	-33286.9	-32638.6	-32537.8	-31817.8

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to an engineering program, zero otherwise (conditional on having received an offer). All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE A4.7: Full Computer Science Acceptance Results

	(1)	(2)	(3)	(4)	(5)
Female	-0.126***	-0.111***	-0.0937***	-0.0892***	-0.0904***
	(0.00839)	(0.0244)	(0.0245)	(0.0245)	(0.0250)
Courses Taken					
Biology Only		-0.0631	-0.0662	-0.0686	-0.0800*
		(0.0358)	(0.0357)	(0.0356)	(0.0357)
Chemistry Only		0.0586**	0.0585**	0.0558**	0.0508*
		(0.0204)	(0.0204)	(0.0204)	(0.0207)
Physics Only		0.103***	0.103***	0.102***	0.102***
		(0.0143)	(0.0143)	(0.0143)	(0.0145)
Biology and Chemistry		-0.168***	-0.155***	-0.160***	-0.163***
		(0.0201)	(0.0201)	(0.0201)	(0.0206)
Biology and Physics		-0.0510	-0.0458	-0.0517	-0.0492
		(0.0338)	(0.0338)	(0.0337)	(0.0338)
Physics and Chemistry		-0.0708***	-0.0550***	-0.0529***	-0.0521***
		(0.0123)	(0.0125)	(0.0125)	(0.0128)
All Three		-0.158***	-0.131***	-0.135***	-0.138***
		(0.0144)	(0.0148)	(0.0148)	(0.0152)
Female*(Biology Only)		0.0157	0.0190	0.0183	0.0201
		(0.0630)	(0.0626)	(0.0628)	(0.0642)
Female*(Chemistry Only)		-0.000286	-0.000121	-0.00182	-0.00164
		(0.0466)	(0.0467)	(0.0466)	(0.0471)
Female*(Physics Only)		-0.0159	-0.0178	-0.0136	-0.0120
		(0.0373)	(0.0375)	(0.0375)	(0.0381)
Female*(Biology and Chemistry)		0.0339	0.0275	0.0237	0.0363
		(0.0330)	(0.0331)	(0.0331)	(0.0339)
Female*(Biology and Physics)		0.0681	0.0717	0.0675	0.0484
		(0.0718)	(0.0720)	(0.0713)	(0.0713)
Female*(Physics and Chemistry)		0.0441	0.0370	0.0398	0.0386
		(0.0303)	(0.0307)	(0.0306)	(0.0310)
Female*(All Three)		0.0327	0.0185	0.0138	0.0166
		(0.0296)	(0.0302)	(0.0302)	(0.0309)
Course Marks					
English			-0.0240***	-0.0246***	-0.0242***
			(0.00430)	(0.00433)	(0.00457)
Calculus			-0.00125	0.000376	0.00256
			(0.00574)	(0.00573)	(0.00593)
Functions			-0.0152**	-0.0132*	-0.0140*
			(0.00558)	(0.00559)	(0.00577)
Female*(English)			-0.00141	-0.00442	-0.00424
			(0.0101)	(0.0101)	(0.0104)
Female*(Calculus)			0.00756	0.00820	0.00507
			(0.0130)	(0.0130)	(0.0134)
Female*(Functions)			0.00445	0.00463	0.0102
			(0.0129)	(0.0128)	(0.0132)
Language Spoken at Home					
French				0.0300	0.0208
				(0.0615)	(0.0617)
Other				0.0122	0.00269
				(0.0100)	(0.0105)
Years in Canadian Education					
Yrs. Cdn. Educ.				0.00836**	0.00653*
				(0.00274)	(0.00284)
>12 Years in Cdn. Educ.				0.0930***	0.0688**
				(0.0241)	(0.0251)
Permanent Resident Status					
Permanent Resident				0.00818	-0.00587
				(0.0156)	(0.0160)
Neighbourhood Demographics					
Household Income ($ 1000s)				-0.000268***	-0.000147**
				(0.0000419)	(0.0000499)
Share Immigrants				-0.0862**	0.0131
				(0.0308)	(0.0438)
Share Visible Minority				0.0113	-0.0322
				(0.0239)	(0.0324)
Constant	0.469***	0.514***	0.495***	0.421***	0.288***
	(0.00388)	(0.0107)	(0.0110)	(0.0238)	(0.0760)
N	20590	20590	20590	20590	20590
R^2	0.0102	0.0385	0.0426	0.0464	0.101
ll	-14708.9	-14411.2	-14367.2	-14325.7	-13717.4

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to a computer science program, zero otherwise (conditional on having received an offer). All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.8: Full Engineering Acceptance Results with Other Offers

	(1)
Female	0.0153
	(0.00789)
Courses Taken	
Biology	-0.0533***
	(0.00503)
Female*(Biology)	-0.0255*
Course Marks	
	(0.0105)
English	-0.000547
	(0.00286)
Physics	0.0423***
	(0.00380)
Chemistry	0.0402***
	(0.00365)
Calculus	0.0367***
	(0.00400)
Functions	0.00197
	(0.00378)
Female*(English)	-0.00776
	(0.00678)
Female*(Physics)	0.000488
	(0.00851)
Female*(Chemistry)	-0.0273**
	(0.00867)
Female*(Calculus)	-0.0151
	(0.00959)
Female*(Functions)	-0.00478
	(0.00906)
Other Offers in Portfolio	
With STEM Offers Only	-0.319***
	(0.00503)
With Non-STEM Offers Only	-0.197***
	(0.00894)
With STEM and Non-STEM Offers Only	-0.407***
	(0.00919)

Female*(With STEM Offers Only)	0.0128
	(0.0107)
Female*(With Non-STEM Offers Only)	-0.0451*
	(0.0195)
Female*(With STEM and Non-STEM Offers Only)	-0.0106
	(0.0168)
Language Spoken at Home	
French	-0.0795*
	(0.0328)
Other	-0.0128*
	(0.00607)
Years in Canadian Education	
Yrs. Cdn. Educ.	-0.00203
	(0.00162)
>12 Years in Cdn. Educ.	0.000204
	(0.0143)
Permanent Resident Status	
Permanent Resident	-0.0118
	(0.00971)
Neighbourhood Demographics	
Household Income ($ 1000s)	0.0000250
	(0.0000307)
Share Immigrants	-0.0201
	(0.0250)
Share Visible Minority	0.0102
	(0.0189)
Constant	0.941***
	(0.0369)
N	51020
R^2	0.173
ll	-28844.5

Standard errors in parentheses

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

Table A4.9: Full Computer Science Acceptance Results with Other Offers

	(1)
Female	-0.00169
	(0.0305)
Courses Taken	
Biology Only	-0.0674*
	(0.0326)
Chemistry Only	0.0104
	(0.0191)
Physics Only	0.0516***
	(0.0135)
Biology and Chemistry	-0.105***
	(0.0195)
Biology and Physics	-0.0319
	(0.0314)
Physics and Chemistry	-0.0323**
	(0.0124)
All Three	-0.0943***
	(0.0149)
Female*(Biology Only)	-0.00492
	(0.0602)
Female*(Chemistry Only)	-0.0151
	(0.0437)
Female*(Physics Only)	-0.0128
	(0.0359)
Female*(Biology and Chemistry)	0.0253
	(0.0336)
Female*(Biology and Physics)	0.0155
	(0.0652)
Female*(Physics and Chemistry)	0.0234
	(0.0307)
Female*(All Three)	0.00778
	(0.0315)
Course Marks	
English	-0.00332
	(0.00431)
Calculus	0.0155**

	(0.00561)
Functions	0.00224
	(0.00543)
Female*(English)	-0.0154
	(0.00994)
Female*(Calculus)	0.00877
	(0.0126)
Female*(Functions)	-0.000971
	(0.0125)
Other Offers in Portfolio	
With STEM Offers Only	-0.431***
	(0.00911)
With Non-STEM Offers Only	-0.417***
	(0.0137)
With STEM and Non-STEM Offers	-0.537***
	(0.0115)
Female*(With STEM Offers Only)	-0.0586*
	(0.0254)
Female*(With Non-STEM Offers Only)	-0.0297
	(0.0340)
Female*(With STEM and Non-STEM Offers)	-0.0248
	(0.0274)
Language Spoken at Home	
French	0.00484
	(0.0551)
Other	0.00174
	(0.00985)
Years in Canadian Education	
Yrs. Cdn. Educ.	0.00689*
	(0.00269)
>12 Years in Cdn. Educ.	0.0618**
	(0.0237)
Permanent Resident	
Permanent Resident	-0.000436
	(0.0151)
Neighbourhood Demographics	
Household Income ($ 1000s)	-0.0000961*
	(0.0000489)
Share Immigrants	0.0138

	(0.0411)
Share Visible Minority	-0.0175
	(0.0303)
Constant	0.690***
	(0.0727)
N	20590
R^2	0.212
ll	-12357.0

Standard errors in parentheses

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

TABLE A4.10: Full Engineering Top Three Application Results

	(1)	(2)	(3)	(4)	(5)
Female	-0.0693***	-0.0214***	-0.0197***	-0.0170***	-0.0171***
	(0.00327)	(0.00349)	(0.00356)	(0.00357)	(0.00367)
Courses Taken					
Biology		-0.0829***	-0.0867***	-0.0887***	-0.0908***
		(0.00294)	(0.00297)	(0.00296)	(0.00304)
Female*(Biology)		-0.0468***	-0.0468***	-0.0455***	-0.0451***
		(0.00638)	(0.00649)	(0.00645)	(0.00649)
Course Marks					
English			-0.00985***	-0.00999***	-0.00879***
			(0.00135)	(0.00135)	(0.00144)
Physics			0.0213***	0.0197***	0.0222***
			(0.00203)	(0.00202)	(0.00215)
Chemistry			0.0114***	0.00820***	0.00828***
			(0.00195)	(0.00194)	(0.00206)
Calculus			-0.00409*	-0.00251	-0.00384
			(0.00206)	(0.00205)	(0.00215)
Functions			-0.00945***	-0.00642***	-0.00562**
			(0.00191)	(0.00190)	(0.00197)
Female*(English)			-0.00244	-0.00480	-0.00554
			(0.00425)	(0.00422)	(0.00425)
Female*(Physics)			0.00331	0.00386	0.00329
			(0.00592)	(0.00588)	(0.00592)
Female*(Chemistry)			-0.000543	-0.000597	-0.000620
			(0.00585)	(0.00582)	(0.00584)
Female*(Calculus)			0.0113	0.0120	0.0120
			(0.00648)	(0.00643)	(0.00645)
Female*(Functions)			-0.00445	-0.00503	-0.00396
			(0.00601)	(0.00596)	(0.00595)
Language Spoken at Home					
French				0.0107	0.0108
				(0.0159)	(0.0165)
Other				-0.0134***	-0.0109**
				(0.00361)	(0.00370)
Years in Canadian Education					
Yrs. Cdn. Educ.				-0.00174	-0.00185
				(0.000943)	(0.000960)
>12 Years in Cdn. Educ.				-0.00509	-0.00775
				(0.00818)	(0.00837)
Permanent Resident Status					
Permanent Resident				-0.00356	-0.00331
				(0.00577)	(0.00582)
Neighbourhood Demographics					
Household Income ($ 1000s)				-0.000137***	-0.0000722***
				(0.0000163)	(0.0000187)
Share Immigrants				-0.0985***	-0.0469**
				(0.0106)	(0.0147)
Share Visible Minority				-0.00245	-0.0141
				(0.00890)	(0.0113)
Constant	0.932***	0.959***	0.958***	0.969***	1.007***
	(0.00118)	(0.00113)	(0.00122)	(0.00719)	(0.0184)
N	58361	58361	58361	58361	58361
R^2	0.0107	0.0379	0.0435	0.0530	0.0699
ll	-7361.4	-6547.8	-6378.9	-6087.7	-5562.9

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has placed an engineering program in their top three choices, zero otherwise (conditional on having applied). All students are Engineering-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.11: Full Computer Science Top Three Application Results

	(1)	(2)	(3)	(4)	(5)
Female	-0.137***	-0.0866***	-0.0820***	-0.0721***	-0.0739***
	(0.00729)	(0.0191)	(0.0193)	(0.0190)	(0.0195)
Courses Taken					
Biology Only		0.0127	0.0123	0.00596	-0.00399
		(0.0223)	(0.0223)	(0.0220)	(0.0228)
Chemistry Only		0.0813***	0.0813***	0.0768***	0.0717***
		(0.0112)	(0.0112)	(0.0111)	(0.0116)
Physics Only		0.0898***	0.0889***	0.0867***	0.0872***
		(0.00842)	(0.00844)	(0.00837)	(0.00876)
Biology and Chemistry		-0.186***	-0.183***	-0.194***	-0.190***
		(0.0164)	(0.0164)	(0.0163)	(0.0164)
Biology and Physics		0.0101	0.0110	-0.00451	-0.0133
		(0.0217)	(0.0217)	(0.0216)	(0.0221)
Physics and Chemistry		-0.0463***	-0.0445***	-0.0404***	-0.0439***
		(0.00837)	(0.00864)	(0.00855)	(0.00886)
All Three		-0.144***	-0.140***	-0.145***	-0.154***
		(0.0111)	(0.0114)	(0.0113)	(0.0116)
Female*(Biology Only)		-0.0709	-0.0726	-0.0746	-0.0765
		(0.0501)	(0.0500)	(0.0495)	(0.0505)
Female*(Chemistry Only)		0.00496	0.00400	-0.00187	0.00471
		(0.0319)	(0.0320)	(0.0320)	(0.0328)
Female*(Physics Only)		-0.0180	-0.0156	-0.00821	-0.0150
		(0.0275)	(0.0276)	(0.0273)	(0.0279)
Female*(Biology and Chemistry)		0.00677	0.000909	-0.0113	-0.00746
		(0.0278)	(0.0279)	(0.0276)	(0.0280)
Female*(Biology and Physics)		-0.0687	-0.0726	-0.0819	-0.0753
		(0.0556)	(0.0556)	(0.0555)	(0.0562)
Female*(Physics and Chemistry)		0.0334	0.0349	0.0399	0.0425
		(0.0245)	(0.0248)	(0.0246)	(0.0251)
Female*(All Three)		-0.0112	-0.0152	-0.0274	-0.0303
		(0.0250)	(0.0254)	(0.0251)	(0.0256)
Course Marks					
English			-0.00764**	-0.00998***	-0.00779*
			(0.00294)	(0.00294)	(0.00311)
Calculus			0.00630	0.00959*	0.0100*
			(0.00396)	(0.00393)	(0.00406)
Functions			-0.00592	-0.00300	-0.00194
			(0.00375)	(0.00372)	(0.00388)
Female*(English)			0.0163*	0.0115	0.0102
			(0.00830)	(0.00823)	(0.00843)
Female*(Calculus)			-0.0151	-0.0141	-0.0124
			(0.0107)	(0.0105)	(0.0106)
Female*(Functions)			0.00266	0.00232	0.00437
			(0.0104)	(0.0103)	(0.0104)
Language Spoken at Home					
French				-0.0340	-0.0206
				(0.0516)	(0.0502)
Other				-0.00869	-0.0116
				(0.00794)	(0.00824)
Years in Canadian Education					
Yrs. Cdn. Educ.				0.00854***	0.00731**
				(0.00224)	(0.00230)
>12 Years in Cdn. Educ.				0.0884***	0.0764***
				(0.0196)	(0.0202)
Permanent Resident Status					
Permanent Resident				-0.00866	-0.0158
				(0.0125)	(0.0127)
Neighbourhood Demographics					
Household Income ($ 1000s)				-0.000352***	-0.000163***
				(0.0000448)	(0.0000450)
Share Immigrants				-0.140***	-0.0209
				(0.0235)	(0.0332)
Share Visible Minority				-0.0274	-0.0823***
				(0.0188)	(0.0247)
Constant	0.809***	0.841***	0.836***	0.780***	0.754***
	(0.00283)	(0.00705)	(0.00738)	(0.0187)	(0.0663)
N	24162	24162	24162	24162	24162
R^2	0.0178	0.0581	0.0586	0.0741	0.118
ll	-12743.6	-12236.8	-12230.1	-12030.2	-11440.2

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has placed a computer science program in their top three choices, zero otherwise (conditional on having applied). All students are Computer Science-ready. Column (1) includes only a binary variable for student gender. Column (2) adds controls for science courses completed outside of prerequisites, while Column (3) includes controls for marks in prerequisite courses. Column (4) incorporates individual demographic and neighbourhood controls, while Column (5) includes high school and application year fixed effects. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE A4.12: Likelihood of Offer Given Number of Applications - Engineering Ready (Full Results)

	(1) 1 Engineering Application	(2) 3+ Engineering Application
Female	0.0194	0.000521
	(0.0173)	(0.00370)
Courses Taken		
Biology	0.00231	-0.0154***
	(0.0114)	(0.00264)
Female*(Biology)	0.00978	-0.00164
	(0.0210)	(0.00510)
Course Marks		
English	0.0360***	0.0179***
	(0.00675)	(0.00195)
Physics	0.0603***	0.0226***
	(0.00859)	(0.00265)
Chemistry	0.0543***	0.0252***
	(0.00824)	(0.00261)
Calculus	0.0167	0.0248***
	(0.00923)	(0.00295)
Functions	0.0457***	0.0209***
	(0.00866)	(0.00273)
Female*(English)	0.00134	-0.00494
	(0.0127)	(0.00426)
Female*(Physics)	0.0188	0.00263
	(0.0151)	(0.00583)
Female*(Chemistry)	0.00476	-0.00274
	(0.0152)	(0.00582)
Female*(Calculus)	0.00711	-0.0192**
	(0.0169)	(0.00673)
Female*(Functions)	0.00939	0.000430
	(0.0159)	(0.00675)
Language Spoken at Home		
French	0.138*	-0.0128
	(0.0591)	(0.0196)
Other	-0.00253	-0.00806*
	(0.0129)	(0.00356)
Years in Canadian Education		
Yrs. Cdn. Educ.	0.000357	0.000973
	(0.00359)	(0.000973)
>12 Years in Cdn. Educ.	0.0231	0.00734
	(0.0319)	(0.00853)
Permanent Resident Status		
Permanent Resident	0.00501	-0.0153**
	(0.0216)	(0.00588)
Neighbourhood Demographics		
Household Income ($ 1000s)	-0.0000417	-0.00000107
	(0.0000713)	(0.0000113)
Share Immigrant	-0.0244	-0.0264
	(0.0552)	(0.0140)
Share Visible Minority	-0.0690	0.0107
	(0.0446)	(0.0107)
Constant	0.687***	0.966***
	(0.0640)	(0.0191)
N	10490	37732
R^2	0.269	0.163
ll	-5559.7	7340.2

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has received an offer to an engineering program, zero otherwise (conditional on having applied). All students are Engineering-ready. Column (1) includes students who have applied to only one engineering program. Column (2) includes students who have applied to three or more engineering programs. Both columns include all controls. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.13: Likelihood of Offer Given Number of Applications - Computer Science Ready (Full Results)

	(1) 1 Comp. Sci. Application	(2) 3+ Comp. Sci. Application
Female	0.0785**	-0.0145
	(0.0275)	(0.0176)
Courses Taken		
Biology Only	-0.0255	-0.0123
	(0.0498)	(0.0258)
Chemistry Only	-0.00250	0.00620
	(0.0346)	(0.0130)
Physics Only	0.0603**	0.00287
	(0.0227)	(0.00956)
Biology and Chemistry	0.0195	0.00525
	(0.0227)	(0.0192)
Biology and Physics	-0.00150	0.0207
	(0.0413)	(0.0187)
Physics and Chemistry	0.0632***	-0.00571
	(0.0173)	(0.00860)
All Three	0.0331	-0.00110
	(0.0188)	(0.00996)
Female*(Biology Only)	-0.0188	0.0765
	(0.0735)	(0.0394)
Female*(Chemistry Only)	-0.0678	0.0139
	(0.0581)	(0.0251)
Female*(Physics Only)	-0.0300	-0.00153
	(0.0447)	(0.0239)
Female*(Biology and Chemistry)	-0.0578	0.0192
	(0.0347)	(0.0297)
Female*(Biology and Physics)	-0.144*	0.0174
	(0.0727)	(0.0306)
Female*(Physics and Chemistry)	-0.0440	0.00921
	(0.0329)	(0.0213)
Female*(All Three)	-0.101**	0.0180
	(0.0321)	(0.0194)
Course Marks		
English	0.0542***	0.0292***
	(0.00560)	(0.00364)
Calculus	0.0601***	0.0288***
	(0.00758)	(0.00463)
Functions	0.0863***	0.0329***
	(0.00739)	(0.00450)
Female*(English)	-0.0238*	-0.0149
	(0.0109)	(0.0101)
Female*(Calculus)	-0.0146	0.00268
	(0.0142)	(0.0123)
Female*(Functions)	-0.00689	-0.0311**
	(0.0138)	(0.0114)
Language Spoken at Home		
French	0.0973	0.0500*
	(0.0541)	(0.0210)
Other	-0.0133	0.00208
	(0.0116)	(0.00712)
Years in Canadian Education		
Yrs. Cdn. Educ.	0.00631	0.00368
	(0.00336)	(0.00219)
>12 Years in Cdn. Educ.	0.0543	0.0357
	(0.0303)	(0.0198)
Permanent Resident Status		
Permanent Resident	-0.00847	-0.0140
	(0.0194)	(0.0125)
Neighbourhood Demographics		
Household Income ($ 1000s)	-0.00000121	-0.0000466
	(0.0000511)	(0.0000258)
Share Immigrant	-0.0250	-0.0116
	(0.0485)	(0.0308)
Share Visible Minority	0.00981	0.00851
	(0.0370)	(0.0217)
Constant	0.719***	0.910***
	(0.0911)	(0.107)
N	11156	7359
R^2	0.233	0.210
ll	-4973.8	2201.0

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i has received an offer to an computer science program, zero otherwise (conditional on having applied). All students are computer science-ready. Column (1) includes students who have applied to only one computer science program. Column (2) includes students who have applied to three or more computer science programs. Both columns include all controls. All course marks are standardized within subject, application year and ready category. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.14: Application Results (Distribution) - Engineering Ready (Full Results)

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.132***	-0.107***	-0.159***
	(0.0177)	(0.00748)	(0.0261)
Courses Taken			
Biology	-0.394***	-0.367***	-0.305***
	(0.00713)	(0.00486)	(0.00740)
Female*(Biology)	-0.106***	-0.138***	-0.106***
	(0.0148)	(0.00919)	(0.0133)
Course Marks			
English	-0.0235***	-0.0332***	-0.0749***
	(0.00345)	(0.00324)	(0.00675)
Physics	0.0624***	0.0713***	0.0958***
	(0.00392)	(0.00395)	(0.0104)
Chemistry	0.0134***	-0.00207	-0.0261*
	(0.00387)	(0.00393)	(0.0111)
Calculus	-0.00174	0.00527	-0.00708
	(0.00394)	(0.00439)	(0.0144)
Functions	0.00698	0.00355	0.00731
	(0.00378)	(0.00406)	(0.0128)
Female*(English)	0.000653	-0.00860	0.0144
	(0.00626)	(0.00559)	(0.0108)
Female*(Physics)	-0.0240***	-0.0117	-0.00141
	(0.00667)	(0.00602)	(0.0144)
Female*(Chemistry)	-0.00626	-0.0167*	-0.0188
	(0.00680)	(0.00659)	(0.0167)
Female*(Calculus)	0.0102	0.000959	0.0280
	(0.00686)	(0.00683)	(0.0207)
Female*(Functions)	0.0156*	0.0119	0.0326
	(0.00653)	(0.00658)	(0.0187)
Language Spoken at Home			
French	-0.0343	-0.00961	-0.0953*
	(0.0391)	(0.0298)	(0.0450)
Other	0.0143	-0.00145	-0.00239
	(0.00782)	(0.00558)	(0.00879)
Years in Canadian Education			
Yrs. Cdn. Educ.	-0.00534*	-0.00361*	-0.00230
	(0.00221)	(0.00151)	(0.00243)
>12 Years in Cdn. Educ.	-0.0925***	-0.0584***	-0.0351
	(0.0194)	(0.0134)	(0.0219)
Permanent Resident Status			
Permanent Resident	-0.00686	0.00291	0.0301*
	(0.0126)	(0.00907)	(0.0150)
Neighbourhood Demographics			
Household Income ($ 1000s)	0.000111	0.0000963**	0.0000485
	(0.0000606)	(0.0000318)	(0.0000349)
Share Immigrant	0.0226	-0.0131	-0.0345
	(0.0335)	(0.0230)	(0.0356)
Share Visible Minority	0.0228	0.0474**	0.0379
	(0.0249)	(0.0175)	(0.0281)
Constant	0.973***	1.010***	0.899***
	(0.0650)	(0.0326)	(0.0571)
N	26047	52095	25566
R^2	0.340	0.332	0.255
ll	-13352.1	-26686.9	-14674.1

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) are for those in the bottom 25 % of achievement among engineering-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in engineering prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE A4.15: Offer Results (Distribution) - Engineering Ready (Full Results)

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.0983***	-0.0311***	-0.00390
	(0.0154)	(0.00596)	(0.0246)
Courses Taken			
Biology	-0.0973***	-0.124***	-0.159***
	(0.00523)	(0.00401)	(0.00623)
Female*(Biology)	-0.0158	-0.0193*	-0.0111
	(0.0116)	(0.00809)	(0.0116)
Course Marks			
English	0.0253***	0.0330***	-0.00598
	(0.00241)	(0.00261)	(0.00559)
Physics	0.0552***	0.0703***	0.0628***
	(0.00283)	(0.00327)	(0.00892)
Chemistry	0.0533***	0.0605***	0.0249**
	(0.00268)	(0.00311)	(0.00933)
Calculus	0.0250***	0.0324***	-0.00768
	(0.00278)	(0.00354)	(0.0122)
Functions	0.0370***	0.0340***	-0.0181
	(0.00262)	(0.00325)	(0.0107)
Female*(English)	-0.0107	-0.000456	-0.00148
	(0.00604)	(0.00558)	(0.0105)
Female*(Physics)	-0.0141*	0.00318	-0.00732
	(0.00668)	(0.00642)	(0.0148)
Female*(Chemistry)	-0.0137*	-0.00279	-0.00649
	(0.00659)	(0.00642)	(0.0163)
Female*(Calculus)	-0.00830	0.00266	-0.0121
	(0.00675)	(0.00722)	(0.0210)
Female*(Functions)	-0.00505	0.00283	-0.00973
	(0.00614)	(0.00687)	(0.0189)
Language Spoken at Home			
French	0.00630	0.0504	0.0394
	(0.0341)	(0.0266)	(0.0483)
Other	-0.00678	-0.0313***	-0.0283***
	(0.00601)	(0.00499)	(0.00773)
Years in Canadian Education			
Yrs. Cdn. Educ.	0.00373*	0.000416	-0.00229
	(0.00160)	(0.00130)	(0.00206)
>12 Years in Cdn. Educ.	0.0345*	0.00551	-0.0128
	(0.0139)	(0.0114)	(0.0187)
Permanent Resident Status			
Permanent Resident	-0.00366	-0.0202**	-0.0318*
	(0.00900)	(0.00782)	(0.0124)
Neighbourhood Demographics			
Household Income ($ 1000s)	-0.000124**	-0.0000865***	-0.000101***
	(0.0000419)	(0.0000228)	(0.0000271)
Share Immigrant	-0.0910***	-0.0119	-0.112***
	(0.0262)	(0.0207)	(0.0319)
Share Visible Minority	0.0428*	-0.0535***	-0.0332
	(0.0196)	(0.0158)	(0.0250)
Constant	0.441***	0.513***	0.655***
	(0.0444)	(0.0243)	(0.0406)
N	14344	29988	14029
R^2	0.257	0.171	0.188
ll	545.3	-3310.2	-1976.9

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i received an offer to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) are for those in the bottom 25 % of achievement among engineering-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in engineering prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.16: Acceptance Results (Distribution) - Engineering Ready (Full Results)

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	0.0549	0.00661	0.00493
	(0.505)	(0.0244)	(0.0509)
Courses Taken			
Biology	-0.0257	-0.0112	-0.0169
	(0.101)	(0.0159)	(0.0116)
Female*(Biology)	0.237	0.0619*	-0.00878
	(0.351)	(0.0307)	(0.0249)
Course Marks			
English	0.0409	0.00456	-0.00991
	(0.0479)	(0.0102)	(0.00954)
Physics	0.0324	-0.00142	0.00540
	(0.0598)	(0.0132)	(0.0186)
Chemistry	0.0862	0.0338*	0.0133
	(0.0715)	(0.0131)	(0.0167)
Calculus	0.00620	-0.000543	-0.00339
	(0.0516)	(0.0145)	(0.0206)
Functions	0.0796	0.0229	0.0222
	(0.0625)	(0.0131)	(0.0190)
Female*(English)	0.0255	-0.0151	0.0175
	(0.125)	(0.0235)	(0.0228)
Female*(Physics)	0.0889	0.00110	-0.0160
	(0.333)	(0.0319)	(0.0360)
Female*(Chemistry)	-0.176	-0.0147	0.0145
	(0.178)	(0.0292)	(0.0354)
Female*(Calculus)	0.0808	0.00752	-0.00557
	(0.202)	(0.0331)	(0.0507)
Female*(Functions)	0.0875	-0.00462	-0.0309
	(0.272)	(0.0338)	(0.0395)
Language Spoken at Home			
French	-0.573	0.0316	-0.0557
	(0.448)	(0.0666)	(0.106)
Other	-0.0468	0.0137	0.00629
	(0.118)	(0.0181)	(0.0162)
Years in Canadian Education			
Yrs. Cdn. Educ.	0.0106	-0.00189	0.00167
	(0.0464)	(0.00532)	(0.00442)
>12 Years in Cdn. Educ.	0.163	0.0130	0.0435
	(0.350)	(0.0466)	(0.0411)
Permanent Resident Status			
Permanent Resident	-0.0224	0.0438	0.0372
	(0.270)	(0.0267)	(0.0280)
Neighbourhood Demographics			
Household Income ($ 1000s)	-0.000189	-0.0000283	0.0000690
	(0.00103)	(0.000127)	(0.0000970)
Share Immigrant	-0.222	0.0397	-0.0337
	(0.513)	(0.0707)	(0.0675)
Share Visible Minority	0.162	0.0211	0.0883
	(0.413)	(0.0525)	(0.0493)
Constant	0.784*	0.835***	0.946***
	(0.356)	(0.153)	(0.0467)
N	511	3392	3812
R^2	0.560	0.241	0.235
ll	-24.56	-179.0	120.2

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to an engineering program, zero otherwise. All students are Engineering-ready. Column (1) are for those in the bottom 25 % of achievement among engineering-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in engineering prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.17: Application Results (Distribution) - Computer Science Ready (Full Results)

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.0891***	-0.0743***	-0.0444***
	(0.00838)	(0.00352)	(0.0114)
Courses Taken			
Biology Only	0.0381**	0.0174	0.0214
	(0.0138)	(0.0104)	(0.0177)
Chemistry Only	0.207***	0.160***	0.0886***
	(0.0139)	(0.0116)	(0.0180)
Physics Only	0.287***	0.302***	0.226***
	(0.00977)	(0.00890)	(0.0159)
Biology and Chemistry	-0.0549***	-0.0125**	-0.00984
	(0.00622)	(0.00467)	(0.00761)
Biology and Physics	0.114***	0.154***	0.203***
	(0.0201)	(0.0187)	(0.0379)
Physics and Chemistry	0.0729***	0.104***	0.147***
	(0.00615)	(0.00426)	(0.00735)
All Three	-0.0532***	-0.0152***	0.0171**
	(0.00603)	(0.00385)	(0.00634)
Female*(Biology Only)	-0.0238	0.00536	-0.0224
	(0.0157)	(0.0118)	(0.0190)
Female*(Chemistry Only)	-0.0996***	-0.0876***	-0.0545**
	(0.0209)	(0.0147)	(0.0206)
Female*(Physics Only)	-0.173***	-0.187***	-0.135***
	(0.0167)	(0.0129)	(0.0210)
Female*(Biology and Chemistry)	0.0756***	0.0340***	0.0181*
	(0.00747)	(0.00528)	(0.00854)
Female*(Biology and Physics)	0.00461	-0.0753**	-0.120**
	(0.0320)	(0.0240)	(0.0444)
Female*(Physics and Chemistry)	0.0133	-0.00650	-0.0620***
	(0.0128)	(0.00718)	(0.0101)
Female*(All Three)	0.0740***	0.0338***	-0.0111
	(0.00760)	(0.00456)	(0.00730)
Course Marks			
English	-0.0276***	-0.0282***	-0.0258***
	(0.00241)	(0.00230)	(0.00433)
Calculus	0.0126***	0.00211	0.0221**
	(0.00272)	(0.00253)	(0.00711)
Functions	-0.0134***	-0.00260	0.0180**
	(0.00255)	(0.00264)	(0.00662)
Female*(English)	0.0173***	0.0158***	0.0197***
	(0.00316)	(0.00283)	(0.00514)
Female*(Calculus)	-0.00615	-0.00427	-0.00918
	(0.00359)	(0.00305)	(0.00810)
Female*(Functions)	0.0169***	0.00310	-0.0132
	(0.00334)	(0.00317)	(0.00762)
Language Spoken at Home			
French	-0.0194	-0.0367**	-0.0189
	(0.0206)	(0.0117)	(0.0174)
Other	-0.00268	0.00661*	0.00878*
	(0.00460)	(0.00307)	(0.00428)
Years in Canadian Education			
Yrs. Cdn. Educ.	0.00337*	0.00350***	0.00381**
	(0.00135)	(0.000870)	(0.00122)
>12 Years in Cdn. Educ.	0.0242*	0.0193*	0.0291**
	(0.0115)	(0.00764)	(0.0109)
Permanent Resident Status			
Permanent Resident	0.0205**	0.00893	0.0159*
	(0.00787)	(0.00532)	(0.00772)
Neighbourhood Demographics			
Household Income ($ 1000s)	-0.0000168	-0.00000478	-0.00000980
	(0.0000273)	(0.0000119)	(0.0000128)
Share Immigrant	-0.0168	0.00475	0.0114
	(0.0190)	(0.0117)	(0.0157)
Share Visible Minority	0.0590***	0.0254**	0.0532***
	(0.0147)	(0.00935)	(0.0132)
Constant	0.0846*	0.0184	-0.0325
	(0.0346)	(0.0172)	(0.0231)
N	51845	103692	50809
R^2	0.124	0.0996	0.111
ll	-17066.0	-21266.3	-6840.2

Standard errors in parentheses

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

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i applied to a computer science program, zero otherwise. All students are computer science-ready. Column (1) are for those in the bottom 25 % of achievement among computer science-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in computer science prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

TABLE A4.18: Offer Results (Distribution) - Computer Science Ready (Full Results)

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.0984*	0.0101	-0.0602
	(0.0493)	(0.0231)	(0.0387)
Courses Taken			
Biology Only	-0.0442	0.0109	0.0240
	(0.0397)	(0.0360)	(0.0178)
Chemistry Only	0.0411	0.0407*	0.00914
	(0.0222)	(0.0180)	(0.0228)
Physics Only	0.0300	0.0755***	0.0416*
	(0.0165)	(0.0122)	(0.0176)
Biology and Chemistry	-0.169***	-0.0228	-0.0199
	(0.0272)	(0.0194)	(0.0275)
Biology and Physics	-0.0524	0.0234	-0.00951
	(0.0420)	(0.0282)	(0.0431)
Physics and Chemistry	-0.0265	0.0411***	0.0215
	(0.0158)	(0.0113)	(0.0151)
All Three	-0.108***	-0.0100	0.00956
	(0.0235)	(0.0141)	(0.0160)
Female*(Biology Only)	0.162*	-0.111	-0.0658
	(0.0723)	(0.0654)	(0.0551)
Female*(Chemistry Only)	-0.146*	-0.00852	-0.00962
	(0.0687)	(0.0387)	(0.0356)
Female*(Physics Only)	0.00640	-0.00485	-0.0436
	(0.0536)	(0.0293)	(0.0334)
Female*(Biology and Chemistry)	-0.0253	-0.0117	-0.0700
	(0.0502)	(0.0321)	(0.0370)
Female*(Biology and Physics)	-0.214*	-0.0806	0.0759
	(0.105)	(0.0680)	(0.0527)
Female*(Physics and Chemistry)	-0.0299	0.00386	-0.0237
	(0.0544)	(0.0265)	(0.0226)
Female*(All Three)	-0.0358	-0.0562	-0.0849***
	(0.0521)	(0.0293)	(0.0256)
Course Marks			
English	0.0858***	0.0296***	0.0000618
	(0.00618)	(0.00515)	(0.00517)
Calculus	0.0997***	0.0344***	0.0158
	(0.00710)	(0.00630)	(0.0116)
Functions	0.103***	0.0409***	0.0146
	(0.00675)	(0.00598)	(0.0107)
Female*(English)	-0.0422*	0.00807	-0.0107
	(0.0172)	(0.0122)	(0.0158)
Female*(Calculus)	-0.0262	-0.00904	0.0447
	(0.0193)	(0.0144)	(0.0271)
Female*(Functions)	-0.0199	0.00762	0.0385
	(0.0186)	(0.0141)	(0.0263)
Language Spoken at Home			
French	0.0237	0.123***	-0.0498
	(0.0771)	(0.0232)	(0.0628)
Other	-0.0164	-0.00184	0.0123*
	(0.0158)	(0.00822)	(0.00555)
Years in Canadian Education			
Yrs. Cdn. Educ.	0.000195	0.0109***	0.00224
	(0.00435)	(0.00245)	(0.00173)
>12 Years in Cdn. Educ.	-0.00444	0.0947***	0.0157
	(0.0375)	(0.0220)	(0.0155)
Permanent Resident Status			
Permanent Resident	-0.0539*	0.0105	-0.00438
	(0.0236)	(0.0136)	(0.00860)
Neighbourhood Demographics			
Household Income ($ 1000s)	-0.000327**	-0.0000210	0.0000466
	(0.000106)	(0.0000472)	(0.0000312)
Share Immigrant	-0.0844	0.0147	0.0410
	(0.0638)	(0.0363)	(0.0316)
Share Visible Minority	-0.00718	-0.0164	0.00146
	(0.0467)	(0.0267)	(0.0222)
Constant	1.064***	0.772***	0.957***
	(0.117)	(0.0781)	(0.0261)
N	7900	11419	4843
R^2	0.217	0.112	0.257
ll	-3928.6	-1901.6	1949.8

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i received an offer to a computer science program, zero otherwise. All students are computer science-ready. Column (1) are for those in the bottom 25 % of achievement among computer science-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in computer science prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Table A4.19: Acceptance Results (Distribution) - Computer Science Ready (Full Results)

	(1) Bottom 25 %	(2) Middle 50 %	(3) Top 25 %
Female	-0.159*	-0.0863*	-0.0517
	(0.0717)	(0.0361)	(0.0958)
Courses Taken			
Biology Only	-0.0500	-0.0519	-0.0294
	(0.0557)	(0.0574)	(0.137)
Chemistry Only	0.0405	0.0822**	0.0990
	(0.0327)	(0.0312)	(0.0735)
Physics Only	0.0846***	0.106***	0.205***
	(0.0237)	(0.0214)	(0.0520)
Biology and Chemistry	-0.150***	-0.185***	-0.116
	(0.0388)	(0.0291)	(0.0621)
Biology and Physics	-0.0108	-0.0671	-0.0222
	(0.0592)	(0.0489)	(0.105)
Physics and Chemistry	-0.0263	-0.0501**	-0.0620
	(0.0225)	(0.0187)	(0.0428)
All Three	-0.0674*	-0.145***	-0.139**
	(0.0321)	(0.0226)	(0.0444)
Female*(Biology Only)	0.265*	-0.186*	0.112
	(0.114)	(0.0865)	(0.202)
Female*(Chemistry Only)	0.0328	-0.0725	0.0492
	(0.0922)	(0.0658)	(0.132)
Female*(Physics Only)	-0.0571	-0.0245	-0.00807
	(0.0754)	(0.0536)	(0.0983)
Female*(Biology and Chemistry)	0.126	0.000522	0.00360
	(0.0692)	(0.0477)	(0.0889)
Female*(Biology and Physics)	0.218	0.0330	-0.0360
	(0.156)	(0.111)	(0.156)
Female*(Physics and Chemistry)	0.0894	0.0183	0.0607
	(0.0699)	(0.0443)	(0.0749)
Female*(All Three)	0.0257	-0.00874	0.0386
	(0.0710)	(0.0446)	(0.0732)
Course Marks			
English	0.00484	-0.0278**	-0.0416*
	(0.00894)	(0.00882)	(0.0170)
Calculus	0.0498***	-0.0207	-0.0159
	(0.0102)	(0.0106)	(0.0321)
Functions	0.0198*	-0.0216*	-0.0426
	(0.00992)	(0.0102)	(0.0326)
Female*(English)	-0.0320	-0.00408	-0.0186
	(0.0238)	(0.0192)	(0.0346)
Female*(Calculus)	-0.0370	0.0232	0.0609
	(0.0273)	(0.0219)	(0.0589)
Female*(Functions)	0.0380	0.00347	-0.0533
	(0.0256)	(0.0218)	(0.0579)
Language Spoken at Home			
French	-0.0156	0.0924	-0.0962
	(0.104)	(0.0913)	(0.141)
Other	-0.00390	0.0147	-0.0105
	(0.0224)	(0.0152)	(0.0215)
Years in Canadian Education			
Yrs. Cdn. Educ.	0.00370	0.00863*	0.00619
	(0.00617)	(0.00407)	(0.00603)
>12 Years in Cdn. Educ.	0.0376	0.105**	0.0453
	(0.0532)	(0.0360)	(0.0545)
Permanent Resident Status			
Permanent Resident	-0.0126	-0.00592	-0.000315
	(0.0327)	(0.0228)	(0.0350)
Neigbourhood Demographics			
Household Income ($ 1000s)	-0.000264	-0.000168*	-0.0000930
	(0.000147)	(0.0000722)	(0.0000738)
Share Immigrant	-0.107	0.129*	-0.109
	(0.0905)	(0.0631)	(0.0930)
Share Visible Minority	-0.000545	-0.0948*	0.0801
	(0.0669)	(0.0473)	(0.0697)
Constant	0.446**	0.240*	0.430*
	(0.168)	(0.0946)	(0.198)
N	5676	10248	4666
R^2	0.169	0.144	0.192
ll	-3591.7	-6578.9	-2708.4

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table presents coefficient estimates from equation (1) where the dependent variable equals 1 if individual i accepted an offer to a computer science program, zero otherwise. All students are computer science-ready. Column (1) are for those in the bottom 25 % of achievement among computer science-ready students, while Columns (2) and (3) are for those in the middle 50 % and top 25 % respectively. Achievement distribution is determined by the average, standardized grade in computer science prerequisite courses. Each column includes all controls. All continuous demographic variables are mean deviated. Source: Ontario University Applications Centre (OUAC) and Statistics Canada.

Chapter 5

Conclusion

This thesis explores three topics in the economics of education. In the first paper, I examine how the income-achievement gaps among elementary school students differs across children of different racial backgrounds. The second paper investigates the impact of switching post-secondary majors on earnings. Lastly, the third paper investigates the gender gaps in the application process to Engineering and Computer Science undergraduate programs. In studying these topics I employ a combination of descriptive and causal inference techniques to provide valuable insights to the broader education literature.

The first paper finds that there is significant heterogeneity in income-achievement gaps across racial groups. In particular, Indigenous students demonstrate both the largest income-achievement gaps and the lowest average test scores across all students. Further investigation into the factors that contribute to this low-level achievement reveals that Indigenous students are more likely to live in substandard housing conditions relative to non-Indigenous students. This first paper provides valuable for both research and policy purposes. First, this paper provides one of the first examinations of how income-achievement gaps vary across racial groups, establishing a foundation for future research. Second, for policy purposes, this paper highlights that addressing lagging academic performance among Indigenous students may require interventions that alleviate inequity beyond the classroom.

Transitioning to post-secondary students, the second paper finds that switching majors has a significant impact on earnings, conditional on student gender and initial major. Indeed, while switching has a relatively small impact on the earnings of men, it can change the earnings of women by as much as \$23 000 annually. This gendered difference in impact is largely a product of major choice (by initial and final). For example, women enrolled in STEM are likely to major in biology-oriented programs which, on average, carry low earnings potential after graduation (conditional on only having a single degree). Accordingly, the decision to switch out of STEM carries with it a positive impact on the earnings of women. This paper provides the first causal estimates of switching on major earnings and demonstrates that major choice, beyond initial enrollment, continues to have a significant impact on the earnings of post-secondary graduates.

The final paper identifies factors that drive gender gaps in the application process for Engineering and Computer Science programs. Using administrative data on applications to undergraduate programs in Ontario I find conditional gender gaps in applications to Engineering and Computer Science programs of 11.9 % and 8.42 %, respectively. Similar to prior studies, I find that performance in, and the taking of, high school science courses explains a considerable portion of the gap in applications to both programs. Interestingly, I also find gender gaps in both the likelihood of offer reception and the likelihood of accepting an offer, suggesting that closing the gender gap in Engineering and Computer Science programs may require intervention at all stages of the application process.