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Essays in Economics of Education: Teacher Labour Markets and Earnings of University Graduates

Tomasz M. Handler, *The University of Western Ontario*

Supervisor: Stinebrickner, Todd R., *The University of Western Ontario*
Joint Supervisor: Mehta, Nirav, *The University of Western Ontario*
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Abstract

This thesis consists of three substantive chapters, which explore topics related to the economics of education. Two of the chapters examine teacher labour markets, and one chapter examines the earnings of university graduates.

In Chapter 2, I create a new and unique dataset to examine how teacher characteristics affect the probability of acquiring a permanent teaching position in the Ontario public school system. This chapter provides evidence of how difficult it was for recent Ontario teachers' college graduates to obtain a teaching job. The odds of finding a position in 2006 were, on average, around four times higher than they were in 2013. Moreover, qualified French-language teachers were, on average, three to five times more likely to find a job than teachers without French-language qualifications.

In Chapter 3, I take advantage of restricted-access data to examine what is more important for earnings — the university that a student attends or the program that he or she pursues. In particular, this chapter uses a method called relative-importance analysis, which partitions the variation in earnings into program and school components and thus allows me to determine the degree to which they affect earnings. The results show that there is more variation in earnings across programs than schools. Programs account for between two and eleven times the amount of variation in earnings than schools, depending on gender, degree type and period since graduation.

In Chapter 4, I estimate the outside-option salaries of recent Ontario teachers' college graduates from the 2007 to 2013 graduating cohorts and compare them to teaching salaries from the same cohorts. To do this, I create a new teacher salary dataset and combine it with the data from the first two chapters. The results show that median teaching salaries did not vary to any great extent across genders, cohorts and time periods since graduation. However, the median outside-option salaries varied substantially across those same factors. Moreover, the median teaching salaries were greater than outside-option salaries across all factors. Also, despite there not being any gender differences in teaching salaries, the outside-option median salaries were substantially greater for males than females.

Keywords: economics of education, returns to education, earnings analysis, labour economics, teacher labour markets, applied microeconomics

Summary for Lay Audience

This thesis consists of three substantive chapters, which explore topics related to the economics of education. Two of the chapters examine teacher labour markets, and one chapter examines the earnings of university graduates.

In Chapter 2, I create a new and unique dataset to provide evidence of how difficult it was for recent Ontario teachers' college graduates to obtain a teaching job. The odds of finding a position in 2006 were, on average, around four times higher than they were in 2013. Moreover, qualified French-language teachers were, on average, three to five times more likely to find a job than teachers without French-language qualifications.

In Chapter 3, I take advantage of data provided by the government to examine what is more important for earnings — the university that a student attends or the program that he or she pursues. In particular, this chapter uses methods that allow me to determine the degree to which programs and schools affect earnings. Overall, the results show that programs have a substantially greater effect on earnings than schools.

In Chapter 4, I estimate salaries of recent Ontario teachers' college graduates from the 2007 to 2013 graduating cohorts who did not acquire permanent teaching jobs in the Ontario public school system (teaching jobs) and compare them to the graduates who did find those jobs. To accomplish this, I create a new teacher salary dataset and combine it with the data from the first two chapters. The results show that median teaching salaries did not vary to any great extent across genders, cohorts and time periods since graduation. However, the median non-teaching salaries varied substantially across those same factors.

Moreover, the median teaching salaries were greater than non-teaching salaries across all factors. Also, despite there not being any gender differences in teaching salaries, the non-teaching median salaries were substantially greater for males than females.

Dedication

To my loving wife Estella and my children Alicia, Matthew and Evan. Also to my sister, Eve, and my parents Bogusław and Jadwiga, who always believed in me.

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[1]Chapters 3 and 4 use the data provided by the Ministry. Further, it is important to note that the views expressed in this dissertation are my own and do not necessarily reflect those of the Ministry.

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Chapter 1

Introduction

This thesis consists of three substantive chapters, which explore topics related to the economics of education. Chapters 2 and 4 contribute to the economics teacher literature by examining topics related to teacher labour markets, and Chapter 3, contributes to the returns to education literature in the context of program and university choice.

In Chapter 2, I examine teacher labour markets from the perspective of recent Ontario teachers' college graduates. Teachers play a vital role in the academic outcomes of students. Typically, research studying teacher labour supply examines contexts where there are fewer qualified teachers than available positions. This shortage environment is helpful for understanding how teachers select themselves in and out of teaching because schools in this position have little discretion about which teachers to hire. Recently, many jurisdictions, including Ontario, have begun to experience teacher surpluses which presents an opportunity to answer a different important policy question: How do teacher characteristics affect the probability of obtaining a teaching job? In this paper, I use duration analysis to provide evidence about this issue.

Suitable data for this type of analysis require information not only about employed individuals but also about individuals who are eligible to teach but do not receive a job; unfortunately, this type of data has not traditionally been available. I overcome the current lack of data by web scraping and processing the Ontario public register of individuals who are eligible to teach.

The results obtained using a duration model show variation in the probability of securing a permanent teaching position across the various cohorts of teacher graduates. The 2006 graduates had a 14 percent probability of acquiring a position in their first year, a probability that had fallen to 5 percent by 2012 for that year's graduating cohort. The results also indicate substantial differences in hiring probabilities across teachers with different subject qualifications. For example, in 2006 male elementary teachers with French qualifications had a 46 percent success rate in their first year, while those with math qualifications only secured a job 21 percent of the time. These results are relevant for policy because the current concerns about the math performance of Ontario elementary students may be related to the math qualifications of those who are teaching.

In Chapter 3, I switch my focus to examine the earnings of university graduates. Prospective university students make a decision about which institution to attend and what degree program to pursue. It is natural for early-career discussions to centre around gaining acceptance to a "top school" based on the widespread notion that graduating from a relatively prestigious institution will result in higher earnings. However, the economic literature suggests that the degree program that students graduate with may also affect their earnings. In this paper, I examine what is more important for earnings — the school that a student attends or the degree program that he or she pursues.

Typically in the literature, the respective effects of school and program choices on earnings are studied separately; yet, the reality is that, when students make these decisions, they have to consider them together. One of the contributions of this study is that I compare the variation in earnings across programs and schools jointly. The type of question that I answer is as follows: How do the earnings of graduates of low-earning programs at highly selective schools compare relative to the earnings of graduates of high-earning programs at less-selective schools? The reason why few studies jointly examine school and program choices is the lack of available data. Most general labour datasets contain observations about education programs but lack the kind of institutional information that would allow researchers to connect observations across the same schools. I overcome these issues by using a unique source of restricted government-administered data, the restricted version of the Ontario Graduate University Survey (OUGS). The public-use version of these data only provides median salaries and only for a limited number of schools. However, the restricted version of this dataset makes this study possible because it contains information on the entire salary distribution (and not just on the median) across all universities and their programs in the province. In particular, this study uses a method called relative-importance analysis, which partitions the variation in earnings into program and school components and thus allows me to determine the degree to which they affect earnings.

The results show that there is substantially more variation in earnings across programs than across schools, both at the undergraduate and the professional-degree levels. For the undergraduate programs, around 21.5 percent of the variation in earnings can be attributed to the programs while around 2.6 percent of this variation can be attributed to the schools (six months after graduation); in other words, the amount of variation in earnings was around eight times greater for programs than for schools. For the professional-degree programs, the variation in earnings was around three times greater than for the schools. The results of this study suggest that students can feel confident about enrolling in their program of choice, even if it is not offered by the most prestigious, highly ranked university, because schools do not explain the majority of the variation in earnings.

In Chapter 4, in addition to creating a new teacher salary dataset, I utilize the data from the first two chapters to study the earnings of recent teachers' college graduates. Economists are typically interested in the basis on which individuals choose to enter, remain in or exit the teacher workforce. A fundamental aspect of understanding these decisions is comprised of the opportunity cost of teaching. Unfortunately, little is known about this opportunity cost and in order to estimate it, we usually need to observe teachers over an extended period in both teaching and non-teaching jobs; however, this type of longitudinal data is challenging to obtain. The ideal data for the estimation of these teachers' opportunity cost would include the many teachers' college graduates who randomly chose to pursue non-teaching positions. In practice, most teachers' college graduates work as teachers for an extended period and, when they eventually leave teaching, they frequently do so for family reasons (e.g., the birth of a child); as a result, there are few opportunities to observe teachers in alternative occupations.

In this study, I estimate the outside-option earnings of the 2007 to 2013 graduates of an Ontario teachers' college. To do this, I take advantage of the unique environment in Ontario, Canada where, instead of the more typical teacher-shortage environment, the teacher labour market has experienced a surplus since around 2005. This environment is similar to the above-mentioned ideal situation, in that the majority of new teacher graduates were unable to find a permanent teaching position and, thus, many had to pursue opportunities outside the public school system. The first step in the estimation of the outside-option earnings uses a unique teacher dataset to determine the salaries of the graduates who did in fact acquire a teaching job within the Ontario public school system. The second step in this estimation process uses the teaching salary information obtained in the first step in combination with a second dataset — the restricted-access and government-administered Ontario University Graduate Survey (OUGS) which contains the salaries of Ontario teachers' college graduates who at the time of the survey were employed in either a teaching or a non-teaching position — to estimate the salaries for the outside option alone (i.e., for non-teaching positions).

The results indicate that the outside-option salaries varied substantially across cohorts, genders and time periods since graduation; the median outside-option salary was highest at $45,357 for the 2007 male cohort at the two-year milestone since graduation, while the lowest was $23,822 for the 2013 female cohort at the six-month milestone since graduation. In contrast, the teaching salaries did not vary to any great extent across any of the factors; the median teaching salary was highest at $49,706 for the 2011 male cohort at two years after graduation, and lowest at $46,800 for the 2007 females at six months after graduation.

Furthermore, when comparing salaries of members of the same graduating cohort year, the teachers at the median earned more than the graduates who had found an outside job, both for males and females and for salaries at the six-month and two-year milestones since graduation. The greatest difference was for the 2012 females at six months after graduation when the median teaching salaries were 103 percent higher than the median outside-job salaries; the smallest difference was for the 2007 males at two years after graduation when the teaching salaries were only 5 percent higher than the outside-job salaries. There were no statistically significant gender differences across teaching salaries within the same cohort year and period since graduation. For the outside-option jobs, males earned more than females in every graduating cohort and for both the six-month and two-year milestone periods since graduation.

Chapter 2

What Teacher Characteristics Do Schools Value? Evidence from Ontario, Canada

2.1 Introduction

Studying teacher labour markets is essential not only because teachers comprise a large portion of the education-system budget, but also because research suggests that teachers play a vital role in the academic outcomes of students (Araujo, Carneiro, Cruz-Aguayo, & Schady, 2016; Gerritsen, Plug, & Webbink, 2017; Hanushek, 2011). Investments in education that improve student achievement can positively impact the economic development of a country. For instance, Hanushek and Woessmann (2012) demonstrate that improving cognitive skills by one standard deviation can improve GDP per capita by as much as two percentage points. Moreover, Hanushek, Ruhose, and Woessmann (2017) claim that differences in educational attainment and cognitive skills are positively correlated with GDP per capita and explain 20 to 30 percent of the income variation across U.S. states. Modern industries rely heavily on quantitative skills; therefore, math achievement at the elementary grade levels is crucial as it improves future academic success and thus results in higher wages and more stable employment later in life (J. James, 2013). An ongoing debate in Ontario is raising questions about the math qualifications of elementary teachers because the proportion of Grade 6 students whose standardized math assessment scores were at least at the provincial standard declined from 63 percent to 49 percent between 2008 and 2017 (Education Quality and Accountability Office [EQAO], 2013, 2018).

Current teacher-market literature focuses on teachers' labour-supply decisions, and the usual concerns deal with how to attract and retain the most qualified teachers.[1] Traditionally, the literature examines contexts where there are fewer qualified teachers than available positions. In such teacher-shortage environments, schools struggle to find qualified teachers; therefore, they have little discretion about which teachers to hire, thus making it difficult to study the teacher characteristics particularly valued by schools. However, recently many jurisdictions, including Ontario, have begun to experience large teacher surpluses which presents a unique opportunity to answer a different important policy question: How do teacher characteristics affect the probability of obtaining a teaching job?[2]

To answer this question, I use duration analysis to examine the effects of subject qualifications, grade divisions, gender and year of graduation from teachers' college on the probability of securing a permanent teaching position in the Ontario public school system. For this study, an ideal dataset requires information about the subject qualifications of the teachers' college graduates, as well as timing information related to when they began the job-search process. A common problem with the datasets that are typically used in labour economics (e.g., NLSY, Youth in Transition) is the small number of respondents who are teachers, and the lack of information about which subjects or grade divisions they are qualified to teach. For these reasons, the literature commonly uses school administrative data pertaining to individuals who often had already been hired as a teacher, thus making them unsuitable for examining how schools select teachers. To overcome these data limitations, I created a new dataset by web scraping and processing the Ontario public register of individ-

[1] A qualified teacher has a teaching licence and the subject qualifications needed for the particular teaching job. For example, a teacher needs to complete a math qualification course in order to be qualified to teach math. An example of an unqualified teacher is someone who is licensed to teach but teaches math without math qualifications. I will also refer to anyone who is licensed to teach as a "teacher," regardless of whether he or she is employed.

[2] In this study, a "teaching job" refers to a permanent position in the Ontario public school system.

uals who are licensed to teach. The main strength of these data is that they contain detailed subject-qualification information about all Ontario teachers' college graduates who are potentially looking for a permanent teaching position.[3] However, these data do not record whether and when a teachers' college graduate acquired a job. I overcome this problem by recognizing that all new permanent teachers are required to complete the New Teacher Induction Program (NTIP) shortly after starting their first teaching job. The NTIP is a program designed to foster the professional development of new teachers and, accordingly, the NTIP completion year is included in the data along with all of the other educational qualifications; this allows me to ascertain when the teachers began their first job (Ontario Ministry of Education [OME], 2010).

The results of this paper illustrate the fact that from 2006 to 2016 it was much more difficult to acquire a permanent teaching job than in 2001, a year in which around three-quarters of that year's graduating cohort found a permanent position (McIntyre, 2002).[4] The simple average probability of acquiring a job within the first year across the cohorts from 2006 to 2013 was nearly 9 percent[5]. Moreover, the probability of acquiring a permanent teaching position in the Ontario public school system decreased for each successive cohort. For example, I found that, for the first cohort in my sample, the probability of finding a job in the first year was around four times higher than for the last cohort. The results also indicate substantial differences in hiring probabilities across teachers with different subject qualifications. For example, in 2006 male elementary teachers with French qualifications had a 46 percent success rate in their first year, while those with math qualifications only secured a job 21 percent of the time. Although there is a benefit associated with graduates having one or more particular subject qualifications in a core area like math, reading and writing, by far the greatest benefit resulted from having French qualifications. One possible reason

[3] I assume that only the graduates who acquired a teaching certification can search for jobs. The data only include graduates who applied for a teaching licence; however, since the Ontario teachers' college enrolments are similar to the number of graduates in the data, it appears that the majority of graduates acquire a teaching licence (Ontario Universities' Application Centre [OUAC], 2006-2013).

[4] In 2001, it was considered "easy" to find a job.

[5] This calculation uses Model A from the analysis in this chapter; refer to Table 2.4 in Section 2.5.

why elementary schools hired teachers with French qualifications more than those with math qualifications is that, unlike math, French usually requires subject qualifications. The regulatory policies governing French teaching in elementary schools are different from and are more rigorous than those governing the teaching of other subjects like math (Ontario College of Teachers [OCT], 2005, 2019d). These results are relevant for policy making because current concerns about Ontario elementary students' math performance may be related to the math qualifications of those who are teaching (Casey & Jones, 2017; Stokke, 2015).

Many studies of the teacher labour markets use duration analysis to examine decisions related to staying in and leaving teaching (Allen, Burgess, & Mayo, 2018; Dolton, 2006; Dolton & Von der Klaauw, 1995; T. R. Stinebrickner, 1998, 1999, 2002). A handful of recent studies use data that contain all licensed teachers, including those without a teaching position, to study entry into teaching. Goldhaber, Krieg, and Theobald (2014) examined the duration to the first teaching job using intern data from six Washington-state teachers' colleges. Bacolod (2007) analyzed the determinants of entry into the teaching profession in the U.S., and the sorting of teachers into rural, urban and suburban schools, using longitudinal data that followed a single 1993 cohort of bachelor's degree graduates.

In Section 2, I briefly outline the qualifications that are needed in order to become a teacher in Ontario. In Section 3, I present descriptive statistics. In Section 4, I introduce the analysis methodology and the results, and, in Section 5, I conclude.

2.2 Teaching in Ontario

The Ontario College of Teachers licenses public-school teachers in Ontario; this study focuses on general and technological education teachers. General education teachers must be certified in at least two consecutive grade divisions: Primary/Junior (Kindergarten to Grade 6), Junior/Intermediate (Grades 4 to 10) and Intermediate/Senior (Grades 7 to 12).

For the elementary grades for the younger students, Primary/Junior teachers do not require any specialist subject qualifications.[6] Junior/Intermediate teachers need at least one specialist subject qualification, and Intermediate/Senior teachers require at least two specialist subject qualifications. In Ontario, elementary school runs from Kindergarten to Grade 8, and high school runs from Grades 9 to 12. Teachers with technological education subjects are qualified to teach in at least one of the high-school technological divisions, Grades 9 to 10 and/or Grades 11 to 12 (OCT, 2019e, 2019f).

In order to fulfill the educational requirements, general education teachers need to complete at least a three-year bachelor's degree, and an accredited teacher education program. Technological education teachers need to complete a combination of experience and education in the technological field that they will teach, and an accredited teacher education program (OCT, 2019e, 2019f).[7]

2.3 Data

The dataset used in this paper was created by web scraping and by gathering and organizing teacher administrative profiles from the public register available on the Ontario College of Teachers website.[8] The dataset that I use in this study contains 62,409 licensed teachers

[6]Even though the younger students, until Grade 6, have the same teacher for most subjects (a generalist teacher), they may still have a specialist for some subjects (e.g., French and music). From Grades 7 to 12, students usually have several teachers, each of whom is specialized in a different subject. It is essential to highlight that the term "specialist" within the context of this paper is used to differentiate between specialist and generalist types of teachers, as opposed to specialist types of subject qualifications. The Ontario College of Teachers Act defines various kinds of subject qualification courses, which are available across different subjects (e.g., math); for instance, there are one-session honour specialist courses, and three-session qualifications, of which the last session is a specialist course. Moreover, in the context of the subject qualification course types, "specialist" refers to the level of proficiency needed to complete these courses; however, this distinction between the different proficiency levels related to subject qualifications is beyond the scope of this study (Government of Ontario, 2017).

[7]During the analysis period of this paper, teachers were required to have completed a one-year teacher education program over two semesters. Since 2015, teachers have been required to have completed a two-year education program over four semesters. It is possible to be a technological teacher without education in the technological field, but it requires five years of on-the-job experience.

[8]A teacher profile can be accessed through a search bar on the OCT website by either inputting the teacher's name or registration number (OCT, 2019b).

who graduated from an Ontario teacher education program and spans the years 2006 to 2016 for the graduating-year cohorts 2006 to 2013. The data exclude 5,344 teachers' college graduates, or 7.8 percent of all Ontario teachers' college graduates, who hold French grade division qualifications and therefore can teach in French-language schools.[9] The following variables are observed in the data: first and last names, year of graduation from an Ontario teachers' college (cohort), the subject and grade-division qualifications and the associated years in which they were acquired, the completion year of the New Teacher Induction Program and the historical status of the licence (e.g., Good Standing or Expired) along with the associated dates.

In practice, many teachers exceed the minimum number of required subject qualifications. To simplify the analysis, I group the teachers into one of the following mutually exclusive subject qualification categories: French, technology, math, reading/writing, no subject and all others.[10] Refer to the Appendix Section A.1.1 for details on how I constructed these groups and for other data-related information.

Tables 2.1 and 2.2 show the number of graduates by graduating-year cohort, who hold certifications in the various subject qualifications and grade divisions, respectively. One of the notable patterns is the increasing trend in the percentage of individuals with French-language subject qualifications for the later cohorts. Furthermore, there was growth across successive cohorts in the proportion of graduates who became certified to teach at both elementary and high school grade levels. Table 2.3 lists the number of graduates who hold various subject qualifications across grade divisions. From this table, it is worth highlighting that French qualifications are most common for teachers certified to teach in both elementary and high school, and math qualifications are most common among high school

[9]The data also exclude 500 graduates who acquired a position before they graduated from teachers' college (under the variable timing assumptions; refer to Appendix Section A.1.3 for more details), 39 graduates who completed more than one teacher education program and 10 native-language-only teachers. Furthermore, I also dropped 65 teachers who had completed a diploma program but were not technology teachers and held no other bachelor's degree.

[10]Throughout the paper, reading/writing refers to a graduate holding qualifications in either reading, writing, or both.

teachers. The dataset does not contain the gender of the individuals, but it does include their first and last names, and in Appendix Section A.1.2 I discuss how I use this information to estimate the probability of the individual being male or female.

Table 2.1: Subject Qualifications by Graduating-Year Cohort

Year	Subject Qualifications						Total[11]
	French	Technology	Math	Reading/Writing	No Subject	All Others	
2006	699	169	973	700	2333	5041	9915
	7.0%	1.7%	9.8%	7.1%	23.5%	50.8%	
2007	857	234	941	823	2473	5358	10686
	8.0%	2.2%	8.8%	7.7%	23.1%	50.1%	
2008	979	240	1095	922	2278	5594	11108
	8.8%	2.2%	9.9%	8.3%	20.5%	50.4%	
2009	997	191	1085	829	2306	5783	11191
	8.9%	1.7%	9.7%	7.4%	20.6%	51.7%	
2010	1057	256	1095	811	2406	5733	11358
	9.3%	2.3%	9.6%	7.1%	21.2%	50.5%	
2011	1088	271	1177	700	2218	5390	10844
	10.0%	2.5%	10.9%	6.5%	20.5%	49.7%	
2012	1087	237	1236	568	2071	5074	10273
	10.6%	2.3$	12.0%	5.5%	20.2%	49.4%	
2013†	969	168	1254	323	1509	4106	8329
	11.6%	2.0%	15.1%	3.9%	18.1%	49.3%	
Total	7733	1766	8856	5676	17594	42079	83704
	9.2%	2.1%	10.6%	6.8%	21.0%	50.3%	

Notes:† Refer to Table 2.2 for non-time-varying totals for each cohort year.

[11] Although the subject qualification and grade division categories are mutually exclusive, the number of individuals across the subject qualifications and grade divisions does not add up to the total number of individuals in the data. The reason for this is that these variables are time-varying (i.e., they are only mutually exclusive in any given period, which means that individuals can move to other categories over time). In any given period, a graduate is in one grade division and one subject qualification category. Note that in Table 2.1, the rows add up to 100 percent (i.e., the denominators are located in the last column).

Table 2.2: Grade Divisions by Graduating-Year Cohort

Year	Grade Divisions			Total	Total*
	Elementary	High School	Elementary/High School[12]		
2006	3202	2589	2642	8433	7716
	38.0%	30.7%	31.3%		
2007	3438	2713	2838	8989	8129
	38.2%	30.2%	31.6%		
2008	3346	2817	3245	9408	8229
	35.6%	29.9%	34.5%		
2009	3378	2798	3370	9546	8265
	35.4%	29.3%	35.3%		
2010	3465	2647	3582	9694	8300
	35.7%	27.3%	37.0%		
2011	3275	2711	3426	9412	8027
	34.8%	28.8%	36.4%		
2012	3097	2442	3381	8920	7548
	34.7%	27.4%	37.9%		
2013†	2458	1908	2893	7259	6195
	33.9%	26.3%	39.9%		
Total	25659	20625	25377	71661	62409
	35.8%	28.8%	35.4%		

Notes: "Total*" refers to the sums across the cohorts only (i.e. does not account for grade divisions and subject qualifications); thus, it is not time-varying. Also, the rows add up to 100% (i.e., the denominators are located in the "Total" column). † The number of graduates in 2013 is lower relative to 2012 due to the exclusion of teachers who acquired their teaching certification after 2013; refer to Section A.1.4 for more details. Furthermore, Section A.1.4 reports descriptive statistics that are similar to Tables 2.1 and 2.2, with the difference being that Section A.1.4 only includes information about the first year on the job market (i.e., not time varying).

[12]Throughout the paper, Elementary/High School refers to Elementary and High School.

Table 2.3: Subject Qualifications by Grade Divisions

Subject Qualifications	Grade Divisions			Total
	Elementary	High School	Elementary/High School	
French	2767	2099	3526	8392
	7.3%	9.5%	11.8%	9.3%
Technology	0	1682	99	1781
	0.0%	7.6%	0.3%	2.0%
Math	1092	4381	3814	9287
	2.9%	19.7%	12.8%	10.3%
Reading/Writing	3445	146	2560	6151
	9.1%	0.7%	8.6%	6.8%
No Subject	17594	0	0	17594
	46.5%	0.0%	0.0%	19.6%
All Others	12927	13901	19825	46653
	34.2%	62.6%	66.5%	51.9%
Total	37825	22209	29824	89858

Notes: The columns add up to 100% (i.e., the denominators are located in the last row).

2.3.1 When Do the Teachers Obtain a Permanent Job?

The data do not directly indicate when the teachers acquire a permanent position. However, this information can be obtained from the New Teacher Induction Program (NTIP) completion date which is available in the data. Starting in 2006, the law has required that all new permanent teachers in the Ontario public school system complete the NTIP. The majority of teachers pass this program within one year and, although failing is possible, it is uncommon in practice (Maharaj, 2014; Miller, 2009; OME, 2010). I assume that people start looking for a job as soon as they graduate from teachers' college and that they start the permanent job one year before their NTIP completion date.[13]

[13] In the collected data, between around 80 and 95 percent of graduates acquired a teaching licence in the same year in which they graduated. See Appendix Section A.1.3 for more details.

2.4 Duration Analysis

The analysis in this paper relies on discrete-time duration models which account for right censoring. In Section 2.4.1, the Kaplan-Meier survival curves provide a preliminary comparison of durations until the start of the first teaching job across several groups (Kaplan & Meier, 1958). In Section 2.4.2, a semi-parametric hazard function incorporates teacher characteristics to analyze the probability of attaining a permanent position in the Ontario public school system.

2.4.1 Kaplan-Meier Survival Function

Letting T be a discrete random variable, with $t \geq 0$ denoting the number of years since the graduate began looking for a job. The Kaplan-Meier survival function characterizes the probability of not finding a job until after time t as follows:

$$S(t) = Pr(T > t). \tag{2.1}$$

Figure 2.1: Kaplan-Meier Survival Function: Duration Until First Permanent Teaching Job by Graduating-Year Cohort

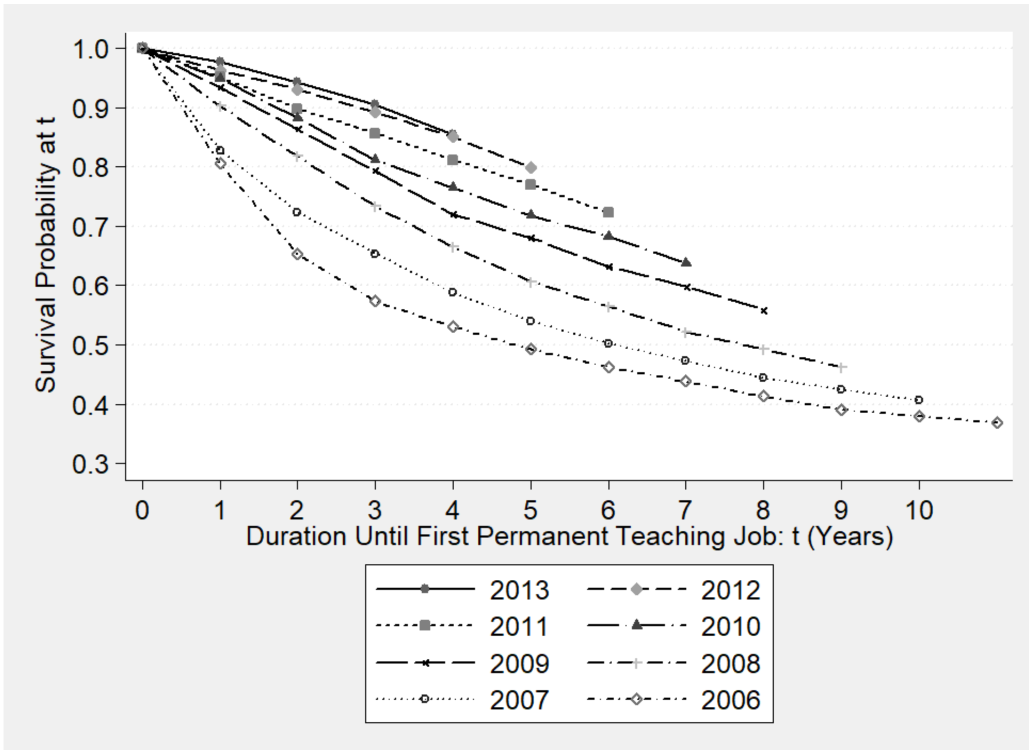


Figure 2.1 shows the survival functions based on the year in which the individual graduated and started searching for a permanent teaching job in the Ontario public school system.[14] The probability of acquiring a job decreased for each successive cohort in my sample. For example, 35 percent of teachers from the 2006 cohort and only 18 percent of teachers from the 2008 cohort found a job within two years.

[14]I assumed that individuals began to search for a job in the same year in which they graduated (for majority of graduates). Refer to Appendix Section A.1.3 for more details on the timing in the data. The Kaplan-Meier curves are shorter for subsequent cohorts due to right censoring resulting from the end of the analysis period.

Figure 2.2: Kaplan-Meier Survival Function: Duration Until First Permanent Teaching Job by Subject Qualifications (Elementary Teachers)

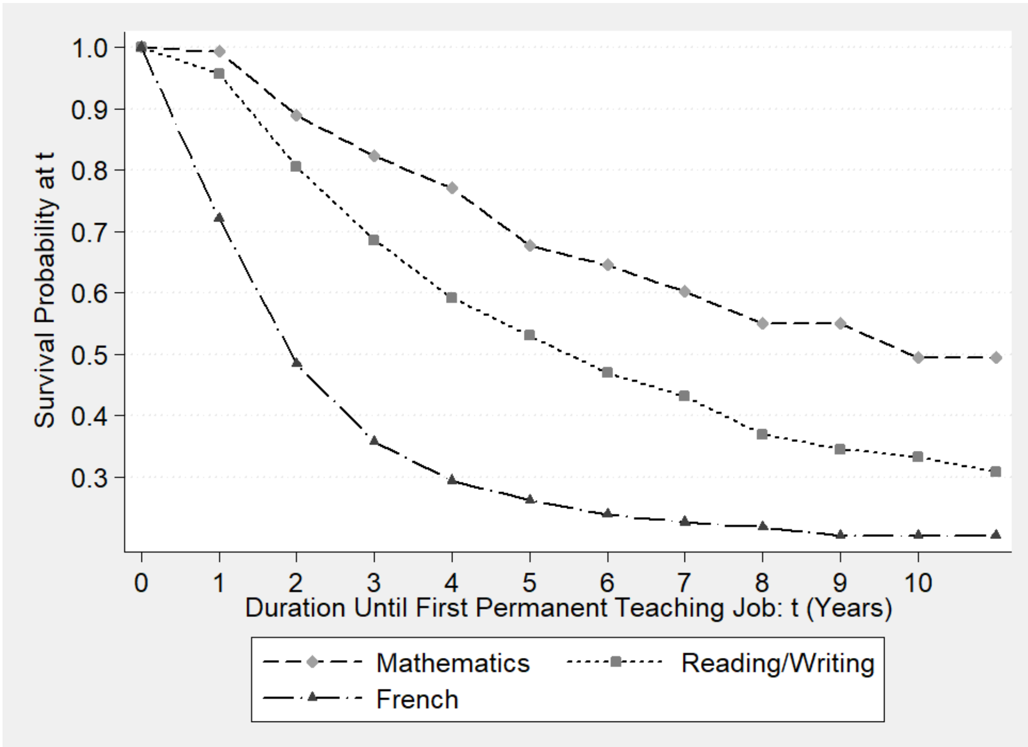


Figure 2.2 shows the survival functions for the reading/writing, math and French qualifications and, even though it does not apply to a particular cohort, it offers a preliminary sense of the amount of time in which graduates were able to secure a position within the analysis period across the various subject qualifications.[15] The elementary school teachers with French-language qualifications had a much higher probability of being hired for a job than teachers with qualifications in reading/writing or math.[16] After two years, 11 percent of teachers with math qualifications had a job, in contrast with 19 percent for reading/writing and 51 percent for French. At four years, the percentage of individuals who

[15]Since the standard Kaplan-Meier analysis does not allow time-varying covariates, I only include observations from teachers who had the subject qualifications no later than one year after starting to search for a job and who had acquired the qualifications before finding a job. Further, I only include graduates who never acquired high-school-level qualifications.

[16]In this paper, I refer to graduates as "elementary" school teachers when they only hold elementary grade division qualifications, rather than necessarily having obtained a primary school teaching position. Moreover, in reality, teachers can be assigned elementary grade level positions without having elementary grade level qualifications (Government of Ontario, 2011).

had a position was 22 percent for math, 41 percent for reading/writing and 70 percent for French.

2.4.2 Discrete-Time Hazard-Based Duration Model

The central component of a duration model is the hazard function, which is the probability of finding a job at time t conditional on not finding one in an earlier period: $h = Pr(T = t|T \geqslant t)$.[17] The hazard function with covariates measures the effect of teacher characteristics on the probability of securing a job.[18]

The hazard probability for each individual i at time t and gender j is:

$$h_{i,t}^{j} = \frac{\exp(x_i\beta + \mathbb{1}_{i,j=f}\beta_f + d_{i,t}\beta_{d,t})}{1 + \exp(x_i\beta + \mathbb{1}_{i,j=f}\beta_f + d_{i,t}\beta_{d,t})}. \tag{2.2}$$

For individual i at time t, $x_{i,t}$ is the vector of covariates (apart from the gender and baseline hazard indicator variables) and β is the corresponding vector of coefficients, $\mathbb{1}_{i,j=f}$ is the indicator variable for gender (=1 for $j = f$) where $j = \{m, f\}$ for male and female, β_f is a coefficient for female and $y_{i,t}$ is an indicator variable denoting whether individual i acquired a job (job=1) at time t. The non-parametric baseline hazard indicator variable is $d_{i,t}$, which means that, if this variable equals one, it follows that individual i found a job in year t, and the corresponding coefficient is $\beta_{d,t}$.

The model is estimated using maximum likelihood. I evaluate the log-likelihood function for each individual i over time t, starting from the graduation year and ending when the individual obtains a job or is censored. Censoring occurs when the individual is no longer licensed or when the study ends.

Although gender is not directly reflected in the data, I obtain the probability of an individual i being female, $p_{f,i}$, by using their first and last names which are available in the

[17] This model is based on Singer and Willett (1993).

[18] The subject qualifications and grade divisions in this model are time-varying because teachers often acquire qualifications over time in order to improve their chances of finding a teaching job.

data.[19] The contribution of individual i to the likelihood is found by integrating the gender-specific likelihood function, which can be written as $(h^{j}_{i,t})^{y_{i,t}}(1-h^{j}_{i,t})^{1-y_{i,t}}$, over $j = \{m, f\}$. The log-likelihood for the full sample is given by equation 2.3:

$$\ln L(\beta; x) = \sum_{i}\sum_{t} \ln \left[\underbrace{p_{f,i}(h^{j=f}_{i,t})^{y_{i,t}}(1-h^{j=f}_{i,t})^{1-y_{i,t}}}_{female} + \underbrace{(1-p_{f,i})(h^{j=m}_{i,t})^{y_{i,t}}(1-h^{j=m}_{i,t})^{1-y_{i,t}}}_{male} \right]. \tag{2.3}$$

2.5 Results

The results of the hazard-based duration models A to F are provided in Tables 2.4 and 2.5. The dependent variable is binary and equal to one when the teachers' college graduates find a permanent position in the Ontario public school system. Model A includes the baseline hazard, gender and the graduating-year cohorts. Model B is similar to Model A but also includes grade divisions, and Model C additionally includes subject qualifications. Models D to F were estimated separately for each grade division category.[20]

The baseline hazard in each model is non-parametric with indicator variables denoting each year in which an individual was at risk of finding a job. The baseline values vary across the models, but the pattern is similar showing negative duration dependence. For example, from Model C, it is evident that the 2006 graduates with elementary-grade division qualifications and no subject had a 33 percent higher probability of finding a job in their first year relative to their third year on the job market.

The probability of acquiring a teaching position decreased for each successive cohort. For example, based on Model A, the 2006 graduates had a 14 percent probability of ac-

[19] See Section A.1.2 for more details on the process that I use to derive the probability of being female from the first and last names of the teachers..

[20] Technological education is omitted from Model D because it is not available in elementary school, and no-subject is omitted from Models E and F because teachers are required to have subject qualifications in those grade divisions. Model F is for teachers qualified in any combination of overlapping high-school and elementary divisions.

quiring a job in their first year, while this probability had fallen to 5 percent by 2012 for that year's graduating cohort. There is also substantial variation in the probability of finding a job across subject qualifications. Teachers had the highest probability of acquiring a job with French qualifications in every model except for Model E (high school), where it was close to being equal to technological qualifications. For example, for Models C to F, the odds of finding a teaching job with French qualifications were around 3 to 5 times higher relative to all-others qualifications. In the elementary division based on Models C and D, the probability of obtaining a job with reading/writing or math qualifications was higher relative to all-others qualifications, and was notably higher relative to teachers with no subject. For example, based on Model D, for the 2006 cohort of elementary teachers, the probability of finding a job in the first year was around four to five times higher for teachers with reading/writing or math qualifications than with no subject.[21] Gender has no statistically significant effect in Models A, C and F.[22] In Models B and E, females had a higher probability of acquiring a job and, in Model D, males had a higher probability of acquiring a job.

[21]Teacher graduates in the elementary division in the no-subject group comprised a large portion of all teacher graduates with elementary qualifications only (around 69 percent were in the no-subject category for at least one time period) and, because these teachers are generalists, they are not required by the licensing regulations to have any specific subject qualifications (e.g., math, French).

[22]Statistical significance is assumed to be $p < 0.05$.

Table 2.4: Discrete-Time Hazard-Based Duration Model Results: A to C

	Model A	Model B	Model C – Full Model
Variable	Coefficient (Standard Error)		
Gender: *Reference Group: Male*			
Female	0.03 (0.02)	0.08 (0.02)	0.00 (0.02)
Graduating-Year Cohort: *Reference Group: 2013*			
2006	1.38 (0.04)	1.42 (0.04)	1.66 (0.04)
2007	1.25 (0.04)	1.28 (0.04)	1.50 (0.04)
2008	1.05 (0.04)	1.08 (0.04)	1.25 (0.04)
2009	0.82 (0.04)	0.84 (0.04)	1.01 (0.04)
2010	0.64 (0.04)	0.66 (0.04)	0.79 (0.04)
2011	0.42 (0.04)	0.43 (0.04)	0.53 (0.04)
2012	0.18 (0.04)	0.19 (0.04)	0.25 (0.04)
Grade Divisions*: Reference Group: Elementary*			
Elementary/High Sch.	–	0.40 (0.02)	0.02 (0.02)
High School	–	0.16 (0.02)	-0.31 (0.02)
Subject Qualifications: *Reference Group: All Others*			
No Subject	–	–	-1.14 (0.03)
French	–	–	1.47 (0.02)
Technology	–	–	1.02 (0.04)
Mathematics	–	–	0.31 (0.02)
Reading/Writing	–	–	0.59 (0.03)
Sample Size			
Obs. N	326563	326563	326563
Ind. i	62409	62409	62409
Baseline Hazard †			
d1	-3.19 (0.04)	-3.41 (0.04)	-3.29 (0.04)
d2	-3.22 (0.04)	-3.47 (0.04)	-3.44 (0.04)
d3	-3.32 (0.04)	-3.58 (0.04)	-3.59 (0.04)
d4	-3.37 (0.04)	-3.63 (0.04)	-3.66 (0.04)
d5	-3.51 (0.04)	-3.78 (0.05)	-3.83 (0.05)
d6	-3.64 (0.05)	-3.91 (0.05)	-3.97 (0.05)
d7	-3.77 (0.05)	-4.04 (0.05)	-4.12 (0.05)
d8	-3.89 (0.05)	-4.18 (0.05)	-4.27 (0.06)
d9	-4.10 (0.06)	-4.39 (0.06)	-4.51 (0.06)
d10	-4.65 (0.09)	-4.94 (0.09)	-5.07 (0.09)
d11	-4.90 (0.13)	-5.19 (0.14)	-5.37 (0.14)

Notes: † Indicator variables for each year in which the graduate was at risk of obtaining a job. All coefficients are statistically significant at $p < 0.05$ except for "Female" in Model C.

Table 2.5: Discrete-Time Hazard-Based Duration Model Results: D to F

Variable	Model D – Elementary	Model E – High School	Model F – Elementary/High School
	Coefficient (Standard Error)		
	Gender: *Reference Group: Male*		
Female	-0.14 (0.04)	0.08 (0.03)	-0.01 (0.03)
	Graduating-Year Cohort: *Reference Group: 2013*		
2006	2.00 (0.08)	1.98 (0.08)	1.23 (0.06)
2007	1.75 (0.08)	1.83 (0.08)	1.15 (0.06)
2008	1.42 (0.08)	1.60 (0.08)	0.95 (0.06)
2009	1.11 (0.08)	1.24 (0.08)	0.86 (0.06)
2010	0.83 (0.08)	0.98 (0.09)	0.68 (0.06)
2011	0.62 (0.08)	0.62 (0.09)	0.44 (0.06)
2012	0.36 (0.09)	0.20 (0.10)	0.21 (0.06)
	Grade Divisions: *Reference Group: Elementary*		
Elementary/High Sch.	–	–	–
High School	–	–	–
	Subject Qualifications: *Reference Group: All Others*[23]		
No Subject	-1.15 (0.03)	–	–
French	1.65 (0.03)	1.13 (0.04)	1.53 (0.03)
Technology	–	1.04 (0.04)	0.47 (0.18)
Mathematics	0.71 (0.08)	0.30 (0.03)	0.18 (0.04)
Reading/Writing	0.52 (0.04)	-0.34 (0.27)	0.70 (0.04)
	Sample Size		
Obs. N	116128	92867	117568
Ind. i[24]	25659	20625	25377
	Baseline Hazard		
d1	-3.29 (0.08)	-3.69 (0.08)	-3.34 (0.06)
d2	-3.56 (0.08)	-3.83 (0.08)	-3.32 (0.06)
d3	-3.70 (0.08)	-4.10 (0.09)	-3.35 (0.06)
d4	-3.80 (0.09)	-4.34 (0.09)	-3.32 (0.06)
d5	-3.97 (0.09)	-4.63 (0.10)	-3.44 (0.06)
d6	-4.04 (0.09)	-4.94 (0.10)	-3.56 (0.07)
d7	-4.23 (0.10)	-5.15 (0.11)	-3.66 (0.07)
d8	-4.25 (0.10)	-5.43 (0.13)	-3.83 (0.08)
d9	-4.46 (0.12)	-5.57 (0.15)	-4.09 (0.09)
d10	-5.42 (0.17)	-6.01 (0.20)	-4.46 (0.12)
d11	-5.49 (0.25)	-6.69 (0.37)	-4.75 (0.19)

Notes: All coefficients are statistically significant at $p < 0.05$ except for "Reading/Writing" in Model E.

2.6 Discussion and Conclusion

In this paper, I create a unique dataset by web scraping the Ontario public register of licensed teachers. Taking advantage of this data allows me to examine how teacher characteristics affect the probability of acquiring a permanent teaching position in the Ontario public education system. The data include the 2006 to 2013 graduates of Ontario teacher education programs, and span the years 2006 to 2016.

People were aware of the fact that it was a challenge to find a teaching position in Ontario during this time; however, it is not entirely clear which types of teachers and how many were experiencing difficulties. This paper provides the first comprehensive evidence of how challenging it actually was to obtain a teaching job. The probability of finding a position in 2006 was around four times higher than it was in 2013 (for new graduates in their first year on the job market), and even more striking is the comparison with 2001 when the probability of finding a teaching job was around 20 times higher than it was in 2013.[25] Clearly it has become increasingly difficult for each successive cohort to find a teaching position.

It seems natural to imagine that some teachers may have believed that they could improve their chances of finding a position by acquiring one or more subject qualifications and, even though there was some benefit to having such as qualification in a core area like math, reading or writing, this was still relatively insignificant in comparison with the benefit of having a French-language qualification. One possible explanation for elementary schools' tendency to place a greater value on French qualifications than on math quali-

[23]The results from the hazard Model D contradict the Kaplan-Meier results in figure 2.2. According to the Kaplan-Meier analysis, graduates with mathematics qualifications had a lower probability of acquiring teaching jobs than those with reading/writing qualifications. This demonstrates the importance of including time-varying covariates, which standard Kaplan-Meier analysis does not incorporate. The reason for the difference is likely due to something the individuals with math qualifications (and no reading/writing qualifications) did over time that correlated with their increased chances of obtaining jobs relative to the individuals with reading/writing qualifications (and no math qualifications).

[24]The same individuals can appear in Models D–F since the Grade Divisions are time-varying.

[25]This comparison refers to acquiring a job in the first year on the job market for those graduating-year cohorts. In the sample period between 2006 and 2013, the teacher labour market was in an over-supply environment (more teachers than jobs). On the other hand, it was considered "easy" to find a job in 2001.

fications is the existence of regulatory policies. Teaching French in elementary schools usually requires subject qualifications because of regulations, whereas teaching math does not (OCT, 2005, 2019d). It is apparent to most observers that effective teachers of French should be competent in the subject; however, one might also be concerned that there is a perception that all elementary teachers have the proficiency to teach math, even without a subject qualification. The fact that schools do not capitalize on the opportunity to hire more math-qualified teachers is disconcerting, especially in light of policy discussions related to the recent declines in the math performance of Ontario elementary students. Additionally, the fact that Quebec elementary students are exceeding their Ontario peers in standardized math assessments further amplifies these types of policy discussions, by Ontario government regulators and other stakeholders, about math performance (Alphonso, 2018a).

Some speculate that the discrepancy in math performance between Quebec and Ontario is attributable to the differences in teacher-training regulations between these provinces (Alphonso, 2018b; Peritz, 2013; Valiante, 2017). In Quebec, all teachers finish a four-year teacher program as opposed to a two-year program in Ontario (before 2015 it was just one year). Ontario and Quebec elementary teachers do not require math subject qualifications; however, elementary teacher training in Quebec places more emphasis on math than its Ontario counterpart. Furthermore, in Quebec, students begin high school in Grade 7 as opposed to Grade 9 in Ontario. Since math qualifications are only mandatory at the high-school level, Quebec students benefit from having teachers with more math qualifications in earlier grades (Alphonso, 2018b). The evidence suggests that teachers who are more confident in their math skills are more effective at passing on these abilities (Stokke, 2015). Examining the school hiring processes can help us to understand the types of policy interventions that are appropriate in improving student outcomes.

Chapter 3

What Has the Greater Effect on Earnings, the University You Attend or the Degree Program You Pursue?

3.1 Introduction

Each year, thousands of prospective students apply to university. In the process, they decide which school to attend and what degree program to pursue. It is natural for early-career discussions to centre around gaining acceptance to a "top school" based on the widespread notion that graduating from a more prestigious institution will result in higher earnings. However, the economic literature suggests that the degree program students graduate with may also affect their earnings. The main objective of this paper is to determine the extent to which school choice is important relative to program choice from the standpoint of earnings.

To do the above-mentioned, I use a method called relative-importance analysis which calculates the sum of the squared deviations from the mean and then partitions these deviations into and attributes these deviations to the respective amounts of earnings variation attributable to the programs, schools, interactions and an unexplained factor (i.e., within-group variation). The higher the percentage of variation in earnings that the anal-

This study uses data provided by the Ministry of Training, Colleges and Universities. The views expressed in this study are my own and do not necessarily reflect those of the Ministry.

ysis attributes to the programs or the schools, the greater the importance of that factor for earnings or, put another way, the greater the significance of the effect that the factor has on earnings. Relative-importance analysis is useful in this context because it allows for the convenient analysis of the overall effects of schools and programs on earnings as opposed to just pursuing a narrow focus on the effects of any particular school or program.

A limitation of the existing literature on the effects of school and program choices on earnings is the fact that these decisions are typically studied separately, even though, in practice, students make these decisions jointly. One of the contributions of this paper is the joint comparison of the variation in earnings across degree programs and schools. Analyzing the effects of school and program choices on earnings at the same time allows not only for direct comparison but also for assessment of the interaction effects.

A specific example might help to illustrate the types of decision that a student may consider. Suppose that a student has the opportunity to pursue a humanities program at a selective and prestigious university but does not have high enough grades to be accepted into the school's science program. At the same time, this individual received acceptance into a science program at a less selective and less prestigious university. The separate examination of program and school choices would not make apparent which of these scenarios would provide a better earnings outcome. This lack of clarity points to the following general question: Do individuals earn more money if they graduate from a low-earnings program at a highly selective school rather than from a high-earnings program at a less selective school?[1]

The problem with examining earnings based on schools without considering the specific programs is that, as a result of the omitted variables, the estimates might bias the degree to which schools affect earnings. For instance, a school with more resources might, on average, produce graduates with higher earnings, but only because more students at that school complete high-earnings programs. Focusing only on that school without taking the

[1] Refer to Eide, Hilmer, and Showalter (2016) for a similar scenario.

school's program mix into account would overstate the effect of the school on earnings. Thus, a comparison of institutions that excludes programs might falsely associate other institutional characteristics with earnings. For instance, Betts, Ferrall, and Finnie (2013) provide evidence that the exclusion of university characteristics from the estimation substantially overstated the effect of programs on earnings.

Similarly, the examination of earnings based on programs without considering schools might bias the degree to which programs affect earnings. For example, the examination of high-quality schools that devote more resources to low-earnings programs without considering other schools might lead to an overstatement of the effect of programs on earnings.[2]

The reason why there are few studies that consider the effects of schools and programs on earnings jointly is the lack of available data that contain both schools and programs. Additionally, the ideal data for this kind of research require that many of the schools offer similar programs. Moreover, the definitions of the programs need to be similar across institutions in order to be comparable.[3] I overcame these data issues by taking advantage of a unique restricted-access government-administered survey, the Ontario University Graduate Survey (OUGS). One advantage of using these data within this context is based on the fact that many schools in Ontario offer similar programs in accordance with the high level of homogeneity of the province's post-secondary education system; this high level of homogeneity makes it convenient to make comparisons across schools. Another advantage that provided an extra element that made this study possible is access to the restricted version of the OUGS dataset, which contains information on entire salary distributions across nearly all universities and their respective programs in Ontario. In contrast, the public-use version of these data only provide median salaries for the programs and only cover a limited number of schools.

A unique feature of the OUGS data is the fact that the observations contain not only

[2]Without controlling for school characteristics, such as the level of resources devoted to programs, the program variables might pick up the school effect.

[3]For example, a particular category of business program should have similar courses across multiple schools.

individual program information but also the names of identifiable universities, which is uncommon in these kinds of datasets. Typical general labour datasets contain program information and school characteristics but no school identifiers and, if they do contain school identifiers, there often are not enough observations for each school or for the various school-program combinations.[4] For example, E. James, Alsalam, Conaty, and To (1989) used university fixed effects but did not have many observations per school; they used a data sample with 2,280 students and 519 different schools. Similarly, Rumberger and Thomas (1993) used a sample of 8,021 individuals across 262 schools. In contrast, the OUGS data contain between 99,940 and 110,902 observations across 21 schools and 26 programs, which is a large number of observations not just for schools but for most school-program combinations.

The advantage of observing individuals within schools and across multiple schools is the ability to account for the program mix within the schools and for the unobserved school characteristics by means of fixed effects. Further, even though the OUGS data do not offer researchers a rich set of variables, this database's main strength of including a large number of observations per school-program combination makes it ideal for undertaking a general comparison of the amount of relative variation across both programs and schools. Moreover, the benefit of having access to the entire earnings distribution within each school-program combination allows for the meaningful comparison of the within-group variation in earnings relative to the between-group variation in earnings for schools and programs.[5] This comparison is useful because it is possible for the ratio between the earnings variation for programs and schools to be significant and yet for neither one to account for a sub-

[4] An example of a school-program combination or group is humanities at the University of Toronto. For instance, if the data contain 30 observations for a particular school and if there are only 10 program categories, there will only be a few observations within any particular school-program combination. Furthermore, when conditioned for gender, the number of observations decreases even more, and many school-program combinations would likely have zero observations.

[5] Having only a median salary for each school-program group would mean that there appears to be significantly less variation within each program and school group, and therefore the regression would assign a larger proportion of the variation to the program and school groups. In this case, the within-group variation would be small.

stantial part of the variation. For example, this enables the analysis to distinguish between a scenario in which programs account for 2 percent of the earnings variation and schools account for 0.2 percent of the same on the one hand and, on the other hand, a scenario in which programs account for 20 percent of the earnings variation and schools account for 2 percent of the same.

The economic literature finds differences in earnings across graduates depending in part on the university program that they completed. Arcidiacono (2004) found that, even when accounting for selection bias, large premiums still exist for certain programs. For example, his results show that mathematics is more important for earnings than verbal ability (e.g., the humanities). Additionally, both Arcidiacono (2004) and Wiswall and Zafar (2015) found that earnings differences are predominately attributable to tastes for a particular type of schooling and work, rather than to ability sorting. Moreover, Berger (1988) found that students tend to choose programs that give them higher lifetime earnings, as opposed to earnings in the first few years; his results also show that business, liberal arts and education have flatter lifetime earnings curves than science and engineering. Kinsler and Pavan (2015) found significant returns for science and business programs even after adjusting for selection into the program based on ability.

Much like the literature on program choice, the school-choice literature also reports that it matters for earnings where people go to school. The possible mechanisms for these earnings differences are signalling, based on the admissions selectivity of the various schools, and the human capital accumulation mechanism.[6] Brewer, Eide, and Ehrenberg (1999) found a 39 percent premium for attending a top private U.S. college relative to the bottom public college for a 1982 cohort, and a 26 percent premium for a top public college relative to the bottom public college — even after controlling for the selection of various demographic variables such as test scores, gender, race and family income. Hoekstra (2009)

[6]Signalling refers to the prestige that comes with graduating from a more selective school, which may be considered to "signal" ability to other parties. Furthermore, the underlying premise of the human capital accumulation mechanism is that graduates from higher-quality schools, or schools with more resources, acquire more human capital.

found that attendance at the most selective university in the state resulted in a 20 percent premium for white men. On the other hand, Dale and Krueger (2002, 2014) found that, after adjusting for ability, college selectivity on average makes little difference to earnings — though students from disadvantaged backgrounds seem to benefit the most from attending more selective schools. Further, Dale and Krueger (2002) show results indicating that college graduates from schools with higher tuition fees had higher earnings, presumably due to a higher quality of education; yet, in a follow-up study, Dale and Krueger (2014) found that the effect had disappeared. Lindah and Regner (2005) examined university choices using Swedish sibling data and found that earnings differ across schools, albeit without any apparent causal mechanism. Additionally, they discovered a positive correlation between earnings and the proportion of instructors who hold a doctoral degree, a finding that supports the human capital accumulation mechanism. However, they also found substantial differences in earnings between brothers and sisters within the same family; this discovery, made under the assumption that the quality of education is the same for females and males, contradicts the conclusion that would seem to flow from the human capital accumulation mechanism.

The most closely related research examines the relationship between school choice and program choice. For example, Eide et al. (2016) analyzed how earnings vary across programs for different levels of school selectivity. They found that university selectivity positively affects business programs to the greatest extent and science programs to the smallest extent. Further, Rumberger and Thomas (1993) found that school quality, programs and students' academic performance all contribute to earnings. Even though they were able to account for both schools and programs, they were unable to consider any interactions because of various data limitations (they did separate regressions by program group). E. James et al. (1989) discovered that schools accounted for about 1 to 2 percent of the earnings variance without accounting for programs; however, when controlling for programs, the amount of variation explained by the schools decreased to below 1 percent. They also discovered that the programs, combined with level of GPA, the number of math credits taken and post-graduate degrees, explained about 3 to 5 percent of the variation in earnings. Li, Meng, Shi, and Wu (2012) examined schools but also controlled for programs; they found that, in China, attending an elite institution gave an overall 26.4 percent premium which decreased to 10.7 percent after controlling for selection (e.g., ability, program). They attributed most of the premium from attending an elite institution to the human capital accumulation mechanism. From a Canadian perspective, Betts et al. (2013) studied the effects of school characteristics on earnings. They found, first, that an increase in undergraduate enrolment leads to lower earnings due to the reduced educational quality caused by the crowding-out effect and, second, that for men an increase in the professor-to-student ratio leads to higher earnings. They controlled for programs within schools and, because they had access to school identifiers, they could use school fixed effects to control for unobservable school characteristics.

In this study, instead of examining the effects on earnings of specific school characteristics or of particular programs and instead of reporting regression coefficients (which others did in the studies cited above), I use a more general approach. Specifically, I use relative-importance analysis to examine the respective overall proportions of the variation in earnings that can be attributed to programs, schools and interaction effects. I divide the estimation specifications by type of degree (undergraduate or professional), gender, and the amount of time that has elapsed since graduation (six months and two years). The results of this paper indicate that there is substantially more variation in earnings that can be attributed to the program variables than to the school variables for both the undergraduate and the professional-degree graduates. For the undergraduate-degree holders, the programs accounted for 21.5 percent of the variation in earnings while the schools accounted for just 2.6 percent of the same, a slightly greater than eight-fold difference. For the professional-degree holders, even though the program variables still explained substantially more of the earnings variation than the school variables, the difference was not as large as the difference for the undergraduate programs. The program variables for the professional-degree holders accounted for 17.6 percent of the variation in earnings while the schools accounted for 5.3 percent of the same, a slightly greater than three-fold difference. The results for males and females are similar; in fact, there is no statistically significant difference for schools and interaction effects in any of the specifications. There is a statistically significant difference between males and females in terms of the program variables at both the undergraduate and the professional levels for the six-month data. Gender differences are more pronounced at the professional-degree level than at the undergraduate level. The variation that can be attributed to the programs at the professional level is 5.4 percentage points greater for males, while at the undergraduate level this variation is 1.8 percentage points greater for females. It is essential to highlight that these results are descriptive and not causal because, for example, it is likely that students select different programs according to their ability; something this study cannot address due to data limitations.

In Section 2, I introduce the data. In Section 3, I outline the methodology and the analysis. In Section 4, I present the results and, in Section 5, I conclude.

3.2 Data

The data used in this paper is a subset of the restricted version of the Ontario University Graduate Survey (OUGS), which is an annual survey administered by the Ontario Ministry of Training, Colleges and Universities (MTCU), in collaboration with the province's universities. The survey questionnaire is sent to all Ontario university degree holders two years after their graduation and asks about their employment outcomes at the intervals of six months and two years following graduation (Ontario Ministry of Training, Colleges and Universities [MTCU], n.d., 2013). The restricted version of the data used in this study has several advantages over the public-use version. The public-use data only provide median salaries for a limited number of schools and do not include gender. The restricted data, on the other hand, provide the entire salary distribution for the majority of Ontario universities and include gender. Without access to a dataset that includes all salaries by school, it would not be possible to compare the variation in earnings that is attributable to programs, schools and interaction effects. Furthermore, access to the entire salary distribution within each school-program combination allows for a comparison of the unexplained variation in earnings on the one hand and the earnings variation attributable to the schools and programs on the other hand.

The data spans the years 2007 to 2012 and include demographic variables, earnings outcomes and employment status. The demographic variables are year of graduation, school, program and gender, and the earnings-outcome variables are the six-month and two-year salary bins (11 salary bins for each period since graduation). The employment-status variables are as follows: whether employed, whether offered employment to start at a later date, whether not employed and not in school, and whether in full- or part-time employment.[7] The data are in an aggregate form at the level of the four demographic variables: year of graduation, program, school and gender. The salaries are in the form of binned data at the six-month and two-year milestones after graduation. There are 11 bins, one for each salary group, spaced out by \$10,000 starting at \$0 and ending with an open-ended group of >\$100,000.[8]

3.2.1 Descriptive Statistics

Table 3.1 reports the descriptive statistics for the survey respondents across the various demographic variables. Although the analysis in this study aggregates across the graduating years, the descriptive statistics show the breakdown by graduating year to give a sense of the relative weights attributable to the results for the various cohorts. The number of observations is greater for the 2009 to 2012 cohorts relative to the 2007 and 2008 cohorts across

[7] The survey questionnaire defines full-time employment as 30 or more hours per week (MTCU, n.d.).
[8] For a more detailed explanation of the data format, refer to Section B.1 of the appendix.

all genders and degree types. The relative proportions across genders and degree types do not appear to change significantly over time. Overall, there are more female graduates than male graduates, with around 66 percent of the total being female; the disparity is especially pronounced at the professional-degree level where the proportion of graduates is around 74 percent female.

Section B.1.3 of the appendix provides more detailed results for the sample sizes by individual program, and a summary of the sample sizes across schools. Table B.3 in the appendix reports the sample sizes for each particular school-program combination by gender and cohort year. The average sample size for any given school-program combination is between 66 and 90 for females and between 42 and 52 for males depending on the cohort year. The large sample sizes for the various school-program combinations ensure that there are enough data for both the direct effects and the interaction effects to acquire statistically significant results.

Table 3.1: Number of Respondents by Graduating Year, Degree Type and Gender

		Graduating Year						
Degree Type	Gender	2007	2008	2009	2010	2011	2012	Total
Combined Programs	Combined Genders	19858	18719	23383	24911	24409	27783	139063
	Female	13545	12369	15288	16116	15860	18049	91227
	Male	6313	6350	8095	8795	8549	9734	47836
Undergraduate	Combined Genders	17133	16053	19899	21122	20760	23834	118801
	Female	11482	10369	12738	13317	13227	15191	76324
	Male	5651	5684	7161	7805	7533	8643	42477
Professional	Combined Genders	2725	2666	3484	3789	3649	3949	20262
	Female	2063	2000	2550	2799	2633	2858	14903
	Male	662	666	934	990	1016	1091	5359

Notes: The descriptive statistics use the six-month data. The two-year data are similar but have slightly more respondents because fewer program-school groups were dropped from the data due to privacy suppression; refer to Section *B.1.1 f* or more details.

3.3 Methodology and Analysis

Similar previous research studies that examine school and program choices use rich data along with a large number of regressors. Often, these papers use regression models and report regression coefficients for various school and program characteristics.[9] This research study employs a different approach. Although the OUGS data do not contain many variables for school and individual characteristics, their main strength is that they contain a large number of observations for each school-program combination, which makes them ideal for studying the "overall" effects of schools and programs.[10] The approach employed in this study involves a method called relative-importance analysis, which is closely related to linear regression models but does not directly report the regression coefficients. The relative-importance analysis method partitions the sums of the squared deviations from the mean earnings into the earnings variation attributed to programs, schools, school-program interactions and the within-group variation (i.e., the unexplained variation).

The OUGS data contain salaries in a binned format, which is not a suitable format for relative-importance analysis, which requires continuous individual salary observations. The simplest method of converting the binned salary data into individual observations is to assume the midpoint value for each interval. For example, in the first bin \$0 to \$10,000 becomes \$5,000 and, if we suppose that there are three people in that interval, then there would be three observations of \$5,000 used in the analysis; this approach is repeated for all of the bins with the exception of the final one. Indeed, the last bin is open-ended and has no midpoint value. Furthermore, often the first and last several bins have missing values due to privacy suppression. Since the applicable privacy regulations suppress some of these data variables, I cannot determine the exact number of observations within each of these variables; nevertheless, as a result of the suppression rules, I know that the values

[9] Refer to the introduction in Section 3.1 which includes the relevant literature.

[10] In this context, "overall" means that the study is not looking at the effect of any particular school or of any particular set of program characteristics. Instead, the analysis makes a general comparison of the effect of programs and schools on earnings.

are between 1 and 5. In order to deal with these problems, I assume that the samples of the salaries in the binned data are drawn from a log-normal distribution.[11] Therefore the methodology can be summarized into two main parts: first, the estimation of the log-normal distributions from the binned data and, second, the relative-importance analysis which decomposes the variation in the data associated with programs and schools. First, I estimate a log-normal distribution for each combination of gender, university program and school, and then I simulate the salary data according to each of those distributions. Second, I apply the relative-importance algorithm to the simulated salary data. In Section 3.3.2.1, I describe the relative-importance procedure, which also incorporates the uncertainty from each step of the algorithm, in order to construct the confidence intervals for the final results.

3.3.1 Distribution Estimation

The salary distributions are estimated from the binned data using the maximum likelihood method. The salary bins with privacy suppression are treated as a missing-data problem with constraints. I incorporate the missing bins and the constraints into the likelihood function.

The likelihood and log-likelihood functions are as follows:

$$\mathcal{L}(\theta|data)_{yr} = \sum_{a=1}^{Z} \frac{1}{Z}\left[\prod_{i=1}^{B} p(l_{i,yr} \le X \le u_{i,yr}|\theta)^{n_i}\left(\sum_{j=1}^{C}\prod_{k=1}^{M} p(l_{k,yr} \le X \le u_{k,yr}|\theta)^{m_{a,j,k}}\right)\right] \tag{3.1}$$

$$= \frac{1}{Z}\left[\prod_{i=1}^{B}\left[F(u_{i,yr}|\theta) - F(l_{i,yr}|\theta)\right]^{n_i}\sum_{a=1}^{Z}\left(\sum_{j=1}^{C_a}\gamma_{a,j}\prod_{k=1}^{M}\left[F(u_{k,yr}|\theta) - F(l_{k,yr}|\theta)\right]^{m_{a,j,k}}\right)\right], \tag{3.2}$$

$$\ln\mathcal{L}(\theta|data)_{yr} = \ln\left(\frac{1}{Z}\right) + \left(\sum_{i=1}^{B} n_i \ln\left[F(u_{i,yr}|\theta) - F(l_{i,yr}|\theta)\right]\right) + \underbrace{\ln\left(\sum_{a=1}^{Z}\sum_{j=1}^{C_a}\gamma_{a,j}\prod_{k=1}^{M}\left[F(u_{k,yr}|\theta) - F(l_{k,yr}|\theta)\right]^{m_{a,j,k}}\right)}_{for\,suppressed\,data}. \tag{3.3}$$

Also, the log-likelihood is aggregated across the cohorts,

[11] The basis for the assumption is premised on a visual examination of the bar graphs, which represent the aggregated salary distribution within the data and are shown in Section B.1.2 of the appendix.

$$\ln \mathcal{L}(\theta|data)_{aggr} = \sum_{yr=2007}^{2012} \ln \mathcal{L}(\theta|data)_{yr}. \tag{3.4}$$

Subject to the constraints:

$$Total(OE) = MIB(OE) + NMIB = EMP + OE \leq NUMSUR \quad \forall OE, \tag{3.5}$$

$$MIB(OE) = Total(OE) - NMIB = \sum_{k} m_{a,j,k} \quad \forall OE, a, j. \tag{3.6}$$

In the constraint equations 3.5 and 3.6, OE represents the number of people who were offered employment at a later date, a figure that is often privacy suppressed. I assume that the missing values for OE have an equal probability of being between 1 and 5. Let MIB(OE) represent the total number of observations in the missing bins, which is conditional on OE. Let EMP be the total number of employed individuals, and let $NMIB$ be the total number of observations in all of the bins that are not missing. $NUMSUR$ refers to the number of completed surveys. (In this regard, it is important to acknowledge that not all of the individuals who complete the survey are employed.)[12] $Total(OE)$ represents the total number of observations in the bins conditional on the unknown OE. For each possible value of OE, there is a new $Total(OE)$; thus Z represents the number of possible totals of observations in the bins due to data suppression, and a denotes the index for the total.[13] B represents the number of non-missing bins, and n_i represents the number of observations in non-missing bin i.[14] The $u_{i,yr}$ and $l_{i,yr}$ are the upper- and lower-bound cut-off points respectively, and these define the bin intervals.[15] $F(u_{i,yr}|\theta)$ is the log-normal cdf for the upper boundary of bin i conditional on the parameters $\theta = (\mu, \sigma)$, and $F(l_{i,yr}|\theta)$ is the same but for the lower boundary. $F(u_{k,yr}|\theta)$ and $F(l_{k,yr}|\theta)$ are the analogous cdfs, but for the missing bin k.

[12] This fact is represented in constraint equation 3.5.

[13] For example, suppose there are three possible OE values 1, 2 and 3. Furthermore, suppose that $Total(OE) = Total(1) = 10$, $Total(2) = 11$, $Total(3) = 12$. Then, $Z = 3$ because there are three different totals 10,11 and 12.

[14] $NMIB$ is the sum of all n_i, $NMIB = \sum_i n_i$.

[15] The $u_{i,yr}$ and $l_{i,yr}$ depend on the year because of an inflation adjustment (with the base year being 2010).

Given the number of missing bins M and the corresponding $MIB(OE)$, the estimation takes into consideration the many possible sets of permutations. For example, if there are two missing bins, $M = 2$ and $MIB(OE) = 4$, then there are two ways to add up to 4, with one permutation for the first way, {(2,2)}, and two permutations for the second way, $\{(3,1),(1,3)\}$.

Let C_a be the total number of possible permutations; this combines the permutations that all add up in different ways to the same total, $Total(OE)$.[16] Each set of permutations is not equally likely, and therefore there needs to be a weight factor $\gamma_{j,a}$ for each permutation j,a.[17] The weight factor for each permutation within a set that adds up to the observations in the bins in a particular way is going to be the same — that is, (1,3) will have the same weight factor as (3,1). Nevertheless, the weight factor may vary across the different ways of adding up to the same total. In other words, the weight factor is not the same for (2,2) and (1,3). For (2,2), the weight factor is 6 and, for (1,3), the weight factor is 4.[18] The privacy-suppressed observations are denoted by $m_{a,j,k}$, which represents the possible number of observations for part a, in bin k, in permutation j. In equation 3.4, the distribution estimation aggregates across the graduating cohort years, and so the final log-likelihood is the sum of the log-likelihoods for all of the years.

3.3.2 Relative-Importance Analysis: Variance Decomposition

In the context of this paper, the goal of the variance decomposition is to determine whether the schools or the programs in general have a greater effect on their graduates' earnings.

[16]For the example set out above that adds up to $Total(OE) = 4$, $C_a = 3$, because the number of elements across all of the permutations adds up to 3, it follows that $\Big\{\{(2,2)\},\{(3,1),(1,3)\}\Big\}$.

[17]The weight factor γ is as follows:

$$\gamma = \prod_{i=1}^{M} \binom{s_i}{q_i} = \prod_{i=1}^{M} \frac{s_i!}{q_i!(s_i - q_i)!}$$

where $s_i = \sum_{j=i}^{M} q_j$, q_i is the number of observations in bin i, and M is the number of missing bins.

[18]Refer to Section B.2 in the appendix for a detailed example outlining how the weight factor calculation works.

The starting point is the OLS model which is as follows:

$$Y = ln(Y^*) = \alpha + \underbrace{\sum_j X_j \beta_j}_{Programs} + \underbrace{\sum_k X_k \beta_k}_{Schools} + \underbrace{\sum_j \sum_k X_j \times X_k \beta_{jk}}_{Interactions} + \varepsilon \tag{3.7}$$

where Y is the natural log of the annual salary, and X_j and X_k are the indicator variables denoting program j and school k. Finally, β_j and β_k are the regression coefficients for program j and school k. In order to determine the effect on the dependent variable (earnings) of one factor relative to another, we have to establish a methodology to decompose the total variation in the data. The total variation in the data is decomposed into the parts explained by the observable factors in the regression, and into the unexplained parts.

This can be done using a standard sum-of-squares decomposition: Total Sum of Squares (TSS) = Explained Sum of Squares (ESS) + Residual Sum of Squares (RSS),

$$\begin{aligned} \underbrace{\sum_i (y_i - \bar{y})^2}_{TSS} &= \underbrace{\sum_i (\hat{y}_i - \bar{y})^2}_{ESS} + \underbrace{\sum_i (y_i - \hat{y}_i)^2}_{RSS} \\ &= \sum_i (\sum_j x_{i,j} \hat{\beta}_j + \sum_k x_{i,k} \hat{\beta}_k + \sum_j \sum_k X_j \times X_k \hat{\beta}_{jk} - \bar{y})^2 + \sum_i \varepsilon_i^2 \end{aligned} \tag{3.8}$$

where for observation i, y_i denotes the simulated salary from the log-normal distribution, $\hat{y}_i$ is the predicted OLS estimate and $\bar{y}$ is the estimated overall mean salary. Equation 3.8 can be used to form the coefficient of determination $R^2 = \frac{ESS}{TSS}$, which is a percentage of the variation in earnings that can be explained by the independent variables in the regression model. In order to decompose the R^2 further by incorporating multiple explanatory variables into the model, the analysis uses sequential sums of squares. First, the model is estimated with one covariate, and R_1^2 is calculated; then the model is estimated with a second covariate, and R_2^2 is calculated. The amount of variation explained by the first covariate is then said to be R_1^2, and the amount of variation explained by the second covariate is the difference, $R_2^2 - R_1^2$. The main problem with this approach in an unbalanced design is that the order of adding the regressors matters.[19] In this case, since I am interested in programs and schools as groups, there are two possibilities, namely (i) programs + schools and (ii) schools + programs. For (i), indicator variables representing each program enter first into the regression equation (the order of the individual program-indicator variables does not matter because the total sum of squares for the programs will be the same). After the last program-indicator variable enters the equation, the school-indicator variables enter in a similar manner. The same applies for (ii) but in the reverse order. At this point in the analysis, the two possible orderings are yielding two different results. To resolve this issue, I use the LMG approach, as described by Grömping (2007).[20] The LMG approach involves the arithmetic average over the sum of squares for the orderings (i) and (ii).[21]

In summary, the results of the above-described procedure yield the total sum of squares (TSS) and the explained sum of squares (ESS). The explained sum of squares (ESS) are further divided into their respective components, sum of squares attributed to programs, schools, and interactions of schools and programs; each of these are denoted as ESS^{avg}_{prg}, ESS^{avg}_{sch}, $ESS^{avg}_{prg,sch}$, respectively.[22] The leftover variation is the residual sum of squares (RSS).

The analysis uses the following equations to determine the percentage of variation for each component:

$$\text{\% Explained by Programs} = \frac{ESS^{avg}_{prg}}{TSS},$$

[19] An unbalanced design refers to the different sample sizes across groups.

[20] The LMG approach (as cited by Grömping, 2007) was named after and initially introduced by Lindeman, Merenda, and Gold (1980).

[21] The sum of squares for programs from (i) is averaged with the sum of squares for programs from (ii). This process is repeated for the schools and for the interaction effects. There are no mixed orders between schools and programs, such as Sch1 + Prg1 + Sch2 + Prg2. Therefore, there are only two orderings — in this case, program + school and school + program. Interactions always are the last elements to enter into the regressions.

[22] ESS^{avg}_{prg}, ESS^{avg}_{sch}, $ESS^{avg}_{prg,sch}$ are averaged over the orderings (i) and (ii).

$$\%\text{ Explained by Schools} = \frac{ESS^{avg}_{sch}}{TSS},$$

$$\%\text{ Explained by Interactions} = \frac{ESS^{avg}_{prg,sch}}{TSS},$$

$$\%\text{ Unexplained} = \frac{RSS}{TSS}.$$

3.3.2.1 Confidence Intervals

This procedure accounts for the uncertainty that is associated with the salary distribution estimates. Let μ_i and $\widetilde{\sigma}_i$ be the log-normal distribution parameters for group i, and let Σ_i be the corresponding variance-covariance matrix estimated from the procedure in Section 3.3.1.[23] I perform the following steps in order to acquire the standard errors:

1. For each log-normal distribution i, I randomly sample 1,000 values of μ_i and $\widetilde{\sigma}_i$ from the bivariate normal distribution, $N(\Upsilon_i, \Sigma_i)$, where $\Upsilon_i = \begin{bmatrix} \mu_i \\ \widetilde{\sigma}_i \end{bmatrix}$ and $\Sigma_i = \begin{bmatrix} \sigma^2_{\mu,i} & \sigma_{\mu,\widetilde{\sigma},i} \\ \sigma_{\widetilde{\sigma},\mu,i} & \sigma^2_{\widetilde{\sigma},i} \end{bmatrix}$. This results in 1,000 datasets of μ and $\widetilde{\sigma}$ parameters, and thus represents all of the groups.

2. For each set from (1), I simulate the individual salaries for each group, weighted proportionally to the number of people in the original survey. Then I scale the entire set by 5 in order to increase the sample size of the smallest group.[24]

3. I apply the relative-importance procedure outlined in Section 3.3.2, which results in 1,000 estimates for each percentage-of-variation parameter (i.e., a parameter for

[23] In this case, a "group" refers to a particular combination of: gender, program, school. An example might be a female graduate from the humanities program at the University of Toronto.

[24] The smallest group is in the six-month data, and increases from 6 to 30 when scaled by five; however, the two-year data are scaled by five as well.

programs, schools and interactions).[25] These estimates form the basis of the point estimates and of the 95 percent confidence intervals outlined in the results section.[26]

3.4 Results

3.4.1 Estimated Salaries

Table 3.2 reports the estimated median salaries across the various undergraduate programs, and Table 3.3 reports the estimated median salaries for the various professional-degree programs; both tables report salaries at the six-month and two-year milestones following graduation respectively. The tables show an increase in salaries from six months to two years after graduation for every program. The undergraduate programs with the greatest increase in median salary were food science and nutrition, kinesiology and journalism, which all increased by more than 25 percent. However, these programs also had the lowest median salaries at six months following graduation.

The programs described in the tables are ordered from the highest earning to the lowest earning. The high-earning programs tend to be STEM-related programs or to require many STEM subjects.[27] For example, many high-earning undergraduate programs are health related, including pharmacy and nursing, and mathematics related, including engineering, computer science and business/commerce. Similarly, high-earning professional degrees tend to be health related, including dentistry and optometry.

There is a substantial disparity among median salaries across undergraduate programs. There are many programs for which the median salaries are in the $40,000 to $50,000 range; examples are engineering and computer science. Moreover, there are many programs for which the median salaries are in the $20,000 to $30,000 range; examples are

[25] I repeat all of the steps for the six-month and two-year data.

[26] The average is the point estimate, and the percentile placements of the ordered values form the confidence intervals.

[27] STEM stands for science, technology, engineering, and mathematics.

the humanities and kinesiology. The professional degrees mostly yield higher salaries than the undergraduate degrees, which is a reasonable outcome given the fact that they also require more education. Some exceptions are the education programs (teacher training) and theology, which would be at the lower end of the undergraduate salary spectrum.[28]

[28] Refer to Chapter 1 of this thesis for the reasons why teacher salaries are so low.

Table 3.2: Estimated Median Salaries by Undergraduate Programs at Six Months and Two Years

Programs	Period After Graduation				
	(2010 $) Median Salary (95 % C.I.)		%Δ (6 Mos	N Sample[29]	
	6 Months	2 Years	to 2 Yrs)	6 Mos	2 Yrs
Pharmacy	76006	84896	12%	588	598
	(69735–82998)	(79341–90932)			
Nursing	52775	55172	5%	5548	5813
	(50675–55006)	(53061–57437)			
Engineering	49780	55578	12%	7505	8539
	(47583–52134)	(53301–58069)			
Computer Science	47997	54421	13%	1687	1869
	(43703–52948)	(49658–59851)			
Therapy and Rehab.	44683	49377	11%	96	95
	(41013–48732)	(44907–54361)			
Mathematics	40778	46258	13%	1089	1385
	(36845–45907)	(42037–51307)			
Business/Commerce	40044	46741	17%	14058	15136
	(38301–41890)	(44798–48789)			
Forestry	35957	41901	17%	20	25
	(29454–43896)	(35301–49735)			
Health Professions	34231	38476	12%	1868	2106
	(30394–38736)	(34600–42967)			
Other Arts and Science	32413	35893	11%	3344	3644
	(28511–37134)	(31680–40959)			
Archit. & Lands. Archit.	30302	31545	4%	402	319
	(25911–35659)	(25932–40322)			
Physical Sciences	27005	28916	7%	698	876
	(21018–34970)	(22985–36569)			
Journalism	26336	33309	26%	345	393
	(23077–30587)	(29946–37173)			
Social Sciences	25995	31320	20%	22466	25261
	(24713–27366)	(29899–32825)			
Agr. and Bio. Sciences	23183	28375	22%	4577	5027
	(20792–25991)	(25465–31756)			
Food Science/Nutrition	22787	30161	32%	884	1104
	(20659–25376)	(27589–33238)			
Kin./Recr./Phys. Ed.	22675	29141	29%	3208	3619
	(19926–25910)	(25930–32827)			
Humanities	22044	27164	23%	10772	12456
	(20441–23845)	(25388–29125)			
Fine and Applied Arts	19858	23664	19%	3790	4299
	(17668–22577)	(21066–26863)			

Table 3.3: Estimated Median Salaries by Professional Programs at Six Months and Two Years

Programs	Period After Graduation (2010 $) Median Salary (95 % C.I.) 6 Months	2 Years	%Δ (6 Mos to 2 Yrs)	N Sample 6 Mos	2 Yrs
Dentistry	109415 (71633–178922)	200440 (85113–694340)	83%	163	155
Optometry	80043 (68539–93620)	103330 (87069–125218)	29%	188	188
Veterinary Medicine	63513 (59809–67565)	67212 (63058–71729)	6%	253	238
Medicine	54177 (51356–57262)	63586 (58356–70457)	17%	1006	1069
Law	53721 (49636–58180)	64943 (59681–70723)	21%	2487	2535
Education (Teacher Training)	29688 (28237–31231)	35494 (33960–37111)	20%	12815	14051
Theology	27665 (19400–40669)	29981 (22974–40289)	8%	83	102

3.4.2 Employment Rates and the Proportion of Survey Respondents that Acquired Jobs

The estimation of the salary distributions and the subsequent relative-importance analysis exclude unemployed graduates, as well as those individuals who were not included in the labour force. The average employment rate was 88 percent for undergraduate-degree holders and 90 percent for professional-degree holders at the six-month milestone following graduation. The employment rates were slightly higher at the two-year milestone following graduation; at this point, the average employment rate was 93 percent for undergraduate-degree holders, and 95 percent for professional-degree holders. The employment rates were relatively high and similar across all programs, and thus the exclusion of unemployed graduates should not have a significant impact on the results. The complete list of employment

[29]The N sample refers to the number of employed graduates and, as a result of privacy suppression, it is calculated as the midpoint between the minimum and the maximum possible number of employed individuals.

rates by program can be found in Tables B.29 and B.30 of Appendix Section B.2.3.[30]

The proportion of survey respondents who found a job, denoted as EMPSURV, is determined through a calculation that is slightly different from the calculation that is used to determine the employment rate because it also considers graduates who were not in the labour force (usually because they went back to school). The resulting values of the EMPSURV rate are similar to the employment rates for professional-degree holders because it is less likely that those graduates will continue their studies. However, among individuals who completed an undergraduate degree, the EMPSURV rate results vary substantially from the employment rates for certain programs. For example, fewer than 60 percent of survey respondents from the physical sciences, the agricultural and biological sciences, and the health professions had found a job at the six-month milestone after graduation. The six-month employment rates were much higher for these programs, namely 83 percent for the physical sciences, 85 percent for the agricultural and biological sciences, and 86 percent for the health professions. For those in the labour force, 88 percent had found a job at the six-month milestone after graduation, while only 70 percent of survey respondents had found a job at that point in time.

It is not clear whether the exclusion of graduates who were not in the labour force biases the results one way or the other. The implicit assumption is that the graduates who were not in the labour force would draw their salary from the same distributions as those who were in the labour force.[31] For the results to be unbiased, this assumption would have to be true.

[30]The definition of the employment rate is the proportion of graduates who found (or who were offered employment to begin at a later date in) a full- or part-time job conditional on searching for a job and not being in school. Refer to Section B.2.3. for the detailed calculations.

[31]In other words, the assumption seems to contend that the only difference between the graduates is that some of them chose not to be in the labour force.

3.4.3 Relative-Importance Analysis

I estimate 24 different specifications of the model. There are four program-group categories based on the type of degree: combined programs, undergraduate programs, professional programs and professional programs other than dentistry — also denoted as professional (no dentistry). Within each program category, I estimate the specifications of the model based on gender (male, female, and combined genders) and based on two periods after graduation (six months and two years). The combined-genders category refers to a specification in which the genders were combined in the estimate. The combined-programs category consolidates all of the available programs in the data and thus includes both undergraduate- and professional-degree programs. The undergraduate category only includes programs that lead to a bachelor's degree and do not require a prior degree as a prerequisite for admission.[32] The professional category includes programs that require previous post-secondary education as a necessary condition for admission. The professional (no dentistry) category excludes dentistry because the estimated values for that category are less reliable due to the small sample sizes as well as due to the large number of observations falling into the open-ended salary bin (>$100,000). This is evident from the wide confidence intervals for the dentistry median salaries as set out in Table 3.3 of Section 3.4.1.[33]

Table 3.4 reports the results for the six-month data, and Table 3.5 reports the results for the two-year data.[34] I start with the most straightforward estimates which include combined genders and combined programs together. For the six-month data denoted as specification (A1), the programs account for 21.8 percent of the variation in earnings while the schools account for only 2.1 percent of the same; this disparity is slightly over 10 times the dif-

[32]The education programs (namely teacher training) are in the professional-degree category. Although there are education-degree programs that admit students straight from high school, these programs are still predominantly offered at the graduate level.

[33]For the two-year data, the range of the confidence interval for the median dentistry salary is $609,227.

[34]The specifications are labelled by letters for each row (A–H) and by numbers for each column (1–3). For example, (A3) refers to the specification that includes "combined programs" for males using the six-month data.

ference. The interactions account for 2.9 percent of the earnings variation which is similar to the school variables.[35] The total explained variation in earnings is 26.8 percent, which means that just under three-quarters of the variation is due to unexplained factors; the latter might presumably be attributable to various individual characteristics such as ability, personality and workforce connections. Similarly, for the two-year data denoted as specification (E1), the programs explain 18.9 percent of the earnings variation, while the schools explain 2.5 percent of the same, which is only around eight times the difference (in comparison with the six-month case and the scenario of 10 times the difference).

The 22 other specifications examine the earnings variation for each combination of degree type and gender for both the six-month and the two-year data. Separate regressions were performed for females and males because of the gender differences in the numbers of people within the programs, and because of the gender differences in the salaries of the graduates from each program. Overall, 66 percent of the graduates are female; however, there are also large gender disparities in the number of graduates from certain programs; for example, there are 5,701 female nurses and only 398 male nurses, while there are 8,219 male engineers and only 206 female engineers. The differences in the program mix across genders may potentially affect the levels of earnings variation that can be attributed to programs. For instance, a skewed proportion of individuals towards the lower- or higher-paying programs would produce less earnings variation than an equal number of individuals in those programs.

Furthermore, there are gender differences in salaries across programs. Males earn more than females in all programs except for computer science, the health professions and journalism, and they do so at both the six-month and the two-year milestones after graduation.[36] The gender differences in salary may in part be due to the gender differences in part-time

[35] The convention in this type of analysis is to examine the main effects first and then always to add the interaction term at the end of the process to examine the leftover variation that is not accounted for by the main effects.

[36] In medicine the salaries are similar, males earn slightly more at six months since graduation, and females earn slightly more at two years after graduation.

rates. Table B.33 of Appendix Section B.2.5 shows that the part-time job rates are higher for females for both undergraduate and professional degrees. Sections B.2.2 and B.2.5 show median salaries and part-time rates by programs and gender. Programs with a higher proportion of part-time earners tend to have lower median salaries. A skewed proportion of individuals at the lower salary level may reduce the earnings variance of that particular program.

The notable result across all specifications, (A1) to (H3), is that the programs account for the majority of the explained variation when compared with the schools and the interactions. A separate examination of the undergraduate and professional-degree groups for the six-month data reveals that the program variables affect earnings to a greater extent for members of the undergraduate group than for members of the professional-degree group. For specification (B) which uses the six-month data, the undergraduate programs account for 21.5 percent of the variation, while the schools account for 2.6 percent of the variation, which is slightly greater than eight times the difference. However, professional-degree programs account for 17.6 percent of the variation, while the schools account for 5.3 percent of the same, which is only slightly greater than three times the difference. When comparing the six-month data specifications across genders, (A–D, 2–3), there are no statistically significant differences for the schools and the interaction effects; however, there are statistically significant differences for the programs for both the undergraduate and the professional degrees.[37] For the undergraduate group specifications, (B2) and (B3), the programs account for 20.7 percent of the variation for the females and for 18.9 percent of the variation for the males, a difference of only 1.8 percentage points. For the professional group specifications, (C2) and (C3), the programs account for 15.2 percent of the variation for females and for 20.6 percent of the variation for males, a slightly greater difference of 5.4 percentage points in the opposite direction when compared with the undergraduate group.

[37](A–D,2–3) refers to specifications in rows A to D and columns two and three of Table 3.4.

The pattern for the two-year data is similar to that for the six-month data in that the programs account for substantially more earnings variation than both the schools and interactions in every specification. The main notable difference is that, for the undergraduate group, the program variables explain less of the variation within the two-year data than within the six-month data. The interaction and the school variables account for roughly the same amount of earnings variation in all of the specifications for the undergraduates across the six-month and the two-year data. Another difference between the results from the six-month and the two-year data is that the programs account for less of the earnings variation for undergraduate degrees than for professional degrees in the two-year data, a result that is the opposite of that for the six-month data. For (F1), undergraduate programs account for 17.8 percent of the variation in earnings, while for (G1), professional programs account for 19.4 percent of this variation. However, this anomaly might be attributable to the dentistry program because the dentistry salary distribution estimates are substantially noisier for the six-month data than for the two-year data. From (H1), the specification that excludes dentistry, programs account for 16.2 percent of the variation in earnings, which is lower than the 17.8 percent for undergraduate programs from the two-year data. The patterns across genders for the two-year data are similar to those for the six-month data with the main difference being that there is no statistically significant gender difference for undergraduate programs. When comparing specifications (F2) and (F3), they are almost identical.

Table 3.4: Relative-Importance Analysis for Salaries at Six Months

Type of Degree	Regressors	Gender: 1) Combined Genders	2) Female	3) Male
		Proportion of Earnings Variation : (95 % C. I.)		
(A) Combined Programs	Programs	0.218	0.208	0.202
		(0.213–0.223)	(0.203–0.213)	(0.193–0.212)
	Schools	0.021	0.021	0.027
		(0.020–0.023)	(0.019–0.023)	(0.023–0.030)
	Programs × Schools	0.029	0.032	0.038
		(0.027–0.032)	(0.029–0.035)	(0.033–0.045)
	Total R^2	0.268	0.262	0.267
		(0.263–0.273)	(0.256–0.268)	(0.257–0.279)
(B) Undergraduate	Programs	0.215	0.207	0.189
		(0.210–0.220)	(0.201–0.212)	(0.181–0.199)
	Schools	0.026	0.027	0.032
		(0.024–0.028)	(0.025–0.030)	(0.028–0.035)
	Programs × Schools	0.029	0.032	0.038
		(0.026–0.032)	(0.029–0.036)	(0.032–0.046)
	Total R^2	0.270	0.266	0.259
		(0.265–0.276)	(0.259–0.273)	(0.248–0.271)
(C) Professional	Programs	0.176	0.152	0.206
		(0.165–0.188)	(0.141–0.164)	(0.179–0.235)
	Schools	0.053	0.053	0.059
		(0.048–0.060)	(0.047–0.060)	(0.047–0.072)
	Programs × Schools	0.008	0.007	0.015
		(0.005–0.013)	(0.005–0.011)	(0.005–0.034)
	Total R^2	0.238	0.213	0.279
		(0.224–0.252)	(0.200–0.226)	(0.245–0.315)
(D) Professional (No Dentistry)	Programs	0.157	0.137	0.175
		(0.148–0.167)	(0.128–0.147)	(0.154–0.196)
	Schools	0.054	0.054	0.060
		(0.048–0.061)	(0.048–0.061)	(0.048–0.073)
	Programs × Schools	0.006	0.007	0.009
		(0.004–0.009)	(0.004–0.010)	(0.004–0.015)
	Total R^2	0.218	0.198	0.243
		(0.207–0.230)	(0.186–0.211	(0.218–0.268)

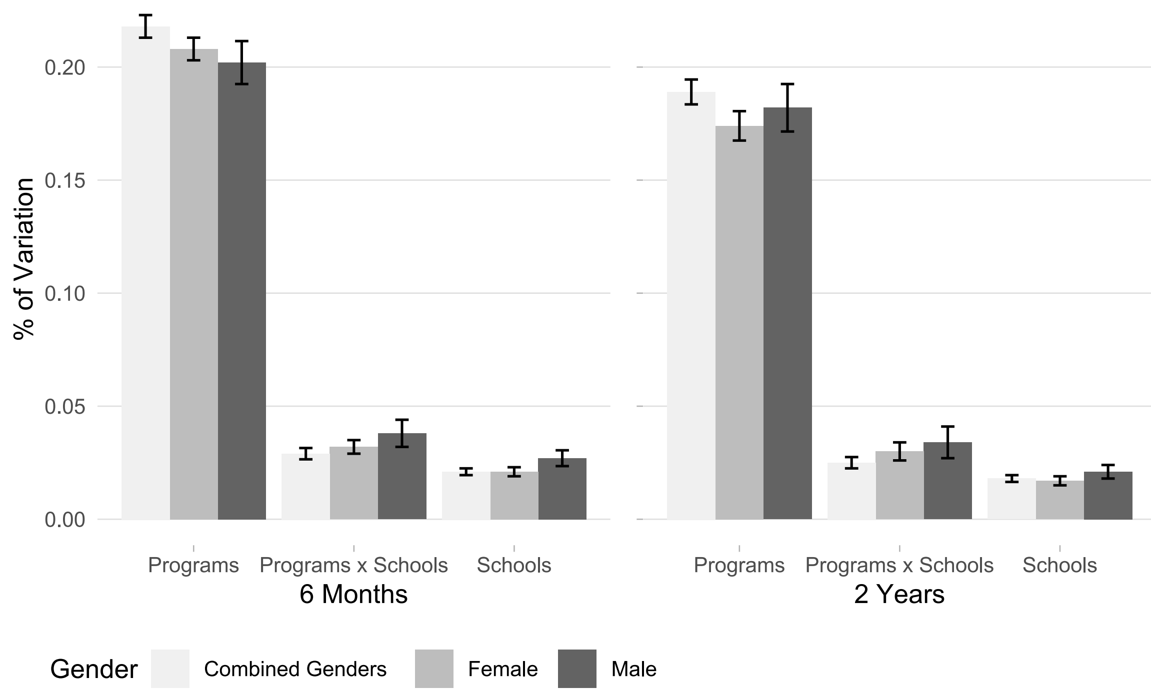
Table 3.5: Relative-Importance Analysis for Salaries at Two Years

Type of Degree	Regressors	Gender: 1) Combined Genders	2) Female	3) Male
		Proportion of Earnings Variation : (95 % C. I.)		
(E) Combined Programs	Programs	0.189 (0.184–0.195)	0.174 (0.168–0.181)	0.182 (0.172–0.193)
	Schools	0.018 (0.016–0.019)	0.017 (0.015–0.019)	0.021 (0.018–0.024)
	Programs × Schools	0.025 (0.023–0.028)	0.030 (0.027–0.035)	0.034 (0.028–0.042)
	Total R^2	0.233 (0.227–0.239)	0.221 (0.214–0.231)	0.237 (0.226–0.250)
(F) Undergraduate	Programs	0.178 (0.173–0.182)	0.162 (0.157–0.167)	0.161 (0.153–0.170)
	Schools	0.022 (0.020–0.023)	0.021 (0.019–0.023)	0.025 (0.022–0.029)
	Programs × Schools	0.024 (0.021–0.026)	0.027 (0.024–0.030)	0.034 (0.028–0.044)
	Total R^2	0.223 (0.218–0.228)	0.210 (0.204–0.216)	0.221 (0.210–0.233)
(G) Professional	Programs	0.194 (0.174–0.216)	0.167 (0.146–0.191)	0.235 (0.195–0.281)
	Schools	0.054 (0.048–0.060)	0.057 (0.050–0.064)	0.055 (0.043–0.067)
	Programs × Schools	0.009 (0.004–0.021)	0.016 (0.006–0.043)	0.013 (0.006–0.026)
	Total R^2	0.257 (0.236–0.282)	0.240 (0.212–0.285)	0.303 (0.260–0.350)
(H) Professional (No Dentistry)	Programs	0.162 (0.152–0.172)	0.139 (0.129–0.150)	0.186 (0.165–0.209)
	Schools	0.055 (0.049–0.060)	0.058 (0.052–0.065)	0.055 (0.042–0.069)
	Programs × Schools	0.006 (0.004–0.009)	0.007 (0.004–0.012)	0.011 (0.006–0.018)
	Total R^2	0.223 (0.211–0.235)	0.205 (0.193–0.219)	0.252 (0.224–0.282)

Figure 3.1 summarizes Tables 3.4 and 3.5, which make it clear that the degree programs account for substantially more of the variation in earnings than the schools. Further, the overlapping error bars make it easy to see that there are no statistically significant differences between the genders for most of the variables, except for the two-year earnings for

the program degrees, where the earnings variation for females is slightly lower than for the combined-genders category.

Figure 3.1: Relative-Importance Analysis: Combined Programs at Six Months and Two Years



3.5 Discussion and Conclusion

In this paper, I examine whether the school or the program choice has a more substantial impact on the salaries of recent university graduates. In particular, I use a relative-importance analysis method, which involves a sum-of-squares decomposition to analyze the differences in the variation in salaries across programs, schools and school-program interactions, as well as to examine any unexplained variation.

The results show that the program variables account for substantially more of the variation in earnings than the school variables, and that is the case in both the undergraduate and the professional-degree groups. For the undergraduate level, with respect to salaries at the six-month milestone after graduation and at the two-year milestone after graduation, the program variables accounts for about six to eight times more of the variation in earnings than that which is accounted for by the school variables. Moreover, with respect to the professional level at the six-month and the two-year milestones after graduation, the programs account for about three to four times more of the earnings variation than the schools. The school-program interaction effects account for roughly the same amount of variation in earnings as the school variables at the undergraduate level, or for around 2.1 to 3.8 percent of the variation in the same. At the professional-degree level, the school-program interaction effects on the variation in earnings were much lower than those of the school variables, or were around 0.6 to 1.5 percent.

It is also important to highlight first the fact that between around 70 to 80 percent of the variation is unexplained, and second the likelihood that at least some portion is attributable to individual characteristics, such as personality, intelligence, and talent. The results provided in this paper may be useful to prospective university students in differing ways, depending on their personal and professional goals. For example, at the undergraduate level, if the student has not yet selected the program that he or she is going to take, then any school should be as good as any other. However, if the individual has his or her heart set on a specific program, then the interaction effects (which are virtually equal to the school effects for undergraduates) suggest that there are some program-school combinations that require closer attention during the decision-making process. Moreover, the results do not specify any direction, and some program-school combinations may yield below- or above-average earnings. It conceivable that some schools specialize in particular subjects and produce excellent graduates, while other schools — even those with an otherwise strong reputation — might be weak in those subjects. This study is descriptive and, hence, there also could be other explanations. For example, a particular program could be offered at a school in an area of the province where the employment and overall economic opportunities are better; this scenario would make it more likely that graduates from that school would receive a higher salary than graduates from equivalent or similar programs offered at schools in areas with fewer opportunities. Finally, if individuals would like to maximize their earnings, they should mostly be concerned with their choice of program. We should interpret the results for the professional-degree level with more caution. Even though program choice matters to an extent that is substantially greater than school choice as a result of the fact an undergraduate degree is generally an admission requirement for a professional program, many students might have limited their options at a premature stage of their post-secondary academic career. For example, if an individual took a humanities undergraduate degree, he or she might have a difficult time gaining acceptance into medical school; in that sense, program choice takes on a different meaning. Given the fact that program choices are more limited at the professional-degree level, the results are even less conclusive because the school decision might matter to an even greater or an even lesser extent than the result might imply. The number of school choices at the professional level might also be limited because some programs are only offered by a few schools; for example, in the data only two schools offer dentistry, and optometry and veterinary medicine are only available at a single school.

In Canada, the post-secondary education system appears to be more standardized than in the United States. Canada has a higher proportion of relatively large, publicly funded schools, and the expectation is for the greater homogeneity in the system to produce a smaller amount of variation in salaries that can be attributed to schools. Since the popular culture in the United States often emphasizes the role of prestigious schools in being "better," as evidenced by the recent bribery scandal, some people will go to great lengths to gain admission (Nadworny & Kamenetz, 2019). However, it is not entirely clear whether these differences in prestige translate into differences across salaries.

In the U.S., "getting into a top program" can have a drastically different meaning than in Canada. The presence of "Ivy League" schools establishes a more explicit benchmark and aspirational standard for the prestige of U.S. institutions. The Canadian university system is generally much more homogeneous than that of the U.S., and this is the case according to several measures. In the United States, the College Scorecard website hosted by the U.S. Department of Education lists 2,441 accredited institutions that offer a four-year bachelor's program, of which 692 are public, 1,340 are private non-profit, and 409 are private for-profit; around 59 percent of these institutions have fewer than 2,000 undergraduates (U.S. Department of Education [DoED], n.d.).

On the other hand, in Canada, there are currently 96 universities, of which 86 offer undergraduate degrees and of which only around 21 percent have fewer than 2,000 undergraduates Universities Canada (UC, n.d.). Moreover, the relatively standardized definitions for the categories of programs in the data make it relatively convenient to compare them across schools.

This paper emphasizes the finding that, since schools do not explain a large proportion of the variation in earnings, students should not feel disadvantaged if they are unable to attend the one of the most prestigious institutions. This is important because an uninformed decision about either the school or the degree program has the potential to be costly for students if there is an academic mismatch in terms of the students having overly optimistic expectations about their performance and grades in a particular school or program. Many students who struggle academically have to switch their program and school or even drop out altogether — an outcome that is likely to be expensive and demoralizing. For instance, T. R. Stinebrickner and Stinebrickner (2012) found that, when students initially enter university, they on average have inflated expectations for their grade performance, and those who drop out often do so because they learn about their actual academic ability. Further, Astorne-Figari and Speer (2019) found that students with low grades not only tend to switch programs but also tend to switch into less-related programs depending on how low their grades are.[38]

[38] "Less related" refers to the similarity in the curriculum. Some subjects are more similar than others; for example, accounting and business are more related than accounting and English.

Chapter 4

How Much Do Teachers Earn Outside the Public Education System? Evidence from Ontario, Canada

4.1 Introduction

Previous research has shown that high-quality teachers are a prerequisite for student achievement (Hanushek & Rivkin, 2006). Therefore, it is of utmost policy relevance to attract and retain the highest-quality teachers, and one way to do this is by gaining and implementing an understanding of the ways in which teachers make labour-supply decisions. Economists are typically interested in the factors that teachers consider when they make decisions whether to enter, stay in or exit the teacher workforce. Ordinarily, the modelling of these decisions requires the teacher or the prospective teacher to compare the teaching salary to the salary that he or she would have received if he had chosen a different career path. Thus, a fundamental aspect of understanding these decisions is comprised of the opportunity cost of teaching. The main goal of this study is to estimate the outside options of recent Ontario teachers' college graduates from the 2007 to 2013 graduating cohorts.[1]

This study uses data provided by the Ministry of Training, Colleges and Universities. The views expressed in this study are my own and do not necessarily reflect those of the Ministry.

[1] In this study, a "teacher" is a graduate who has found a permanent Ontario public-school teaching job. On the other hand, "non-teaching option/job" and "outside option/job" refer to any position other than that of a permanent Ontario public-school teacher (including a private-sector teacher and a non-permanent public-school teacher; as well as non-teaching positions).

Furthermore, I estimate public-school teaching salaries of members of these cohorts and compare them with the non-teaching salaries of other members of the same.

Little is known about this opportunity cost or about the outside options because it is difficult to obtain suitable data. Typically, in order to estimate this opportunity cost, longitudinal data are needed; the gathering of these data would require the researcher to follow the teachers over an extended period of time and to potentially observe them in alternative occupations. Another issue is that, since the main objective is to understand how much teachers would earn in a non-teaching position, the ideal data for this estimation would contain many teachers' college graduates who randomly chose a non-teaching job. In reality, most teachers' college graduates work as teachers for an extended period, and those who exit the profession often leave the workforce altogether for family reasons; this leaves very few opportunities to observe teachers in alternative occupations (T. R. Stinebrickner, 2002).

One of the contributions of this paper is based on the fact that I take advantage of a unique environment in Ontario, Canada, where, instead of the more prevalent context in which there are more available jobs than qualified teachers (i.e, a teacher shortage), the teacher labour market has experienced a surplus since around 2005. As is stated in Chapter 1, the probability of a 2006 Ontario teachers' college graduate acquiring a full-time teaching position in the Ontario public school system in the first year was around 14 percent — a figure that had fallen to under 5 percent by 2013 for that year's graduating cohort. The one benefit of this environment is that, due to these low employment rates in public schools, the salary distribution of Ontario teachers' college graduates is mostly comprised of individuals who are not full-time public-school teachers. Moreover, the examination of this opportunity cost over time as it became increasingly challenging to acquire a teaching position can provide insight into the relationship between the teaching employment rate and the non-teaching income of teachers' college graduates.

Even though the Ontario teacher labour market has many of the characteristics of the ideal environment, as mentioned above, in regard to examining teachers' outside options, access to suitable data still comes with certain challenges. For example, traditional Canadian labour datasets, such as the Survey of Labour and Income Dynamics (SLID) and the National Graduate Survey (NGS), do not contain enough teachers.[2] I overcome this issue by utilizing four separate types of data source, and one strength of these data is that they are recent, as they pertain to the graduating cohorts of 2007 to 2013 — an ideal time frame given the fact that it coincides with the teacher-surplus labour market.[3]

The first data were drawn from the Ontario University Graduate Survey (OUGS), which is a restricted-access dataset administered by the Ontario Ministry of Training, Colleges and Universities. The data contain salaries at six months and two years after graduation for male and female education-program graduates who are working in teaching and non-teaching positions. The main benefit of these data is that they are focused on Ontario alone and therefore contain relatively large sample sizes for graduates of Ontario teacher-education programs.

For the data referred to hereunder as "teacher data," I created a new and unique dataset by web scraping, processing and combining teacher profiles from the Ontario public register of individuals who are licensed to teach in Ontario.[4] The data are used to determine how likely it was for teachers' college graduates to acquire a teaching job. One of the strengths of these data is that they encompass almost the entire population of teachers in Ontario and exclude only those teachers who did not register with the Ontario College of Teachers.[5]

For this study, I specifically created a third set of data, referred to as "salary-grid data," by collecting and combining salary information from Ontario teachers' collective agreements. These data were used in combination with the "teacher data" to determine the

[2]The popular U.S. National Longitudinal Study of 1972 (NLS-72) over-sampled teachers in order to overcome this problem. To the best of my knowledge, there are no Canadian datasets that do this.

[3]Note that this is true with the exception of the QECO data which are only valid for the 2015 year; however, I assume that they are also valid for the years in the study. Refer to Section 4.2 for more details.

[4]The teacher profiles are publicly available on the Ontario College of Teachers (OCT) website (OCT, 2019b).

[5]The Ontario College of Teachers regulates and certifies all public-school teachers in the province. Refer to Chapter 1 for more details related to teaching-profession requirements in Ontario.

number of teachers' college graduates who had found a teaching job as well as these individuals' teaching salary. To the best of my knowledge, up until the present, there are no other sets of Ontario teacher salary data that contain a comprehensive collection of public-school salaries across the various qualification levels. The fourth type of data source comes from two Qualifications Evaluation Council of Ontario (QECO) documents. The first document contains regulations that outline the ways in which teaching experience and education level translate into teachers' qualification category placement in the teaching salary grids. For example, there are 10 principal ways of qualifying for the A2 qualification category, such as completing a four-year undergraduate degree or a three-year degree with at least a second-class standing.[6] The second document contains QECO presentation materials that provide information about how likely it was for a teacher to be in particular qualification categories. These "teacher data" in combination with the "salary-grid data" and the QECO documents were then used to determine the salaries of the teachers' college graduates who had acquired a permanent teaching position in the Ontario public school system. The information pertaining to the teaching salaries of Ontario teachers' college graduates were then combined with the OUGS salary dataset, which contains the salaries of teachers' college graduates who work as a public-school teacher and the salaries of those who work in a position outside the Ontario public school system, to estimate the salaries for just the outside-option jobs.

The most closely related literature examines the ways in which non-teaching salaries (or relative teaching salaries) contribute to teacher mobility — in terms of entering and exiting the teaching profession (i.e., starting a family), as well as switching occupations. For instance, Manski (1987) found that increasing teachers' relative earnings attracts a greater number of both low- and high-ability students, and Hanushek and Pace (1995) found that teachers' relative earnings have little effect on who becomes a teacher. Dolton and Make-

[6]Qualification categories range from A1 to A4, with A1 being the lowest qualification category with the lowest salary level and A4 being the highest qualification category with the highest salary level. Technically there is also an A qualification category; however, this does not require a university degree and therefore does not apply to any current recently hired teachers.

peace (1993) found that increases in relative earnings increased the labour-market participation of female teachers in the United Kingdom. Further, Murnane and Olsen (1989a, 1989b, 1990), Murnane, Singer, and Willett (1989) and T. R. Stinebrickner (1998) found that teachers who received a relatively large salary remained in the teaching profession for more years. Ortega (2010) found that, in Venezuela, relative earnings between the teaching profession and various non-teaching professions make little difference in terms of attracting people to teaching. Moreover, Gilpin (2011) found that the work environment had a greater effect on attrition than relative-income differences between the teaching profession and other professions and that relative earnings only mattered for teachers with fewer than six years of teaching experience. Similarly, Feng (2009) showed that teacher attrition is more sensitive to working conditions than to income differentials with other occupations. She reports that a 12 percent salary increase, which would make the average teacher salary equal to those available through the outside option, would only increase teacher retention by a mere 0.48 percentage points. For a comprehensive review of the literature on the relationship between teacher supply and income level, refer to the handbook chapter in Dolton (2006).

In this study, I examine the opportunity cost of teachers' college graduates and compare it with teaching salaries. The results indicate that the outside-option salaries varied substantially across cohorts, genders and periods since graduation; the median outside-option salary was highest at $45,357 for the 2007 male cohort at the two-year milestone since graduation, while the lowest was $23,822 for the 2013 female cohort at the six-month milestone since graduation. In contrast, teaching salaries did not vary to any great extent across any of the factors; the median teaching salary was highest at $49,706 for the 2011 male cohort at the two-year milestone since graduation and lowest at $46,800 for the 2007 female cohort at the six-month milestone since graduation. Furthermore, when comparing salaries among members of the same graduating cohort year, teachers at the median earned more than those graduates who found an outside job, both for males and females and for salaries six months and two years after graduation. In this regard, the greatest difference was found to be among the 2012 females six months after graduation when the median teaching salary was 103 percent higher than the median outside-job salary, while the smallest difference was found to be among the 2007 males two years after graduation when the median teaching salary was only 5 percent higher than the median outside-job salary. There were no statistically significant gender differences across teaching salaries within the same cohort year and within the same time period since graduation. For the outside option, there were gender differences in earnings at both the six-month and the two-year milestones since graduation; more specifically, males earned between 20 and 30 percent more than females at the six-month milestone and between 13 and 30 percent at the two-year milestone. Further, the later cohorts (namely 2012 and 2013) earned more through the outside option than the earlier cohorts (namely 2007 and 2008). It is imperative to note that these results are descriptive and not causal because, for example, students may be selecting into teachers' college according to their ability; something this study cannot address due to data limitations. Nevertheless, I believe that this study provides a useful step in furthering the understanding of the opportunity costs of teaching and how they are related to teaching salaries.

Section 2 shows the data and descriptive statistics, Section 3 introduces the analysis methodology, Section 4 contains the results, and Section 5 presents the conclusion and discussion.

4.2 Data

This study uses four distinct sources of data: 1) the Ontario University Graduate Survey (OUGS); 2) the "teacher data"; 3) the "salary-grid data"; and 4) the Qualifications Evaluation Council of Ontario (QECO) data. The OUGS data contain aggregated binned salaries of Ontario teacher education program graduates. The "teacher data" are employed to estimate the probabilities of acquiring a teaching job in the Ontario public school system, as well as the probabilities of being placed in the highest qualification category. The "salary-grid data" are employed to determine the likelihood of particular teaching salaries falling within specific bin intervals for particular years of experience and for particular qualification levels. Furthermore, the QECO data help to determine several probabilities that were difficult to obtain reliably from the other data sources (Qualifications Evaluation Council of Ontario [QECO], 2016).[7]

Chapters 1 and 2 provide more details about the "teacher data" and the OUGS data respectively. In Chapter 1, I use the "teacher data" to explore the amount of time required to find a teaching job in Ontario. In Chapter 2, I use the OUGS data to examine the relative effects of degree programs and schools on earnings.

4.2.1 Ontario University Graduate Survey (OUGS)

The Ontario University Graduate Survey (OUGS) is a restricted-access data source provided and administered by the Ontario Ministry of Training, Colleges and Universities (MTCU, 2013). The portion of the data for this study pertains to Ontario teachers' college graduates from the 2007 to 2013 cohorts and include part- and full-time salary information collected at six months and two years after graduation for both males and females. The salaries within the data are aggregated into bins; these are equal-sized $10,000 intervals for the first 10 bins (i.e., bin 1 is [$0,$10,000], bin 2 is [$10,001,$20,000] and so on), while the last bin is an open-ended interval of ≥ $100,000. Refer to Chapter 2 for more details about the OUGS data.

The analysis excludes all of the graduates who did not find any employment. This study considers a graduate to be employed if he selected as applicable one of the following survey statements: "Offered Employment," "Employed in a Paid Job (PT/FT)" and "Self-employed." Table 4.1 lists the samples sizes by graduating-year cohort, gender and

[7] QECO is an organization that evaluates teacher credentials for salary-grid category placement.

the amount of time that has elapsed since graduation, while “Num” refers to the number of individuals covered by the survey and “Empl” refers to the total number of employed individuals. The sample sizes were larger for the later cohorts (2010 and beyond) for both males and females. Further, there were significantly more females than males; the proportion was around 75 to 80 percent female depending on the cohort, a finding that is consistent with Statistics Canada data that shows that the female proportion of all teacher-education graduates in Ontario ranged between 76 and 78 percent over the same period (Statistics Canada [StatCan], 2019).

The implicit assumption is that the graduates who did not seek or find any type of employment would draw their salary from the same known salary distribution as the employed individuals. Even if there is a violation of this assumption, given the fact that the percentage of employed individuals in the data is relatively high (ranging between 78 and 92 percent six months after graduation and between 88 and 96 percent two years after graduation), it follows that, if there is any bias, it should not be substantial.[8]

[8]It is worth emphasizing that this is similar to but not precisely the employment rate because it includes graduates who were not in the labour force since they were not looking for work due to schooling and other reasons.

Table 4.1: OUGS: Sample Size by Cohort, Gender and Period Since Graduation

		Cohort (Graduating Year)						
		2007	2008†	2009	2010	2011	2012	2013
					Female			
6 Months	Num	1755	1629	2030	2256	2083	2267	2476
	Empl	1564	1423	1626	1769	1717	1903	2085
	% Empl	92%	85%	79%	80%	81%	81%	84%
2 Years	Empl	1630	1486	1781	2001	1907	2107	2306
	% Empl	96%	91%	89%	88%	92%	91%	92%
					Male			
6 Months	Num	429	428	592	647	685	706	710
	Empl	396	364	466	516	555	572	595
	% Empl	89%	87%	80%	78%	82%	84%	84%
2 Years	Empl	411	388	527	569	630	642	653
	% Empl	93%	91%	88%	89%	92%	93%	93%
% Female		80%	79%	77%	78%	75%	76%	78%

Notes: † For the 2008 graduating cohort males two years after graduation, the "Offered Employment" observation was missing due to suppression (privacy). I assumed a value of 5 (data are suppressed when the values are between 1 and 5). The basis for this assumption is the relative proportion of the "Offered Employment" value to the "Num" value of the non-missing observations.

4.2.2 Teacher Data

The "teacher data" was created by web scraping and by gathering and organizing teacher administrative profiles from the public register of Ontario teachers available on the Ontario College of Teachers website. The portion of the data that I used contains 56,004 graduates of Ontario teachers' colleges for the graduating-year cohorts 2007 to 2013. Table 4.2 reports the sample sizes by graduating year. The sample sizes are similar across the years 2007 to 2011, followed by a decrease in 2012 and 2013.[9] The Ontario College of Teachers regulates all public-school teachers in Ontario, and thus the vast majority of Ontario teachers' college graduates are represented in the data. Refer to Chapter 1 for more details about

[9] The number of graduates in 2013 was lower relative to 2012 and 2011, for the same reasons as in Chapter 1, due to the exclusion of teachers from this analysis who acquired their licence after 2013. Moreover, the lower number of graduates in 2012 and 2013 is also indicative of the lower enrolments in Ontario teachers' colleges for those years . Refer to Section C.2.2 for more details.

the "teacher data," including the relevant background information related to the teacher qualification regulations and the teacher labour markets.

Table 4.2: "Teacher Data" Sample Size by Graduating-Year Cohort

Year	Sample N
2007	8344
2008	8518
2009	8399
2010	8441
2011	8180
2012	7740
2013	6382
Total	56004

4.2.3 Salary Grid Data

I created the "salary-grid data" specifically for this study by collecting and combining Ontario public school-salary grids from 392 separate collective agreements. These collective agreements cover the vast majority of the school boards outlined in the 2013 "Ontario public schools enrolment" data found on the official Government of Ontario website (Government of Ontario, 2013). All major categories of school board are represented at both the elementary- and secondary-school levels, including public, Roman Catholic and French-language school boards. Refer to Section C.2.4 of the appendix for the assumptions used to fill in any salary grids that were not directly drawn from the collective agreements. To the best of my knowledge, up until the present, there are no other Ontario datasets that contain a comprehensive collection of public-school teacher salaries across multiple qualification levels.

Each salary grid has at least four columns and usually 13 rows. The columns represent the qualification levels ranging from A1 to A4. A1 is the lowest qualification level and A4 is the highest qualification level.[10] The rows of the salary grid represent years of experience,

[10]Some salary grids include an extra column as the first column representing the lowest qualification level

while moving down the grid represents an increase in earnings based on additional years of experience; typically, a permanent teacher reaches the top experience level after 11 years of employment. Table 4.3 summarizes the salary grids for the initial experience level. The difference between the maximum and the minimum salary for any given year and qualification level can be as low as \$14,445 and as high as \$19,229. The range in salaries across the same qualification and experience levels is large enough that graduates from the same graduating cohort sometimes fall within one of two or three different salary bins. For example, a 2007 graduate at the initial experience level with the qualification level A1 can earn a salary that might fall within the interval representing bins four through six, depending on the location and the local union where he found a job. However, it is worth noting that the standard deviations are relatively low, which means that the results are more affected by the year and qualification levels in which the average salaries are near the interval cut-off points. For example, the year 2007 salary grid at the initial experience level and at the qualification level A3 has an average salary of \$45,083 with a standard deviation of \$1,264, which is not close to a salary-bin cut-off; looking at the "salary-grid data," 99.9 percent of all of the teachers to whom these salary grids would apply would earn a salary that falls within the same \$40,000 to \$50,000 bin.[11] However, the 2007 salary grids at the initial experience level and at the qualification level A1 have an average salary of \$39,607 with a standard deviation of \$1,216, which is close to the interval cut-off; this means that, for the teachers to whom these salary grids apply, around 41.2 percent of the salaries in the data fall within the \$40,000 to \$50,000 bin, and around 58.8 percent of the salaries in the data fall within the \$30,000 to \$40,000 bin.

A. However, this column does not apply to any new current newly hired teacher because it does not require a university degree. All current newly hired teachers start at least at level A1.

[11] This conclusion is premised on the assumption that the number of teachers to whom these salary grids apply is proportional to the student enrolment numbers within the respective jurisdictions of the collective agreements considered in the current study.

Table 4.3: Summary of Teacher Salary Grids at Step 0 Experience Level

Year	Qualification	Average Salary	Standard Deviation	Minimum	Maximum	Difference (Max-Min)
2007	A1	39607	1216	35291	50415	15124
	A2	41534	1192	38428	54527	16099
	A3	45083	1264	42056	56501	14445
	A4	47608	1365	44269	58791	14522
2008	A1	41097	1237	36502	52655	16153
	A2	43104	1207	39737	56949	17212
	A3	46780	1289	43499	59011	15512
	A4	49397	1396	46219	61402	15183
2009	A1	42149	1286	37232	54234	17002
	A2	44206	1263	40532	58657	18125
	A3	47977	1373	44369	60781	16412
	A4	50661	1476	47143	63244	16101
2010	A1	43414	1325	38349	55861	17512
	A2	45533	1301	41748	60417	18669
	A3	49416	1415	45700	62605	16905
	A4	52180	1518	48557	65142	16585
2011–2013	A1	44716	1365	39500	57537	18037
	A2	46899	1340	43000	62229	19229
	A3	50898	1457	47071	64483	17412
	A4	53746	1564	50014	67096	17082
2014	A1	45105	1376	40260	57537	17277
	A2	47306	1337	43848	62229	18381
	A3	51339	1403	47998	64483	16485
	A4	54212	1533	50522	67096	16574

Notes: The average and the standard deviation are weighted by the relative student enrolment across the 147 school boards. The salary grids for 2011 to 2013 are the same because of a teacher salary freeze. These salaries are not adjusted for inflation.

4.2.4 Qualifications Evaluation Council of Ontario (QECO) Documents

I use two QECO documents to estimate the respective probabilities of Ontario teachers' college graduates falling within the teaching salary-grid qualification levels A1 to A4. The first document, entitled "Teachers' Qualifications Evaluation: Program 5," outlines the regulations that translate specific teaching qualifications and specific levels of education and experience into placements on the salary grids. The second document is a QECO presentation material that states that 73 percent of new Ontario teachers' college graduates qualify at the A3 level and that more than 95 percent of new teachers qualify at the A2 level or above (QECO, 2016).

I use the "teacher data," which contain the education and qualification information for Ontario teachers' college graduates, in combination with the "Program 5" document, to evaluate the likelihood that an individual graduate has the highest qualification level A4. I then use the information from the presentation document, subject to certain assumptions, to determine the probabilities for the other three qualification categories. Refer to Section 4.3.1 and Table 4.4 for the details about the various assumptions and their use in the estimation.

4.3 Methodology and Analysis

4.3.1 Outside-Option Salaries

The main goal of this study is to estimate the salaries of Ontario teachers' college graduates employed outside the Ontario public school system.[12] In the first step, I use the "teacher data" and the "salary-grid data" along with the QECO documents to determine the number of individuals at each salary level who acquired a teaching job in the Ontario public school system. In the second step, I use the values calculated in the first step in combination with the OUGS data to determine the number of individuals who found a job outside the public school system along with their respective salaries. The result of this procedure is a new set of salary bins containing only the outside-job salaries; these are then used to fit the log-normal distributions (similar to Chapter 2).

[12]The outside option or outside job and non-teaching job possibilities, in addition to referring to non-teaching positions, include non-permanent teaching jobs in the Ontario public school system and teaching jobs in the private sector. In other words, these definitions apply to anything other than a permanent Ontario public-school teaching position.

The Outside-Option Salary Estimation for the Six-Month and Two-Year Milestones Since Graduation

In equation 4.1, $N^{O}_{i,yr,fem,k}$ defines the number of individuals of gender fem who graduated from an Ontario teachers' college in year yr with an outside job that pays a salary contained within the interval of bin i.

$$N^{O}_{i,yr,fem,k} = \begin{cases} N_{i,yr,fem} - N^{T}_{i,yr,fem,Sal_{k=yr+1,q=1}} - N^{T}_{i,yr,fem,Sal_{k=yr+1,q=0}} & \\ \quad = N_{i,yr,fem} & \text{if } k = yr+1 \\ \quad\quad -N_{yr,fem}\left[\sum_{q=0}^{1} p(l_i \leq X < u_i, T_{k-q}, fem, Sal_{k=yr+1,q})\right] & \text{(using two-year data)} \\ & \\ N_{i,yr,fem} - N^{T}_{i,yr,fem,Sal_{k=yr,q=0}} & \\ \quad = N_{i,yr,fem} & \text{if } k = yr \\ \quad\quad -N_{yr,fem}\left[p(l_i \leq X < u_i, T_{k=yr}, fem, Sal_{k=yr,q=0})\right] & \text{(using six-month data)} \end{cases} \tag{4.1}$$

$N_{i,yr,fem}$ and $N^{T}_{i,yr,fem}$ represent the number of individuals with a salary that falls within the interval of bin i, respectively for the entire set (both teaching jobs and outside jobs) and for teaching jobs only. Moreover, $N_{yr,fem}$ refers to the OUGS survey respondents for graduating year yr. The $p(l_i \leq X < u_i, T_{\widetilde{yr}}, fem, Sal_{k,q})$ in equation 4.1 refers to the probability of receiving a teaching salary that falls within the interval $[l_i, u_i)$ of bin i; l_i and u_i define the corresponding lower- and upper-bound cut-off points of interval i. $T_{\widetilde{yr}}$ refers to the graduate finding a teaching job in year $\widetilde{yr}$. $Sal_{k,q}$ refers to the salary grid used in the estimation, where k represents the salary-grid year and q refers to the level of experience ($q = 0$ for step 0 and $q = 1$ for step 1 which represents an extra year of experience). The estimations for the six-month data are developed in one step because all of the individuals who are hired start at the same experience level on the salary grid; this is shown in the second line of equation 4.1. However, the estimations for the two-year data have to be developed in two parts because it is necessary to separately identify not only the individuals who found a job in the second year but also those individuals who found a job in the first year. Further, the individuals who found a job in the first year will now be on the next step of the salary grid.[13] Therefore, for the two-year data, there are two groups of individuals who have to be considered separately in the OUGS data: the individuals who acquired a job in the first year, and the individuals who acquired a job in the second year; refer to the first line in equation 4.1.

The joint probability used in equation 4.1 can be expanded into conditional probabilities to illustrate the components of the data that are used in the estimation:

$$
\begin{aligned}
p(l_i \leq X < u_i, T_{\widetilde{yr}}, fem, Sal_{k,q}) &= \sum_{s=A1}^{A4} p(l_i \leq X < u_i, s, T_{\widetilde{yr}}, fem, Sal_{k,q}) && (4.2)\\
&= \sum_{s=A1}^{A4} p(l_i \leq X < u_i | s, T_{\widetilde{yr}}, Sal_{k,q}) p(s, T_{\widetilde{yr}}, fem) && (4.3)\\
&= \sum_{s=A1}^{A4} p(l_i \leq X < u_i | s, T_{\widetilde{yr}}, Sal_{k,q}) p(s | T_{\widetilde{yr}}, fem) p(T_{\widetilde{yr}}, fem) && (4.4)
\end{aligned}
$$

$T_{\widetilde{yr}}$ indicates that the individual acquired a teaching job in year $\widetilde{yr}$, which is $T_{\widetilde{yr}} = T_{k-q}$ in the estimation using the two-year data and $T_{\widetilde{yr}} = T_k$ in the estimation using the six-month data. It is essential to highlight that the estimation at two years is using salary grids from the following year after graduation. The $p(l_i \leq X < u_i | s, T_{\widetilde{yr}}, Sal_{k,q})$ in equation 4.2 represents the probability of having a salary in bin i conditional on qualification level $s \in \{A1, A2, A3, A4\}$ for an individual who secured a job in year $\widetilde{yr}$, and the estimation is using the salary grids for year k at experience level q (note that the salary grids do not vary with gender). The $p(s, T_{\widetilde{yr}}, fem)$ denotes the joint probability of acquiring a teaching job in year $\widetilde{yr}$ for a gender denoted by fem and for qualification level s; these probabilities are estimated using the "teacher data."

[13]For example, in the six-month calculation, the individuals who graduated and acquired a job in 2007 would be on the 2007 salary grid at the step 0 experience level. However, for the two-year calculation, the individuals who graduated in 2007 and acquired a job within six months would be on the 2008 salary grid at the step 1 experience level, and those who acquired a job in year two would be on the 2008 salary grid at the step 0 experience level.

The Probability Estimations from the "Teacher Data"

The probabilities, $p(T_{k-q}, fem)$ and $p(A4|T_{k-q}, fem)$ $\forall k,q$ from equation 4.2 could not be directly extracted from the "teacher data" because the gender variable was not directly observed and therefore these probabilities were estimated using logistic regressions (refer to Chapter 1 for more details).

$$p(T_{k-q}, fem) = \frac{\exp(\beta_{0,k-q} + \beta_{fem,1,k-q} fem)}{1 + exp(\beta_{0,k-q} + \beta_{fem,1,k-q} fem)} \tag{4.5}$$

$$p(A4|T_{k-q}, fem) = \frac{\exp(\beta_{1,k-q} + \beta_{fem,2} fem)}{1 + \exp(\beta_{1,k-q} + \beta_{fem,2,k-q} fem)} \tag{4.6}$$

where fem is an indicator variable denoting gender (=1 for female), β_0, β_1 are the constants in each of the respective equations, $\beta_{fem,1}$ is the coefficient on the female variable in the probability of acquiring a teaching job in year $k-q$, and $\beta_{fem,2}$ is the coefficient on the female variable in the probability of being in the highest qualification level category.

Although the data does not contain the gender variable directly, each observation n contains the probability of being female, which is denoted by $p_{f,n}$. The contribution of individual n to the likelihood is found by integrating the gender-specific likelihood function, which can be written as $[p(m, fem)]^{y_{n,\hat{yr}}} [p(m, fem)]^{1-y_{n,\hat{yr}}}$, over $fem = \{1,0\}$ (=1 for female). The log-likelihood for the full sample is given by equation 4.7:

$$\ln L(\beta; fem) = \sum_n \ln \left[\begin{array}{c} \underbrace{p_{f,n} [p(m, fem=1)]^{y_{n,k-q}} [1 - p(m, fem=1)]^{1-y_{n,k-q}}}_{female} + \\ \underbrace{(1 - p_{f,n}) [p(m, fem=0)]^{y_{n,k-q}} [1 - p(m, fem=0)]^{1-y_{n,k-q}}}_{male} \end{array} \right]. \tag{4.7}$$

Equation 4.7 is estimated for $\forall m \in \{(T_{k-q}), (A4|T_{k-q})\}$ $\forall k,q$. Moreover, $y_{n,k-q}$ is an indicator variable denoting whether individual n acquired a job in year $k-q$ for equation 4.5 and it denotes whether this individual was in the highest qualification category for equation 4.6. Further, $p(m, fem)$ does not vary with n and, therefore, there is a separate estimation for each combination of k and q for both the six-month and the two-year data.

It is important to note that the probabilities for the other qualification categories like, for example, $p(A3|T_{k-q}, fem)$, were partially derived from the QECO documents as described in Section 4.2.4, and that they were evaluated under four different assumptions (see summary in Table 4.4). Assumption 2 means that all of the teachers' college graduates have at least a four-year bachelor's degree (as opposed to a three-year degree). This is a reasonable assumption given the fact that 94 percent of Ontario university students complete at least a four-year degree, with the vast majority of graduates of an Ontario teachers' college also having earned their prerequisite degree in Ontario (Rushowy, 2012). Moreover, assumption 3 means that in addition to the four-year degree, the teachers' college graduates have also achieved a GPA that is consistent with a second-class standing or a minimum B average as defined by the QECO (QECO, 2013). Thus, assumption 3 is also reasonable given the fact that many Ontario concurrent teacher-education programs list a B to B- average as a minimum admission requirement.[14] Assumptions 1 and 4 represent the extreme opposite values of the probabilities for the A4 qualification level; for assumption 1, the value in the estimations is $\hat{p}_1(A4|\cdot) = 0.22$ and, for assumption 2, it is $\hat{p}_4(A4|\cdot) = 0$. These extreme values of the probabilities of being in the highest qualification level $A4$ will translate into the extreme values of the salaries within the framework of these assumptions because the average salary is increasing in $\hat{p}_j(A4|\cdot)\,\forall j$.

[14]Typically, a B to B- average must be achieved for the last two full-time years of the preliminary degree. Currently, as of June 2019, a B to B- is around a 70 percent GPA in most Ontario universities (Carleton University, n.d.; OUAC, 2019a, 2019b).

Table 4.4: Assumptions Summary for the Qualification Categories

Qualification Level	Assumption j 1	2/3	4
A1	0.05	$\hat{p}_j(A1\|\cdot) = \begin{cases} 1-\sum_{A=A1}^{A4}\hat{p}_j(A\|\cdot) & \text{if } \hat{p}_j(A4\|\cdot) > 0.95 \\ 0.05 & \text{otherwise} \end{cases}$	0.05
A2	0	$\hat{p}_j(A2\|\cdot) = \begin{cases} 0.22-\hat{p}_j(A4\|\cdot) & \text{if } 0 \le \hat{p}_j(A4\|\cdot) < 0.22 \\ 0 & \text{otherwise} \end{cases}$	0.22
A3	0.73	$\hat{p}_j(A3\|\cdot) = \begin{cases} 0.73-\left[\hat{p}_j(A4\|\cdot)-0.22\right] & \text{if } 0.22 < \hat{p}_j(A4\|\cdot) \le 0.95 \\ 0.73 & \text{if } 0 \le \hat{p}_j(A4\|\cdot) \le 0.22 \\ 0 & \text{if } \hat{p}_j(A4\|\cdot) > 0.95 \end{cases}$	0.73
A4	0.22	$\hat{p}_j(A4\|\cdot),\ 0 \le \hat{p}_j(A4\|\cdot) \le 1$	0

Distribution Estimations from the Binned Salary Data

Equation 4.1 results in a set $\{N^O_{i,yr,fem,k} | i \in \mathbb{N}, 1 \le i \le 11\}$ representing the estimated number of individuals with an outside-option job at a salary corresponding to each bin i; a separate set is estimated for each yr, fem, k combination. These salary bins are fitted to the log-normal distribution using the maximum likelihood method.

The likelihood function is

$$\mathcal{L}(\theta|data) = \sum_{a=1}^{Z} \frac{1}{Z}\left[\prod_{i=1}^{B} p(l_i \le X \le u_i|\theta)^{n_i}\left(\sum_{j=1}^{C}\prod_{k=1}^{M} p(l_k \le X \le u_k|\theta)^{m_{a,j,k}}\right)\right] \tag{4.8}$$

$$= \sum_{a=1}^{Z} \frac{1}{Z}\left[\prod_{i=1}^{B}\left[F(u_i|\theta)-F(l_i|\theta)\right]^{n_i}\left(\sum_{j=1}^{C}\prod_{k=1}^{M}\left[F(u_k|\theta)-F(l_k|\theta)\right]^{m_{a,j,k}}\right)\right] \tag{4.9}$$

$$\ln \mathcal{L}(\theta|data) = \ln\left(\frac{1}{Z}\right) + \left(\sum_{i=1}^{B} n_i \ln\left[F(u_i|\theta)-F(l_i|\theta)\right]\right) + \underbrace{\ln\left(\sum_{a=1}^{Z}\sum_{j=1}^{C}\gamma_{a,j}\prod_{k=1}^{M}\left[F(u_{k,yr}|\theta)-F(l_{k,yr}|\theta)\right]^{m_{a,j,k}}\right)}_{for\, suppressed\, data} \tag{4.10}$$

where Z is the number of possible bin totals stemming from the data missing as a result of privacy suppression. Furthermore, B represents the number of non-missing bins and n_i represents the number of observations in the non-missing bin i. $F(u_i|\theta)$ and $F(l_i|\theta)$ are the cdfs for the log-normal distributions at the upper and lower boundaries respectively of the salary bin i interval, conditional on the parameters $\theta = \{\mu, \sigma\}$; $F(u_k|\theta)$ and $F(l_k|\theta)$ are the analogous cdfs, but for the missing bin k interval. C_a is the number of possible permutations for the unobserved observations in the missing bins, which are conditional on a, since the permutations vary based on the total number of observations (observed plus unobserved). M is the total number of missing bins and $\gamma_{j,a}$ is the weight factor for each permutation j,a.[15] The unobserved values are denoted by $m_{a,j,k}$, which represents the total possible number of unobserved individuals for part a, bin k, in permutation j.

4.3.2 Teaching Salaries

Another objective of this study is to compare the outside-option salaries with the public-school teaching salaries. The latter were estimated by means of simulation using the probabilities from the "salary grid data" and the "teacher data." The following algorithm was used for the salary point estimates and for the 95 percent confidence intervals for each combination of gender fem, graduating year yr and each k milestone period since graduation (where $k = yr + 1$ for the two-year data and $k = yr$ for the six-month data):

1. Using the salary grids, I created four new teacher-salary datasets, one for each qualification level $s \in \{A1, A2, A3, A4\}$; the salaries were drawn proportionally to the student enrolment numbers for each school district.

2. With a similar approach to the first step in Section 4.3.1, I estimated the number of individuals who acquired a teaching job in the Ontario public school system for each qualification category level s. The difference with Section 4.3.1 is that, instead of estimating the number of graduates in each salary bin, here I estimate the number of graduates for each qualification level. Furthermore, the estimations using the two-year data require a two-step process analogous to that employed in Section 4.3.1:

[15] The weight factor γ:

$$\gamma = \prod_{i=1}^{M} \frac{s_i!}{r_i!(s_i - r_i)!}$$

where $s_i = \sum_{j=i}^{M} r_j$, r_i is the number of observations in bin i and M is the number of missing bins.

$$N^{\widetilde{T}}_{s,yr,fem,k} = \begin{cases} N_{yr,fem}\left[\sum_{q=0}^{1} p(s, T_{k-q}, fem)\right] & \\ \quad = N_{yr,fem}\left[\sum_{q=0}^{1} p(s|T_{k-q}, fem, sal_{k,q}) p(T_{k-q}, fem)\right] & \text{if } k = yr+1 \\ & \text{(using two-year data)} \\ N_{yr,fem} p(s, T_k, fem) & \\ \quad = N_{yr,fem} p(s|T_k, fem) p(T_k, fem) & \text{if } k = yr \\ & \text{(using six-month data)} \end{cases} \tag{4.11}$$

3. For each qualification category s I sampled $N^{\tilde{T}}_{s,yr,fem}$ values from the corresponding dataset created above in step 1 (with replacement). I repeated this step for 1,000 samples and calculated the median for each sample.

4. In calculating the confidence intervals, it has to be taken into account that the probabilities determined in step 2 were estimated with an element of error. For each estimated probability, I drew 1,000 samples for each coefficient from a joint normal distribution given the mean and the variance-covariance matrix (refer to Section 4.3.1 for the regression equations 4.5 and 4.6).

5. For each of the 1,000 samples in step 4, I repeated steps 1 to 3. This resulted in a larger combined sample of median teaching salaries; I calculated the median and the 95 percent confidence intervals from this sample.

4.4 Results

The analysis was done under four separate assumption scenarios that were related to the probabilities of the graduates being within the various salary-grid qualification levels. There was not enough information in the data to precisely pin down the qualification levels of the graduates and thus these assumption scenarios reflect the various possibilities; refer to Table 4.4 in Section 4.3.1 for the explanation and summary of the assumptions. The results for assumption 2, which reflect results that are roughly in the middle, are provided in Table 4.5 and are illustrated in figure 4.1. However, the resulting estimates are very similar under all of the assumptions; refer to Appendix Section C.3 for the results under the three remaining assumptions.

The results are organized across four main categories based on gender (male and female) and milestone period since graduation (six months and two years). Furthermore, within each of these categories there are 28 different specifications based on the outside-option salaries and the teaching salaries for each of the seven graduating-year cohorts. Much like in Chapter 2, a separate analysis is performed for each gender because there are substantial gender differences in salaries that may be partially attributable to the gender differences in part-time rates. For example, a weighted average of median salaries across undergraduate programs at the two-year graduation milestone is \$34,508 for females and \$43,650 for males, a result that is around 26 percent greater for males. Furthermore, females are more likely to work in a part-time job; for example, the part-time rate for females in the undergraduate group is 24 percent, while for males it is only 14 percent of the same.[16] The analysis for the overall salaries with the combined genders is not necessary, mainly because 75 to 80 percent of the teachers were female and because the overall salaries would be very similar to the female salaries.

The results show that the teaching salaries were substantially greater than the outside-option salaries for each cohort, gender and milestone period since graduation. The greatest difference was for the 2012 female cohort where the median teaching salary at the six-month milestone since graduation was 103 percent higher than the median outside-option salary. The smallest difference was for the 2007 male cohort where the median teaching salary at the two-year milestone since graduation was just around 5 percent higher than the median outside-option salary. The median teaching salaries were virtually the same for the

[16] Refer to Chapter 2 Appendix Sections 6.4 and 6.7 for more details about the salaries and part-time rates across programs and genders.

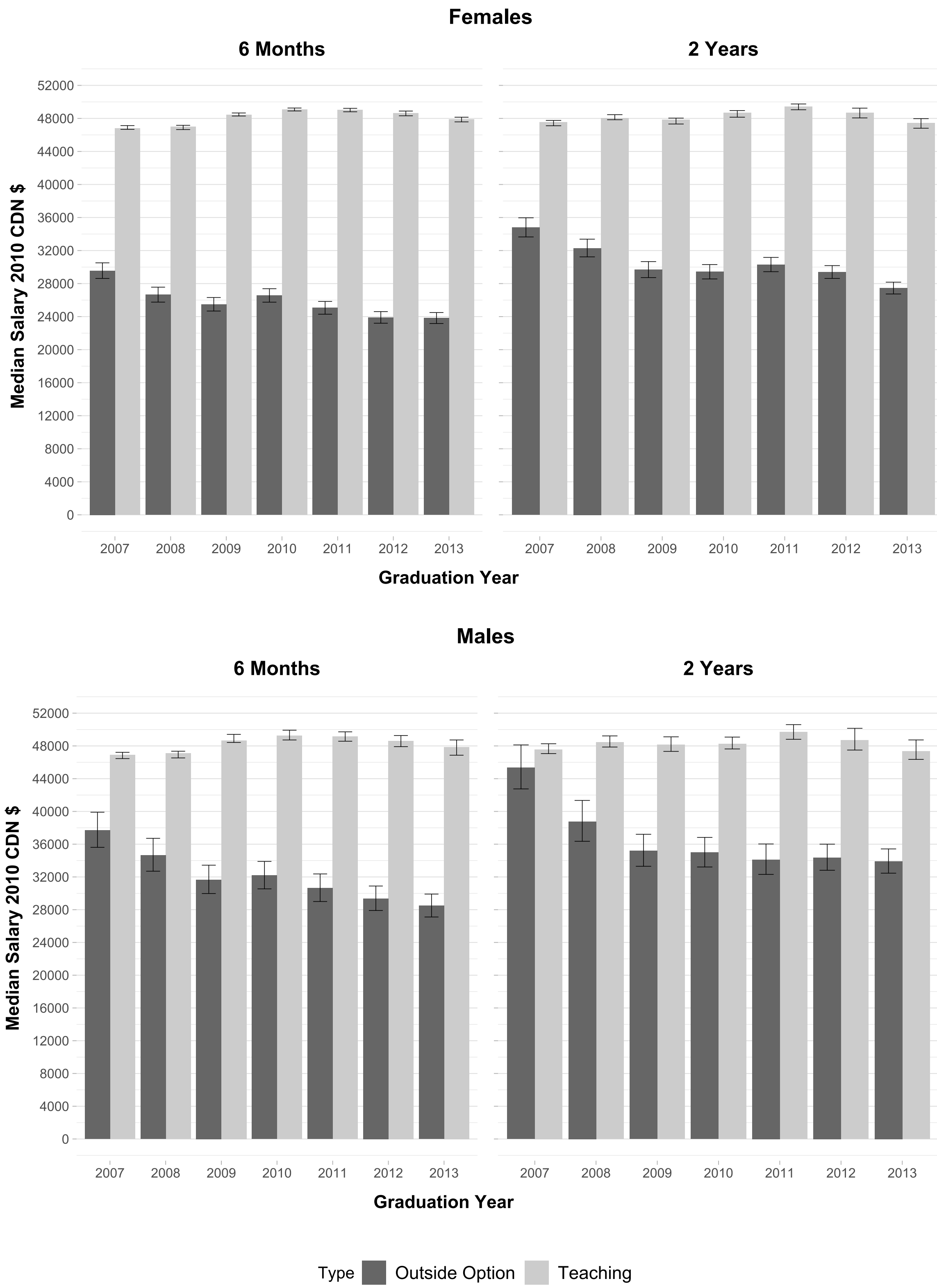
the six-month and the two-year milestones since graduation for all male and female cohorts; there are no statistically significant results that are consistent across all of the assumptions. Moreover, the teaching salaries did not vary to any great extent between the cohort years. For example, the highest median teaching salary, \$49,706 for the 2011 males at the two-year milestone, was only around 6 percent higher than the lowest median teaching salary, \$46,800 for the 2007 females at the six-month milestone. In terms of teaching salaries, there are no statistically significant gender differences across all of the cohort years and across both the six-month and the two-year milestones after graduation.

The outside-option salaries varied substantially across genders: males earned more in every cohort and over both milestone periods after graduation – a difference between 20 to 30 percent at the six-month milestone after graduation and a difference of 13 to 30 percent at the two-year milestone for the same, depending on the cohort. Furthermore, there was a significant difference in the outside-option salaries across cohorts, whereby the more recent cohorts tended to have lower outside-option salaries. For example, in all of the sub-tables A to D in Table 4.5, the 2007 and 2008 cohorts earned more than the 2012 and 2013 cohorts (with statistical significance). For males at the two-year milestone after graduation, the 2007 cohort had the highest outside-option median salary at \$45,357, while the 2013 cohort had the lowest of the same at \$33,909. For males at the six-month milestone after graduation, the 2007 cohort had the highest outside-option median salary at \$37,698, while the 2013 cohort had the lowest of the same at \$28,473. For females at the two-year milestone after graduation, the 2007 cohort had the highest outside-option median salary at \$34,790, while the 2013 cohort had the lowest of the same at \$27,450. For females at the six-month milestone after graduation, the 2007 cohort had the highest outside-option median salary at \$29,557, while the 2013 cohort had the lowest of the same at \$23,822.

Table 4.5: Estimated Median Salaries

A	Median Salary 2010 CDN \$: (95% C.I.)		B	Median Salary 2010 CDN \$: (95% C.I.)	
	Six Months After Graduation: Female			Six Months After Graduation: Male	
Year	Outside Option	Teaching		Outside Option	Teaching
2007	29557	46800		37698	46908
	(28628–30515)	(46677–47131)		(35616–39903)	(46450–47221)
2008	26647	47007		34650	47103
	(25759–27565)	(46648–47166)		(32699–36718)	(46538–47352)
2009	25482	48452		31660	48663
	(24676–26314)	(48290–48660)		(29977–33438)	(48422–49409)
2010	26554	49083		32177	49261
	(25754–27379)	(48906–49261)		(30545–33896)	(48731–49924)
2011	25053	49010		30637	49133
	(24291–25840)	(48804–49221)		(28997–32369)	(48578–49721)
2012	23894	48614		29359	48614
	(23200–24609)	(48320–48889)		(27902–30892)	(47908–49269)
2013	23822	47896		28473	47865
	(23169–24493)	(47583–48145)		(27108–29906)	(46867–48732)
C	Median Salary 2010 CDN \$: (95% C.I.)		D	Median Salary 2010 CDN \$: (95% C.I.)	
	Two Years After Graduation: Female			Two Years After Graduation: Male	
Year	Outside Option	Teaching		Outside Option	Teaching
2007	34790	47532		45357	47573
	(33650–35968)	(47109–47756)		(42750–48123)	(47060–48262)
2008	32289	48025		38768	48453
	(31233–33381)	(47839–48453)		(36352–41345)	(47864–49224)
2009	29681	47852		35200	48149
	(28729–30665)	(47326–48036)		(33300–37209)	(47336–49108)
2010	29418	48681		34977	48238
	(28560–30302)	(48145–48951)		(33217–36831)	(47634–49083)
2011	30293	49421		34119	49706
	(29440–31170)	(49048–49751)		(32310–36030)	(48808–50600)
2012	29394	48696		34373	48696
	(28629–30179)	(48061–49243)		(32818–36002)	(47496–50149)
2013	27450	47430		33909	47338
	(26745–28173)	(46812–47975)		(32460–35424)	(46354–48734)

Figure 4.1: The Teaching and Outside-Option Salaries by Gender



4.5 Conclusion

In this study, I take advantage of a rare teacher-surplus environment in Ontario to estimate the outside earnings options of Ontario teachers' college graduates. Teacher-shortage environments are generally more typical, and economists who study teachers' personal labour-supply decisions mostly try to understand why teachers enter, stay in and exit the teaching profession from an attrition perspective. Typically, the modelling of these decisions requires the relevant economic agents to consider the various outside options. Given the common occurrence of teacher shortages in many jurisdictions, there are few opportunities to observe teachers in non-teaching professional roles, and this makes it challenging to find suitable data. The results of this study may help in understanding not only the earnings of teachers relative to their outside-option counterparts, but also the potential sorting of students into teacher-education programs corresponding to the labour market conditions (i.e. in terms of the probability of finding a teaching job) at the time of their enrolment.

The main results in this study indicate that, in Ontario, the outside-option earnings available to licensed teachers are substantially lower than the salaries paid to their public-school counterparts; this outcome persists for both males and females, even after two years of employment. Interestingly, this outcome also holds for the 2011 to 2013 cohorts, the education-program graduating years that have been most affected by those years' salary-grid freezes. Further, there appears to be an ongoing downward trend: the outside-option salaries are lower for the later cohorts (2012 and 2013) than for the earlier ones (2007 and 2008). This pattern suggests that, as it becomes more difficult to find a public-school teaching position, the downward pressure on the median salaries is becoming increasingly attributable to selection; teachers' colleges may be accepting students with lower potential outside-option earnings at a higher rate than in the past. Males were found to have greater outside-option earnings across all cohorts, which may in part be due to their lower rates of working on a part-time basis.

These results might be useful as inputs into a model examining teachers' labour-supply decisions. An example of a question that one might ask is as follows: Why are so many people going to teachers' college given the considerable difficulty of finding a teaching job? Given the fact that many teachers' college graduates come from an arts and humanities background (including fine and applied arts), it is unsurprising that many of these individuals decide to pursue teaching; this is especially the case because the median salaries for the outside option available to teachers' college graduates appear to be higher than for their counterparts who graduate with an arts degree and who do not pursue a teaching degree (refer to Chapter 2 for details about the arts and humanities salaries). The higher outside-option salaries available to individuals who completed an education degree after graduating from an arts program relative to those who hold only an arts degree suggest either that the extra year of university studies is beneficial for earnings (even for those who are unable to find a permanent teaching position) or that those with higher potential outside-option earnings, despite their decision to pursue one extra year of university studies, tend to go to teachers' college.

Chapter 5

Conclusions

The three essays in this thesis contribute to the economics of education literature. Chapters 2 and 4 examine topics related to teacher labour markets and Chapter 3 examines the earnings of recent university graduates in the context of program and university choice.

In Chapter 2, I take advantage of the recent teacher surplus environment in Ontario, which started around 2005, to examine which teacher characteristics schools value when hiring new teachers' college graduates. In other words, this environment allows me to examine, to a greater extent than was possible before within the typical teacher shortage context, the demand for teachers as opposed to the teacher labour supply. Traditionally, teacher shortages are more common, and in that type of environment, schools have little discretion in terms of whom they hire. People were cognizant of the fact that it was challenging to obtain a teaching job, but it was not entirely clear as to the extent the graduates were experiencing difficulties.

One of the contributions from this chapter is that I create a dataset which allows me to examine the teacher characteristics that affect the probability of acquiring a permanent teaching position in the Ontario public school system. To do this, I use a duration model to incorporate the time variables into the analysis.

The results show that it became increasingly difficult for each successive graduating-year cohort to find a teaching position; the odds of finding a teaching job in 2006 were around four times higher than they were in 2013. Furthermore, this study reports that teachers with French qualifications were around 3 to 5 times more likely to find a teaching job than those of the reference group. It is essential to address this over-supply of teachers because there are related policy-relevant issues. For example, in light of the poor math performance of Ontario elementary students, it would seem desirable to have more teachers with qualifications in math. Although teachers with math qualifications were still more likely to acquire jobs than the reference group, they were not nearly as successful as those with French qualifications. My findings could inform policy-makers to adapt hiring policies that prioritize high priority fields, such as math in this case.

In Chapter 3, I examine whether the school or the program choice has a more significant impact on the earnings of university graduates. I use relative-importance analysis to decompose the variation in earnings into program and school components. To perform the analysis, I use restricted-access government-administered data, the Ontario University Graduate Survey.

The results indicate that the earnings variation attributable to programs was substantially higher than the amount of variation in earnings attributable to schools. For example, from the overall specification across all degree types and genders in the data, at six months since graduation the programs accounted for 21.8 percent of the variation while the schools accounted for 2.1 percent of the variation. Putting this another way, the amount of earnings variation accounted for by the programs was around 10 times to that of the schools. This chapter emphasizes the fact that since the amount of earnings variation attributable to schools is much smaller than to programs, students should feel comfortable choosing a program without feeling disadvantaged if they are unable to attend the most elite institution.

In Chapter 4, I take advantage of the teacher surplus environment in Ontario to examine the outside-option earnings of recent Ontario teachers' college graduates and compare them to teaching salaries from the same cohort. Given the fact that teacher shortages are common, there are few opportunities to examine teachers in non-teaching positions. One of the contributions in this chapter is I that create a new teacher salary dataset by collecting, extracting and organizing salary grid information from teacher bargaining collective agreements. To perform the analysis, I then use the new salary data in combination with the data from the previous two chapters.

According to this study, the median outside-option salaries varied across cohorts, genders and periods since graduation. In contrast, the median teaching salaries did not vary to any great extent. Moreover, there were no gender differences across teaching salaries; however, for the outside-option salaries, males earned more than females in every graduating cohort and for both the six-month and two-year milestone periods since graduation. These results might be useful to researchers since the opportunity cost of teaching is a fundamental aspect of understanding the occupational mobility decisions of teachers.

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Appendix A

Chapter 2 Appendix

A.1 Data Details

A.1.1 Data Construction

In order to simplify the analysis, I constructed the subject group variables in such a way as to avoid overlapping categories for graduates who acquired subject qualifications that span across multiple subject areas (e.g. French and mathematics). I assumed that being qualified in multiple subjects does not necessarily increase the chances of finding a job. Also, I assumed that a subject qualification that provides a much higher probability of finding a job, determined through a process of various regression specifications, drives the majority of the results attributed to that particular subject qualification. First, if teachers hold French or technological qualifications, regardless of any other qualifications they may have, the probability of finding a job is mostly dependent on these qualifications. Thus, teacher graduates who hold French qualifications, whether they have any other qualifications, are grouped into the "French" category. Second, teacher graduates who hold technological qualifications and no French, regardless of any other qualifications, are grouped into the "technology" category. Third, if the individuals have math and no reading/writing, French or technological qualifications, then they are grouped into the "math" category. Next, the "reading/writing" category is similar to the "math" category, in that if the individuals have reading/writing and no math, French or technological qualifications, then they are grouped into the "reading/writing" category. Finally, if teachers' college graduates have qualifications that do not fit into the categories mentioned above, these qualifications are classified as "all others." Furthermore, teachers who are only certified to teach in the elementary grade divisions may not have any subject specialty; a classification denoted as "no subject."

A.1.2 Gender of the Teacher

The teacher profiles, available from the public register of teachers, do not contain the gender of the individuals; however, they do include the first and last names, which are useful in determining the probability of each individual being male or female. The solution employed in this study is software-based (developed by NamSor™Applied Onomastics); it is a RapidMiner add-on extension called Onomastics Extension v.5.3.0 that uses the Gendre API v.0.0.15. This software algorithm extracts information from the combination of first and last names and assigns it a value between -1 and +1 related to how likely the individual is a male or a female (Carsenat, 2014).

For many teacher profiles in the data, the full name variable contains more than two names. Therefore, I assumed that the first and last words in the text field define the first and last names, respectively, and are used as inputs of the algorithm. As mentioned above, the output values are on a scale between -1 and +1 in increments of 0.1 (a negative/positive value represents a higher chance of being male/female). However, the resulting output values from the software cannot directly be used in the analysis because they are not probabilities; the gender component of the likelihood function requires the probability of being male/female. Thus, in the next step, I mapped these output scale values into probabilities. In order to do this mapping, I used a separate independent dataset that contains a large number of full names along with their gender and country of origin. The data I used is the FIDE (Fédération Internationale des Échecs) international database of rated chess players

(Fédération Internationale des Échecs [FIDE], 2014). For privacy reasons, it is generally challenging to find a dataset containing both first and last names as well as the gender. Although the FIDE data is not ideal because only 11.9 percent of the data is female, the dataset is large enough that it still contains enough females to be suitable for this study; overall, the dataset contains 461,934 individuals from 180 countries. Furthermore, I used the NamSor™ software to process the FIDE dataset, which provides the mapping between the output scale results and the actual genders of the individuals.

Before assigning the output scale numbers to the probabilities, I adjusted the ethnic distribution of the FIDE data to mimic the Canadian teacher demographics, because the output values from the software do not map into the same probability distribution across different ethnic groups. For example, the estimates of gender using this algorithm with Chinese names are not as reliable as from French or English names. Moreover, the FIDE dataset has a substantially different distribution of ethnicities than that of Canadian teachers. The weights for the ethnic distribution of Canadian teachers, which are used to adjust the FIDE data, come from the 2006 Census of Population (StatCan, 2006, 2008).

For each scale number, there is a proportion of individuals in the FIDE data who are female or male providing a mapping between the scale number and the gender. Table A.1 reports the probability of being female assigned to each scale value from the NamSor™ software. For example, the table shows that the proportion of individuals whose names, which were used as inputs, produced an output scale of -1 is 5.25 percent female, then it follows that $p(female|scale\# = +1) = 0.0525$; which is a mapping of the scale number to the probability of being female. Furthermore, this table shows that around 75 percent of output values are at the extremes, either +1 or -1, and it also shows that if the software produces these output values respectively, the probabilities of being male or female are high (around 95 percent or higher).

Table A.1: Probability of Being Female (Adjusted FIDE Data)

	Number of Individuals			Probability	Proportion in the Data
Scale	Female	Male	Total	Female	
-1	111.92	2020.55	2132.46	5.25%	21.33%
-0.9	11.97	38.91	50.88	23.53%	0.51%
-0.8	10.55	23.87	34.42	30.65%	0.34%
-0.7	20.28	123.48	143.76	14.11%	1.44%
-0.6	10.76	16.95	27.71	38.83%	0.28%
-0.5	54.41	102.42	156.83	34.69%	1.57%
-0.4	20.62	16.38	37.00	55.73%	0.37%
-0.3	23.34	9.43	32.77	71.22%	0.33%
-0.2	12.06	3.65	15.71	76.77%	0.16%
-0.1	221.51	87.39	308.91	71.71%	3.09%
0	119.85	16.88	136.73	87.65%	1.37%
0.1	237.75	15.62	253.37	93.84%	2.53%
0.2	13.61	5.52	19.13	71.14%	0.19%
0.3	20.62	2.83	23.45	87.93%	0.23%
0.4	58.78	4.16	62.94	93.39%	0.63%
0.5	571.08	10.78	581.86	98.15%	5.82%
0.6	34.04	1.47	35.51	95.86%	0.36%
0.7	464.92	5.00	469.92	98.94%	4.70%
0.8	27.00	2.83	29.83	90.51%	0.30%
0.9	63.77	3.98	67.74	94.14%	0.68%
1	5361.35	15.50	5376.85	99.71%	53.78%
Total	7470.16	2527.63	9997.79	9997.79	100%

A.1.3 Timing of the Variables

This section describes all the assumptions concerning the timing of the variables. The data contain the year an individual acquired a teaching licence; however, the primary time variable is the graduation year from teachers' college. In other words, the graduation year is the starting point, regardless of when the teaching certification was issued.

The periods in this study are discrete in one-year intervals. The first assumption is that each individual graduated from their teacher education program in June of his or her graduating year and immediately began looking for a job. Second, if an individual found a job, then their starting date (and the date they found the job) was in September of the NTIP year.

For example, if the NTIP date was 2015, then the graduate found their job in September of 2014. Nonetheless, there are some notable exceptions to these assumptions due to peculiarities in the data. To acquire a teaching licence, each teacher needs to complete a teacher education program and a separate bachelor's degree. However, there are instances in the data, where the graduation year for the separate bachelor's degree is in a later year than the graduation year from teachers' college. In such situations, I assumed that individuals began searching for a job in June of the year they completed their other (non-teaching) bachelor's degree.

Another time variable is the date of completion for subject qualifications, which includes both month and year in the data; thus, I assumed that the qualifications completed between October and December count for the following year. For example, a qualification completed in September of 2006 counts for 2006, while a qualification completed in October of 2006 counts for 2007. Furthermore, since Basic Qualifications (BQs) are a requirement for teaching and because they are more often than not dated the year that the teacher acquires a teaching licence, those initial BQs were backdated to the year the graduate started the above-assumed search for a job.[1]

Table A.2 shows the number of graduates from each graduating cohort that certified across the various years in the data. In general, the vast majority of graduates acquired their licences in the same year that they graduated. The initial data was downloaded between August 25, 2014 and September 2, 2014.[2] Since 2014 was only a partial year in the data,

[1]A distinction can be made between three types of subject qualifications that a teacher can acquire: Basic Qualifications (BQs), Additional Basic Qualifications (ABQs) and Additional Qualifications (AQs). BQs certify a graduate to teach a specific grade division and subject speciality (if at the high school level, since there are no specialties at the elementary grade level), and graduates usually receive these qualifications right after their initial teacher education program. ABQs are similar to BQs in that they allow a teacher to expand their expertise in a new grade division or subject speciality, except that they are usually acquired later on after the initial teacher certification. Finally, AQs allow a teacher to expand their knowledge in new subjects or subjects that they are already qualified in, but within a grade division they are already certified to teach (the difference being that only BQs and ABQs can add certifications in new grade divisions) (OCT, 2019a, 2019c). In terms of categories for analysis, this paper makes no distinction between these different types of qualifications.

[2]There were subsequent downloads up until 2018 to include updated NTIP dates, licence status and subject qualification information (valid up to 2016); however, this information was only updated for the graduates present in the initial download.

I excluded all graduates who acquired their teaching certification in 2014 (6,097 in total). Of those excluded graduates, 4,734 graduated in 2014; the remaining excluded individuals are reported in the 2014 column of Table A.2.

Table A.2: The Relationship Between the Cohort Year and the Certification Year

Year	Certification Year											
	2006	2007	2008	2009	2010	2011	2012	2013	Total	2014	Total*	% (Year = Year Cert.)
2006	7314	250	78	30	17	11	10	6	7716	8	7724	94.7%
2007	35	7590	338	88	32	25	14	7	8129	10	8139	93.3%
2008	0	40	7684	334	103	43	16	9	8229	8	8237	93.3%
2009	0	1	17	7526	518	119	45	39	8265	18	8283	90.9%
2010	0	1	3	16	7400	695	122	63	8300	36	8336	88.8%
2011	0	0	0	5	35	7269	577	141	8027	70	8097	89.8%
2012	0	0	0	0	7	41	6357	1143	7548	248	7796	81.5%
2013	0	0	0	0	2	1	14	6178	6195	965	7160	86.3%

Notes: The "Year" refers to the year the graduate started searching for a job (primarily based on the graduating-year cohort from teachers' college). For the several later cohorts in the data, especially 2013, the percentage of graduates who obtained a licence in in the same year as their cohort year is likely overstated to a greater extent than for earlier cohorts because of right censoring being closer to the start year (graduation year) of the later cohorts. Although the analysis in the paper excludes graduates who were certified in 2014, the last column uses "Total*" as the denominator which includes the 2014 certification year to give a more realistic idea about the percentage of graduates that became certified in the year they graduated. The "Total" column includes certification years 2006 to 2013.

A.1.4 Descriptive Statistics

Tables A.3 and A.4 report the subject qualifications and grade divisions, respectively, across cohorts in their first year on the job market. Table A.3 is similar to Table 2.1 from Chapter 2, except the latter includes information about all the periods (not just the first). Comparing these two tables shows the number of individuals that added qualifications after the first year on the job market. For example, for the 2006 cohort, the all-others group increased from 4,037 in the first year to 5,041 across all years on the job market.

It is important to highlight that the substantial decrease in the number of graduates from

2012 to 2013 is due to the 965 graduates who although graduated in 2013, did not acquire a teaching certification until 2014 and were excluded from this study.[3]

Table A.3: Subject Qualifications and Grade Divisions by Graduating-Year Cohort: First Year

Year	Subject Qualifications						Total[4]
	French	Technology	Math	Reading/Writing[5]	No Subject	All Others	
2006	422	148	712	64	2333	4037	7716
	5.5%	1.9%	9.2%	0.8%	30.2%	52.3%	
2007	525	218	624	96	2473	4193	8129
	6.5%	2.7%	7.7%	1.2%	30.4%	51.6%	
2008	590	219	668	102	2278	4372	8229
	7.2%	2.7%	8.1%	1.2%	27.7%	53.1%	
2009	620	170	586	76	2306	4507	8265
	7.5%	2.1%	7.1%	0.9%	27.9%	54.5%	
2010	674	236	513	90	2406	4381	8300
	8.1%	2.8%	6.2%	1.1%	29.0%	52.8%	
2011	757	254	542	72	2218	4184	8027
	9.4%	3.2%	6.8%	0.9%	27.6%	52.1%	
2012	752	221	508	78	2071	3918	7548
	10.0%	2.9%	6.7%	1.0%	27.4%	51.9%	
2013	741	160	456	44	1509	3285	6195
	12.0%	2.6%	7.4%	0.7%	24.4%	53.0%	
Total	5081	1626	4609	622	17594	32877	62409
	8.1%	2.6%	7.4%	1.0%	28.2%	52.7%	

[3]To a lesser extent, the number of graduates in 2013 is also lower relative to the number of graduates in 2012 due to a 7.6 percent drop in confirmed enrolments from 2011 to 2012 (OUAC, 2012).

[4]Note that in Table A.3, the rows add up to 100 percent (i.e., the denominators are located in the last column).

[5]The number of graduates with "reading/writing" qualifications increased substantially after the first year because these qualifications are only available as Additional Qualifications as opposed to French or math that are also available as Basic Qualifications. Recall, that all teachers must start with BQs, and do not nceecessarily hold any AQs in the first year; refer to the previous sub-section for more details.

Table A.4: Grade Divisions by Graduating-Year Cohort: First Year

Year	Grade Divisions			Total
	Elementary	High School	Elementary/High School	
2006	3202	2589	1925	7716
	41.5%	33.6%	24.9%	
2007	3438	2713	1978	8129
	42.3%	33.4%	24.3%	
2008	3346	2817	2066	8229
	40.7%	34.2%	25.1%	
2009	3378	2798	2089	8265
	40.9%	33.9%	25.3%	
2010	3465	2647	2188	8300
	41.7%	31.9%	26.4%	
2011	3275	2711	2041	8027
	40.8%	33.8%	25.4%	
2012	3097	2442	2009	7548
	41.0%	32.4%	26.6%	
2013	2458	1908	1829	6195
	39.7%	30.8%	29.5%	
Total	25659	20625	16125	62409
	41.1%	33.0%	25.8%	

Appendix B

Chapter 3 Appendix

B.1 Data Details

Table B.1 shows a fictional example depicting the aggregate data format of the Ontario University Graduate Survey. For instance, the first observation line means that for the 2007 graduating cohort from the University of Western Ontario in the humanities program, 20 female graduates had a salary between \$50,001 and \$60,000 (Bin 6).

Table B.1: Example of the OUGS Data Format for Schools and Programs (Fictional Data)

Demographic Variables					
Obs.	Graduation Year	School	Program	Gender	Number of Respondents
1	2007	University of Western Ontario	Humanities	Female	150
2	2008	University of Toronto	Social Science	Male	122

(continued below)

Employment Outcome Variables: Six-Month Salary Bins (1–11) and Employment Status															
Obs.	1	2	3	4	5	6	7	8	9	10	11	Q1	Q2	Q3	Q4	Q5
1	*	9	7	10	15	20	24	12	10	6	*	115	6	12	91	30
2	6	*	6	7	12	13	15	12	8	7	*	87	7	14	79	15

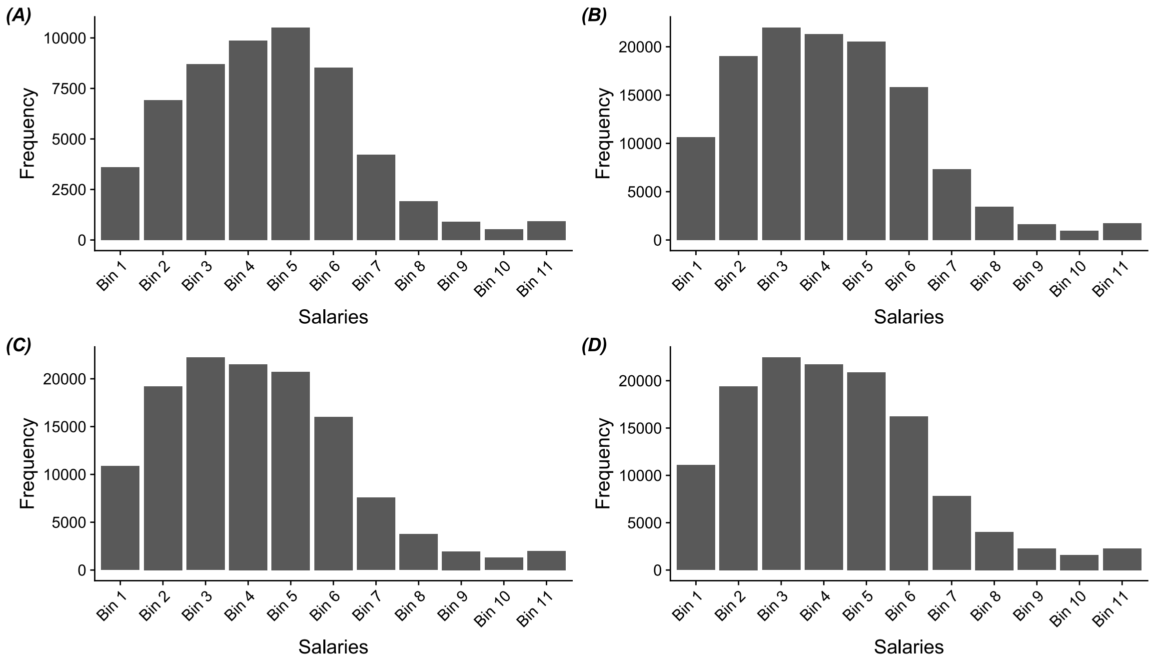
Notes: The numbers in this table are fictional.
Survey Response Choices: Q1 – Employed, Q2 – Offered employment to start at a later date,
Q3 – Not employed and not in school, Q4 – Full-time and Q5 – Part-time.

B.1.1 Data Cleaning

In the data cleaning process all of the observations where the "Number of Completed Surveys" and the "Employed" variables were suppressed were eliminated. This was done separately for the six-month and two-year data variables. Also, the one and only observation where the "Employed" variable had a value of 0 (from the six-month data) was dropped. The original dataset had 3,066 different aggregate observations (simlar to each line of Table B.1) representing a range between 142,064 and 144,488 individuals (MTCU, 2013). The resulting sets had 2,179 observations with 139,075 individuals from the six-month data, and 2,240 observations accounting for 139,657 individuals from the two-year data.

B.1.2 Lognormal Distribution Assumption

Figure B.1: Lognormal Assumption Charts



Notes: Bar graphs (A)–(D) show the overall frequency of salaries at six months since graduation. Graph (A) only includes observations that had no missing bins. Graph (B) is under the assumption that all bins with missing values were replaced with "1". Similarly, graph (C) missing values were replaced with "3", and graph (D) missing values were replaced with "5". The bins in the data are described in Section 3.3. The last bin in each graph tends to be higher than the previous bin because it is an open-ended bin, over \$100,000, which has a range greater than the other bins (greater than \$10,000).

B.1.3 Descriptive Statistics

Table B.2: Summary Statistics: Survey Respondents: School-Program Combinations by Gender

Gender	Mean	Std. Dev.	Min.	Max.	Total N
Combined Genders	556	688	6	4850	139063
Female	395	492	6	3624	91227
Male	220	268	6	1555	47836

Table B.3: Summary Statistics: Survey Respondents: School-Program Combinations by Gender and Cohort

Gender	Year	Mean	Std. Dev.	Min.	Max.	Total N
Combined Genders	2007	59	66	6	605	19858
	2008	56	61	6	569	18719
	2009	66	72	7	521	23383
	2010	65	75	6	631	24911
	2011	64	72	6	637	24409
	2012	71	85	6	668	27783
Female	2007	73	79	6	605	13545
	2008	66	72	6	569	12369
	2009	82	86	7	521	15288
	2010	83	90	6	631	16116
	2011	79	85	6	637	15860
	2012	90	102	6	668	18049
Male	2007	42	39	6	210	6313
	2008	43	41	6	224	6350
	2009	49	47	7	261	8095
	2010	47	50	6	309	8795
	2011	47	50	6	305	8549
	2012	52	55	6	291	9734

Table B.4: Summary Statistics: Survey Respondents: Schools by Gender and Cohort

	Combined Genders			Female			Male		
Year	Mean	Std. Dev.	Total N	Mean	Std. Dev.	Total N	Mean	Std. Dev.	Total N
2007	946	694	19858	645	466	13545	301	240	6313
2008	891	679	18719	589	440	12369	302	251	6350
2009	1113	805	23383	728	511	15288	385	308	8095
2010	1186	842	24911	767	533	16116	419	323	8795
2011	1162	794	24409	755	512	15860	407	300	8549
2012	1323	952	27783	859	610	18049	464	356	9734

Table B.5: Summary Statistics: Survey Respondents: Programs by Gender and Cohort

	Combined Genders			Female			Male		
Year	Mean	Std. Dev.	Total N	Mean	Std. Dev.	Total N	Mean	Std. Dev.	Total N
2007	764	1098	19858	521	810	13545	243	360	6313
2008	720	1021	18719	476	727	12369	244	368	6350
2009	899	1273	23383	588	907	15288	311	445	8095
2010	958	1329	24911	620	946	16116	338	478	8795
2011	939	1306	24409	610	911	15860	329	475	8549
2012	1069	1507	27783	694	1059	18049	374	530	9734

Table B.6: Female Survey Respondents by Undergraduate Programs and Cohort

Programs	Cohort (Graduating Year)						Total
	2007	2008	2009	2010	2011	2012	
Pharmacy	43	55	65	64	107	109	443
Nursing	811	769	936	1010	1053	1122	5701
Engineering	322	260	290	364	343	478	2057
Computer Science	64	45	9	17	27	31	193
Therapy & Rehabilitation	32	22	37	0	0	0	91
Mathematics	119	65	99	127	137	99	646
Business & Commerce	1269	1113	1338	1472	1572	1695	8459
Forestry	0	0	0	0	0	0	0
Health Professions	387	366	506	484	546	572	2861
Other Arts & Science	441	395	496	567	598	718	3215
Architecture & Landscape Architecture	32	38	45	67	39	78	299
Physical Sciences	56	99	68	102	150	98	573
Journalism	45	48	80	74	71	83	401
Social Sciences	3608	3224	4063	4200	4076	4835	24006
Agriculture & Biological Science	1050	926	1287	1154	1004	1252	6673
Food Science & Nutrition	164	169	199	220	228	337	1317
Kinesiology / Recreation / Physical Edu.	670	542	602	646	615	624	3699
Humanities	1840	1685	1967	2040	1963	2243	11738
Fine & Applied Arts	529	548	651	709	698	817	3952
Total	11482	10369	12738	13317	13227	15191	76324

Table B.7: Female Survey Respondents by Professional Programs and Cohort

Programs	Cohort (Graduating Year)						
	2007	2008	2009	2010	2011	2012	Total
Dentistry	0	13	19	21	27	24	104
Optometry	25	18	21	23	27	31	145
Veterinary Medicine	31	41	40	41	38	38	229
Medicine	76	90	143	102	117	125	653
Law	176	209	281	342	315	358	1681
Education	1755	1629	2030	2256	2083	2267	12020
Theology	0	0	16	14	26	15	71
Total	2063	2000	2550	2799	2633	2858	14903

Table B.8: Male Survey Respondents by Undergraduate Programs and Cohort

Programs	Cohort (Graduating Year)						Total
	2007	2008	2009	2010	2011	2012	
Pharmacy	11	17	29	35	44	53	189
Nursing	8	45	68	93	85	99	398
Engineering	1147	1134	1364	1561	1456	1557	8219
Computer Science	287	302	326	316	281	308	1820
Therapy & Rehabilitation	8	0	0	0	0	0	8
Mathematics	107	110	143	204	125	207	896
Business & Commerce	1117	1185	1332	1501	1502	1667	8304
Forestry	0	9	0	0	12	0	21
Health Professions	83	77	170	179	129	200	838
Other Arts & Science	227	236	276	299	307	369	1714
Architecture & Landscape Architecture	28	14	54	46	43	46	231
Physical Sciences	25	71	83	143	128	154	604
Journalism	0	0	9	17	9	0	35
Social Sciences	1152	1196	1552	1551	1628	1882	8961
Agriculture & Biological Science	407	330	559	546	475	616	2933
Food Science & Nutrition	7	0	16	18	8	37	86
Kinesiology/Recreation/Physical Ed.	244	183	255	273	332	328	1615
Humanities	635	636	763	783	710	864	4391
Fine & Applied Arts	158	139	162	240	259	256	1214
Total	5651	5684	7161	7805	7533	8643	42477

Table B.9: Male Survery Respondents by Professional Programs and Cohort

Programs	Cohort (Graduating Year)						Total
	2007	2008	2009	2010	2011	2012	
Dentistry	7	6	22	15	9	15	74
Optometry	0	9	12	9	7	8	45
Veterinary Medicine	7	0	0	11	6	7	31
Medicine	65	65	111	82	76	98	497
Law	154	161	201	220	212	252	1200
Education	429	425	588	645	683	699	3469
Theology	0	0	0	8	23	12	43
Total	662	666	934	990	1016	1091	5359

B.1.4 Inflation Adjusted Bins

Table B.10: Bin Adjustments for Inflation

Year	6 Months	2 Years
2007	1.044763	1.017437
2008	1.009516	1
2009	1.017437	0.970075
2010	1	0.958128
2011	0.970075	0.94801
2012	0.958128	0.928401

Notes: The year refers to the graduating cohort. Everything was adjusted to 2010 dollars (August CPI). Source: Bank of Canada (BOC, 2019).

B.2 Analysis

This is a simplified example with two bins and four observations to illustrate the different possible permutations for the privacy-suppressed data. Let $obs_1, obs_2, obs_3, obs_4$ be the individual observations. Table B.11 shows that there are six ways to arrange the observations within two bins when two observations have to be within each bin. Moreover, Table B.12 illustrates that are six ways to arrange observations when one of the bins has to have one observation and the other bin has to have three observations. Refer to the tables below:

Table B.11: Permutations for Missing Data: Two Observations in Each Bin

Bins for (2,2)	Permutation					
	1	2	3	4	5	6
Bin 1	obs_1, obs_2	obs_1, obs_3	obs_1, obs_4	obs_3, obs_4	obs_2, obs_4	obs_2, obs_3
Bin 2	obs_3, obs_4	obs_2, obs_4	obs_2, obs_3	obs_1, obs_2	obs_1, obs_3	obs_1, obs_4

Table B.12: Permutations for Missing Data: Three Observations in One Bin and One Observation in the Other

		Permutation			
		1	2	3	4
Bins for (1,3)	Bin 1	obs_1	obs_2	obs_3	obs_4
	Bin 2	obs_2, obs_3, obs_4	obs_1, obs_3, obs_4	obs_1, obs_2, obs_4	obs_1, obs_2, obs_3
Bins for (3,1)	Bin 1	obs_2, obs_3, obs_4	obs_1, obs_3, obs_4	obs_1, obs_2, obs_4	obs_1, obs_2, obs_3
	Bin 2	obs_1	obs_2	obs_3	obs_4

B.2.1 Detailed Results with Different Orders of Regressors

Table B.13: Relative-Importance: Combined Programs and Combined Genders

Order	Regressors			
	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
Six-Month Salaries, N = 499700				
Average	0.218	0.021	0.029	0.268
	(0.213–0.223)	(0.020–0.023)	(0.027–0.032)	(0.263–0.273)
Prgs. First	0.229	0.011	0.029	0.268
	(0.224–0.233)	(0.009–0.012)	(0.027–0.032)	(0.263–0.273)
Schs. First	0.207	0.032	0.029	0.268
	(0.202–0.212)	(0.030–0.034)	(0.027–0.032)	(0.263–0.273)
Two-Year Salaries, N = 554510				
Average	0.189	0.018	0.025	0.233
	(0.184–0.195)	(0.016–0.019)	(0.023–0.028)	(0.227–0.239)
Prgs. First	0.199	0.008	0.025	0.233
	(0.193–0.204)	(0.007–0.010)	(0.023–0.028)	(0.227–0.239)
Schs. First	0.180	0.027	0.025	0.233
	(0.175–0.185)	(0.025–0.029)	(0.023–0.028)	(0.227–0.239)

Table B.14: Relative-Importance: Combined Programs and Female

Order	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
	Six-Month Salaries, N = 327330			
Average	0.208	0.021	0.032	0.262
	(0.203–0.213)	(0.019–0.023)	(0.029–0.035)	(0.256–0.268)
Prgs. First	0.217	0.012	0.032	0.262
	(0.212–0.223)	(0.011–0.014)	(0.029–0.035)	(0.256–0.268)
Schs. First	0.199	0.031	0.032	0.262
	(0.194–0.204)	(0.028–0.033)	(0.029–0.035)	(0.256–0.268)
	Two-Year Salaries, N = 363965			
Average	0.174	0.017	0.030	0.221
	(0.168–0.181)	(0.015–0.019)	(0.027–0.035)	(0.214–0.231)
Prgs. First	0.182	0.009	0.030	0.221
	(0.176–0.189)	(0.008–0.011)	(0.027–0.035)	(0.214–0.231)
Schs. First	0.167	0.024	0.030	0.221
	(0.160–0.173)	(0.022–0.027)	(0.027–0.035)	(0.214–0.231)

Table B.15: Relative-Importance: Combined Programs and Male

Order	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
	Six-Month Salaries, N = 172370			
Average	0.202	0.027	0.038	0.267
	(0.193-0.212)	(0.023-0.030)	(0.033-0.045)	(0.257-0.279)
Prgs. First	0.214	0.015	0.038	0.267
	(0.204-0.224)	(0.013-0.018)	(0.033-0.045)	(0.257-0.279)
Schs. First	0.191	0.038	0.038	0.267
	(0.181-0.201)	(0.034-0.043)	(0.033-0.045)	(0.257-0.279)
	Two-Year Salaries, N = 190545			
Average	0.182	0.021	0.034	0.237
	(0.172-0.193)	(0.018-0.024)	(0.028-0.042)	(0.226-0.250)
Prgs. First	0.192	0.011	0.034	0.237
	(0.181-0.203)	(0.009-0.014)	(0.028-0.042)	(0.226-0.250)
Schs. First	0.172	0.031	0.034	0.237
	(0.162-0.184)	(0.027-0.034)	(0.028-0.042)	(0.226-0.250)

Table B.16: Relative-Importance: Professional Programs and Combined Genders

Order	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
	Six-Month Salaries, N = 84975			
Average	0.176	0.053	0.008	0.238
	(0.165-0.188)	(0.048-0.060)	(0.005-0.013)	(0.224-0.252)
Prgs. First	0.206	0.023	0.008	0.238
	(0.194-0.220)	(0.019-0.029)	(0.005-0.013)	(0.224-0.252)
Schs. First	0.146	0.084	0.008	0.238
	(0.134-0.157)	(0.074-0.092)	(0.005-0.013)	(0.224-0.252)
	Two-Year Salaries, N = 91690			
Average	0.194	0.054	0.009	0.257
	(0.174-0.216)	(0.048-0.060)	(0.004-0.021)	(0.236-0.282)
Prgs. First	0.223	0.024	0.009	0.257
	(0.204-0.245)	(0.020-0.030)	(0.004-0.021)	(0.236-0.282)
Schs. First	0.165	0.083	0.009	0.257
	(0.144-0.187)	(0.075-0.092)	(0.004-0.021)	(0.236-0.282)

Table B.17: Relative-Importance: Professional Programs and Female

Order	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
	Six-Month Salaries, N = 62320			
Average	0.152	0.053	0.007	0.213
	(0.141-0.164)	(0.047-0.060)	(0.005-0.011)	(0.200-0.226)
Prgs. First	0.180	0.025	0.007	0.213
	(0.168-0.193)	(0.020-0.031)	(0.005-0.011)	(0.200-0.226)
Schs. First	0.124	0.082	0.007	0.213
	(0.112-0.135)	(0.072-0.091)	(0.005-0.011)	(0.200-0.226)
	Two-Year Salaries, N = 67320			
Average	0.167	0.057	0.016	0.240
	(0.146-0.191)	(0.050-0.064)	(0.006-0.043)	(0.212-0.285)
Prgs. First	0.193	0.030	0.016	0.240
	(0.172-0.216)	(0.024-0.037)	(0.006-0.043)	(0.212-0.285)
Schs. First	0.140	0.083	0.016	0.240
	(0.118-0.166)	(0.073-0.093)	(0.006-0.043)	(0.212-0.285)

Table B.18: Relative-Importance: Professional Programs and Male

Order	Regressors			
	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
	Six-Month Salaries, N = 22655			
Average	0.206	0.059	0.015	0.279
	(0.179-0.235)	(0.047-0.072)	(0.005-0.034)	(0.245-0.315)
Prg. First	0.239	0.025	0.015	0.279
	(0.212-0.271)	(0.016-0.036)	(0.005-0.034)	(0.245-0.315)
Sch. First	0.172	0.092	0.015	0.279
	(0.145-0.201)	(0.076-0.110)	(0.005-0.034)	(0.245-0.315)
	Two-Year Salaries, N = 24370			
Average	0.235	0.055	0.013	0.303
	(0.195-0.281)	(0.043-0.067)	(0.006-0.026)	(0.260-0.350)
Prgs. First	0.272	0.017	0.013	0.303
	(0.230-0.321)	(0.010-0.026)	(0.006-0.026)	(0.260-0.350)
Schs. First	0.198	0.092	0.013	0.303
	(0.158-0.245)	(0.071-0.115)	(0.006-0.026)	(0.260-0.350)

Table B.19: Relative-Importance: Professional Programs (No Dentistry) and Combined Genders

Order	Regressors			
	Prg.	Sch.	Prg. × Sch.	Overall R^2
	Six-Month Salaries, N = 84160			
Average	0.157	0.054	0.006	0.218
	(0.148–0.167)	(0.048–0.061)	(0.004–0.009)	(0.207–0.230)
Prgs. First	0.186	0.025	0.006	0.218
	(0.176–0.197)	(0.020–0.031)	(0.004–0.009)	(0.207–0.230)
Schs. First	0.128	0.083	0.006	0.218
	(0.119–0.138)	(0.074–0.092)	(0.004–0.009)	(0.207–0.230)
	Two-Year Salaries, N = 90915			
Average	0.162	0.055	0.006	0.223
	(0.152–0.172)	(0.049–0.060)	(0.004–0.009)	(0.211–0.235)
Prgs. First	0.190	0.027	0.006	0.223
	(0.179–0.202)	(0.022–0.032)	(0.004–0.009)	(0.211–0.235)
Sch. First	0.134	0.083	0.006	0.223
	(0.124–0.144)	(0.075–0.091)	(0.004–0.009)	(0.211–0.235)

Table B.20: Relative-Importance: Professional Programs (No Dentistry) and Female

Order	Regressors			
	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
Six-Month Salaries, N = 61850				
Average	0.137	0.054	0.007	0.198
	(0.128–0.147)	(0.048–0.061)	(0.004–0.010)	(0.186–0.211)
Prgs. First	0.165	0.026	0.007	0.198
	(0.154–0.177)	(0.021–0.032)	(0.004–0.010)	(0.186–0.211)
Schs. First	0.109	0.082	0.007	0.198
	(0.100–0.119)	(0.073–0.092)	(0.004–0.010)	(0.186–0.211)
Two-Year Salaries, N = 66860				
Average	0.139	0.058	0.007	0.205
	(0.129–0.150)	(0.052–0.065)	(0.004–0.012)	(0.193–0.219)
Prgs. First	0.165	0.032	0.007	0.205
	(0.154–0.178)	(0.026–0.039)	(0.004–0.012)	(0.193–0.219)
Schs. First	0.113	0.084	0.007	0.205
	(0.103–0.124)	(0.076–0.093)	(0.004–0.012)	(0.193–0.219)

Table B.21: Relative-Importance: Professional Programs (No Dentistry) and Male

Order	Regressors			
	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
Six-Month Salaries, N = 22310				
Average	0.175	0.060	0.009	0.243
	(0.154–0.196)	(0.048–0.073)	(0.004–0.015)	(0.218–0.268)
Prgs. First	0.206	0.029	0.009	0.243
	(0.182–0.230)	(0.019–0.041)	(0.004–0.015)	(0.218–0.268)
Schs. First	0.144	0.091	0.009	0.243
	(0.124–0.164)	(0.074–0.110)	(0.004–0.015)	(0.218–0.268)
Two-Year Salaries, N = 24055				
Average	0.186	0.055	0.011	0.252
	(0.165–0.209)	(0.042–0.069)	(0.006–0.018)	(0.224–0.282)
Prgs. First	0.222	0.019	0.011	0.252
	(0.195–0.250)	(0.012–0.028)	(0.006–0.018)	(0.224–0.282)
Schs. First	0.151	0.090	0.011	0.252
	(0.130–0.173)	(0.068–0.116)	(0.006–0.018)	(0.224–0.282)

Table B.22: Relative-Importance: Undergraduate Programs and Combined Genders

Order	Regressors			
	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
		Six-Month Salaries, N = 414725		
Average	0.215	0.026	0.029	0.270
	(0.210–0.220)	(0.024–0.028)	(0.026–0.032)	(0.265–0.276)
Prgs. First	0.229	0.013	0.029	0.270
	(0.224–0.234)	(0.011–0.015)	(0.026–0.032)	(0.265–0.276)
Schs. First	0.202	0.040	0.029	0.270
	(0.197–0.207)	(0.037–0.043)	(0.026–0.032)	(0.265–0.276)
		Two-Year Salaries, N = 462820		
Average	0.178	0.022	0.024	0.223
	(0.173–0.182)	(0.020–0.023)	(0.021–0.026)	(0.218–0.228)
Prgs. First	0.189	0.010	0.024	0.223
	(0.185–0.194)	(0.009–0.012)	(0.021–0.026)	(0.218–0.228)
Schs. First	0.167	0.033	0.024	0.223
	(0.162–0.171)	(0.030–0.035)	(0.021–0.026)	(0.218–0.228)

Table B.23: Relative-Importance: Undergraduate Programs and Female

Order	Regressors			
	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
		Six-Month Salaries, N = 265010		
Average	0.207	0.027	0.032	0.266
	(0.201–0.212)	(0.025–0.030)	(0.029–0.036)	(0.259–0.273)
Prg. First	0.219	0.015	0.032	0.266
	(0.213–0.225)	(0.013–0.017)	(0.029–0.036)	(0.259–0.273)
Sch. First	0.194	0.040	0.032	0.266
	(0.189–0.200)	(0.037–0.043)	(0.029–0.036)	(0.259–0.273)
		Two-Year Salaries, N = 296645		
Average	0.162	0.021	0.027	0.210
	(0.157–0.167)	(0.019–0.023)	(0.024–0.030)	(0.204–0.216)
Prgs. First	0.172	0.012	0.027	0.210
	(0.166–0.177)	(0.010–0.013)	(0.024–0.030)	(0.204–0.216)
Schs. First	0.153	0.030	0.027	0.210
	(0.148–0.158)	(0.028–0.033)	(0.024–0.030)	(0.204–0.216)

Table B.24: Relative-Importance: Undergraduate Programs and Male

Order	Regressors			
	Prgs.	Schs.	Prgs. × Schs.	Overall R^2
Six-Month Salaries, N = 149715				
Average	0.189	0.032	0.038	0.259
	(0.181–0.199)	(0.028–0.035)	(0.032–0.046)	(0.248–0.271)
Prgs. First	0.204	0.017	0.038	0.259
	(0.195–0.213)	(0.014–0.020)	(0.032–0.046)	(0.248–0.271)
Schs. First	0.175	0.046	0.038	0.259
	(0.166–0.184)	(0.041–0.051)	(0.032–0.046)	(0.248–0.271)
Two-Year Salaries, N = 166175				
Average	0.161	0.025	0.034	0.221
	(0.153–0.170)	(0.022–0.029)	(0.028–0.044)	(0.210–0.233)
Prgs. First	0.173	0.014	0.034	0.221
	(0.164–0.182)	(0.011–0.016)	(0.028–0.044)	(0.210–0.233)
Schs. First	0.150	0.037	0.034	0.221
	(0.141–0.159)	(0.032–0.042)	(0.028–0.044)	(0.210–0.233)

B.2.2 Estimated Salaries

Table B.25: Estimated Female Median Salaries by Professional Programs at Six Months and Two Years

Programs	Period After Graduation				
	(2010 $) Median Salary (95 % C.I.)		%Δ(6 Mos	N Sample[1]	
	6 Months	2 Years	to 2 Yrs)	6 Mos	2 Yrs
Dentistry	93191	183899	97%	94	92
	(67686–128765)	(76524–815965)			
Optometry	72677	90639	25%	143	143
	(63827–82755)	(83748–98097)			
Veterinary Medicine	62017	65451	6%	222	214
	(59360–64792)	(62191–68881)			
Medicine	53493	63628	19%	563	604
	(50795–56463)	(58336–70985)			
Law	50570	60539	20%	1434	1469
	(47121–54305)	(56106–65373)			
Education	28212	34085	21%	9962	10884
(teacher training)	(27038–29442)	(32834–35388)			
Theology	24126	23634	-2%	46	58
	(15685–37613)	(17480–33666)			

[1]The N sample refers to the number of employed graduates and, as a result of privacy suppression, it is calculated as the midpoint between minimum and maximum possible number of employed individuals (the same note also applies to Tables B.26 to B.28).

Table B.26: Estimated Female Median Salaries by Undergraduate Programs at Six Months and Two Years

Programs	Period After Graduation				
	(2010 $) Median Salary (95 % C.I.)		%Δ(6 Mos	N Sample	
	6 Months	2 Years	to 2 Yrs)	6 Mos	2 Yrs
Pharmacy	74637	83086	11%	417	421
	(69953–79648)	(79234–87134)			
Nursing	52731	55065	4%	5189	5445
	(50930–54606)	(53293–56905)			
Engineering	46518	51647	11%	1447	1656
	(42966–50485)	(47868–55878)			
Computer Science	51197	57572	12%	160	189
	(44713–59243)	(51152–64921)			
Therapy and Rehab.	44154	48454	10%	88	89
	(40936–47625)	(44514–52743)			
Mathematics	39853	44172	11%	480	642
	(35629–45631)	(39763–49482)			
Business/Commerce	38292	44736	17%	7218	7688
	(36717–39957)	(42973–46590)			
Forestry	–	–	–	0	0
Health Professions	34804	38827	12%	1536	1720
	(31387–38732)	(35444–42624)			
Other Arts and Science	27786	31922	15%	2170	2389
	(24950–31097)	(28887–35375)			
Archit. & Lands. Archit.	29104	28682	-1%	214	184
	(25227–33686)	(22615–37236)			
Physical Sciences	25271	26863	6%	358	494
	(19576–32877)	(21598–33550)			
Journalism	26521	33499	26%	316	355
	(23609–30231)	(30549–36772)			
Social Sciences	24495	29574	21%	16421	18485
	(23484–25563)	(28459–30742)			
Agr. & Bio. Sciences	21943	27286	24%	3222	3551
	(19990–24177)	(24868–30027)			
Food Science/Nutrition	22193	29975	35%	818	1027
	(20176–24670)	(27555–32880)			
Kin./Recr./Phys. Ed.	21800	28263	30%	2226	2504
	(19490–24445)	(25463–31407)			
Humanities	21543	26726	24%	7894	9215
	(20284–22909)	(25331–28225)			
Fine and Applied Arts	19024	22788	20%	2828	3275
	(17299–21020)	(20648–25294)			

Table B.27: Estimated Male Median Salaries by Undergraduate Programs at Six Months and Two Years

Programs	Period After Graduation				
	(2010 $) Median Salary (95 % C.I.)		%Δ(6 Mos	N Sample	
	6 Months	2 Years	to 2 Yrs)	6 Mos	2 Yrs
Pharmacy	79346	89201	12%	171	177
	(69204–91169)	(79593–99968)			
Nursing	53420	56747	6%	359	368
	(46988–60786)	(49633–65311)			
Engineering	50560	56524	12%	6058	6883
	(48686–52528)	(54608–58596)			
Computer Science	47662	54067	13%	1527	1680
	(43597–52289)	(49490–59281)			
Therapy and Rehab.	50497	63060	25%	8	6
	(41860–60917)	(50742–78369)			
Mathematics	41508	48061	16%	609	743
	(37803–46124)	(44001–52884)			
Business/Commerce	41893	48811	17%	6840	7448
	(39972–43931)	(46682–51059)			
Forestry	35957	41901	17%	20	25
	(29454–43896)	(35301–49735)			
Health Professions	31581	36911	17%	332	386
	(25796–38755)	(30837–44498)			
Other Arts and Science	40966	43454	6%	1174	1255
	(35094–48293)	(36996–51590)			
Archit. & Lands. Archit.	31665	35449	12%	188	135
	(26690–37905)	(30452–44527)			
Physical Sciences	28830	31570	10%	340	382
	(22536–37174)	(24779–40472)			
Journalism	24320	31539	30%	29	38
	(17278–34457)	(24311–40920)			
Social Sciences	30069	36081	20%	6045	6776
	(28051–32264)	(33828–38509)			
Agr. & Bio. Sciences	26132	30997	19%	1355	1476
	(22699–30306)	(26901–35916)			
Food Science/Nutrition	30156	32644	8%	66	77
	(26643–34131)	(28035–38010)			
Kin./Recr./Phys. Ed.	24658	31114	26%	982	1115
	(20915–29232)	(26979–36018)			
Humanities	23419	28409	21%	2878	3241
	(20870–26412)	(25548–31684)			
Fine and Applied Arts	22310	26465	19%	962	1024
	(18753–27152)	(22403–31881)			

Table B.28: Estimated Male Median Salaries by Professional Programs at Six Months and Two Years

Programs	Period After Graduation (2010 \$) Median Salary (95 % C.I.) 6 Months	2 Years	%Δ(6 Mos to 2 Yrs)	N Sample 6 Mos	2 Yrs
Dentistry	131517 (77010–247252)	224595 (97654–516728)	71%	69	63
Optometry	103450 (83513–128148)	143659 (97625–211401)	39%	45	45
Veterinary Medicine	74230 (63025–87428)	82918 (70793–97119)	12%	31	24
Medicine	55047 (52068–58279)	63532 (58382–69770)	15%	443	465
Law	58014 (53061–63458)	71013 (64608–78095)	22%	1053	1066
Education (teacher training)	34843 (32422–37475)	40336 (37830–43033)	16%	2853	3167
Theology	32065 (24019–44467)	38348 (30217–49018)	20%	37	44

B.2.3 Employment Rates

The employment rate calculation is as follows:

$$\text{Employment Rate} = \frac{TOT_{EMP}}{TOT_{LF}} = \frac{EMP + OE}{EMP + OE + NE}$$

Where TOT_{EMP} is the total employed and TOT_{LF} is the labour force. EMP is the number of employed graduates, OE is the number of graduates that were offered employment at a later date, and NE is the number of graduates who were not employed but were looking for employment and were not in school.[2]

The calculation of the employment rates has to incorporate the missing data due to privacy suppression. OE and NE have many suppressed observations, and EMP by the data cleaning procedure have no missing observations.[3] Although I do not know the exact

[2]All these variables are dependent on the school, program, graduating year, and gender; however, for simplification, this is omitted from the notation.

[3]Refer to B.1.1 in the appendix for more details.

values which are suppressed, by privacy suppression rules, they must be between 1 and 5. Therefore, for the employment rates which involve suppressed values, there is a minimum and maximum employment rate. The minimum employment rate has to have the smallest numerator and the largest denominator, and the maximum employment rate has to have the largest numerator and the smallest denominator.

$$\text{Minimum Employment Rate} = \frac{EMP+1}{EMP+1+5}$$

$$\text{Maximum Employment Rate} = \frac{EMP+5}{EMP+5+1}$$

Tables B.29 and B.30 in Section 3.4.2 report the midpoint employment rate.

$$\text{Midpoint Employment Rate} = \frac{EMP+3}{EMP+6}$$

Table B.29: Employment Rates by Undergraduate Programs and Gender at Six Months and Two Years

Programs	Period After Graduation and Gender					
	6 Months			2 Years		
	Combined Genders	Female	Male	Combined Genders	Female	Male
Pharmacy	95%	97%	92%	96%	97%	94%
Nursing	93%	94%	88%	98%	98%	95%
Engineering	87%	86%	88%	94%	91%	94%
Computer Science	89%	89%	89%	95%	97%	95%
Therapy & Rehab.	100%	100%	100%	100%	100%	100%
Mathematics	85%	89%	82%	91%	92%	91%
Business & Commerce	90%	92%	88%	95%	96%	94%
Forestry	100%	-	100%	100%	-	100%
Health Professions	86%	87%	80%	92%	93%	85%
Other Arts & Science	88%	88%	86%	91%	92%	91%
Archit. & Lands. Archit.	85%	83%	88%	86%	86%	87%
Physical Sciences	83%	85%	82%	85%	87%	82%
Journalism	87%	87%	84%	92%	91%	100%
Social Sciences	87%	88%	84%	92%	92%	90%
Agr. & Bio. Sciences	85%	86%	82%	90%	90%	90%
Food Science & Nutrition	89%	90%	81%	92%	92%	90%
Kin./Recr./Phys. Ed	90%	92%	87%	92%	92%	90%
Humanities	88%	90%	85%	92%	92%	90%
Fine & Applied Arts	86%	86%	86%	91%	91%	89%
Weighted Average	88%	89%	86%	93%	93%	92%

Table B.30: Employment Rates by Professional Programs and Gender at Six Months and Two Years

Programs	Period After Graduation and Gender					
	6 Months			2 Years		
	Combined Genders	Female	Male	Combined Genders	Female	Male
Dentistry	98%	97%	100%	96%	94%	100%
Optometry	100%	100%	100%	98%	98%	100%
Veterinary Medicine	97%	96%	100%	99%	99%	100%
Medicine	99%	99%	99%	98%	99%	96%
Law	92%	93%	92%	92%	92%	92%
Education (teacher training)	89%	89%	86%	95%	95%	93%
Theology	79%	77%	82%	90%	91%	89%
Weighted Average	90%	90%	89%	95%	95%	93%

B.2.4 The Proportion of Survey Respondents That Acquired Jobs

The proportion of survey respondents that acquired jobs, denoted as EMPSURV, is similar to the employment rate in Section B.2.3 but also considers the graduates that were not in the labour force. The calculation is as follows:

$$\text{EMPSURV} = \frac{TOT_{EMP}}{NUMSUR} = \frac{EMP + OE}{NUMSUR}$$

Similarly to employment rate calculations in Section B.2.3, missing data due to privacy suppression has to incorporated here as well. The method is analogous to Section B.2.3.

$$\text{Minimum EMPSURV} = \frac{EMP + 1}{NUMSUR}$$

$$\text{Maximum EMPSURV} = \frac{EMP + 5}{NUMSUR}$$

$$\text{Midpoint EMPSURV} = \frac{EMP + 3}{NUMSUR}$$

Table B.31: The Proportion of Survey Respondents that Acquired Jobs by Undergraduate Programs and Gender at Six Months and Two Years

Programs	Period After Graduation and Gender					
	6 Months			2 Years		
	Combined Genders	Female	Male	Combined Genders	Female	Male
Pharmacy	93%	94%	90%	95%	95%	94%
Nursing	91%	91%	90%	95%	95%	94%
Engineering	73%	70%	74%	83%	80%	84%
Computer Science	84%	83%	84%	91%	92%	91%
Therapy & Rehab.	97%	97%	100%	96%	98%	75%
Mathematics	71%	74%	68%	82%	85%	80%
Business & Commerce	84%	85%	82%	90%	91%	90%
Forestry	95%	–	95%	91%	–	91%
Health Professions	50%	54%	39%	56%	60%	43%
Other Arts & Science	68%	67%	68%	74%	74%	74%
Archit. & Lands. Archit.	76%	71%	81%	77%	73%	82%
Physical Sciences	59%	62%	56%	66%	70%	62%
Journalism	79%	79%	83%	88%	87%	93%
Social Sciences	68%	68%	67%	77%	77%	75%
Agr. & Bio. Sciences	48%	48%	46%	52%	53%	49%
Food Science & Nutrition	63%	62%	77%	78%	78%	82%
Kin./Recr./Phys. Ed	60%	60%	61%	68%	67%	68%
Humanities	67%	67%	66%	77%	78%	74%
Fine & Applied Arts	73%	72%	79%	82%	81%	82%
Weighted Average	70%	69%	70%	77%	77%	78%

Notes: Due to data suppression, the values in the table are midpoint imputations from the calculated minimum to maximum interval. The average is weighted by the number of survey respondents. The part-time rate calculations in Tables B.33 to B.35 used a similar midpoint rule.

Table B.32: The Proportion of Survey Respondents that Acquired Jobs by Professional Programs and Gender at Six Months and Two Years

Programs	Period After Graduation and Gender					
	6 Months			2 Years		
	Combined Genders	Female	Male	Combined Genders	Female	Male
Dentistry	92%	90%	93%	90%	88%	93%
Optometry	99%	98%	100%	99%	99%	100%
Veterinary Medicine	97%	97%	100%	94%	93%	96%
Medicine	87%	86%	89%	91%	90%	92%
Law	86%	85%	88%	89%	88%	89%
Education (teacher training)	83%	83%	82%	91%	91%	91%
Theology	73%	65%	86%	84%	82%	86%
Weighted Average	84%	84%	84%	90%	90%	91%

B.2.5 Estimated Part-Time Rates By Programs and Degree Type

Table B.33: Summary of Part-Time Rates by Degree Type and Gender at Six Months and Two Years

Degree Type	Period After Graduation and Gender					
	6 Months			2 Years		
	Combined Genders	Female	Male	Combined Genders	Female	Male
Combined	21%	24%	14%	21%	24%	14%
Undergraduate	20%	24%	14%	20%	24%	14%
Professional	24%	26%	17%	24%	26%	17%

Table B.34: Estimated Part-Time Rates by Undergraduate Programs and Gender at Six Months and Two Years

Programs	Period After Graduation and Gender					
	6 Months			2 Years		
	Combined Genders	Female	Male	Combined Genders	Female	Male
Pharmacy	6%	6%	5%	6%	6%	6%
Nursing	12%	12%	13%	12%	12%	13%
Engineering	5%	6%	5%	5%	7%	5%
Computer Science	6%	6%	6%	8%	6%	8%
Therapy and Rehab.	7%	7%	0%	7%	8%	0%
Mathematics	12%	12%	11%	14%	16%	13%
Business/Commerce	7%	8%	7%	8%	8%	7%
Forestry	10%	0%	10%	9%	0%	9%
Health Professions	25%	25%	24%	25%	25%	26%
Other Arts and Science	21%	25%	13%	21%	25%	13%
Archit. & Lands. Archit.	11%	11%	11%	9%	9%	9%
Physical Sciences	23%	23%	23%	26%	28%	24%
Journalism	19%	18%	28%	20%	19%	31%
Social Sciences	27%	29%	20%	27%	29%	20%
Agr. & Bio. Sciences	26%	27%	23%	26%	27%	22%
Food Science/Nutrition	32%	33%	12%	32%	33%	12%
Kin./Recr./Phys. Ed.	27%	27%	26%	27%	27%	28%
Humanities	31%	32%	28%	31%	32%	28%
Fine and Applied Arts	32%	34%	28%	32%	34%	28%
Weighted Average	20%	24%	14%	20%	24%	14%

Table B.35: Estimated Part-Time Rates by Professional Programs and Gender at Six Months and Two Years

Programs	Period After Graduation and Gender					
	6 Months			2 Years		
	Combined Genders	Female	Male	Combined Genders	Female	Male
Dentistry	11%	14%	8%	12%	13%	11%
Optometry	13%	12%	17%	13%	12%	17%
Veterinary Medicine	2%	3%	0%	3%	4%	0%
Medicine	3%	3%	3%	4%	3%	4%
Law	5%	6%	4%	5%	5%	4%
Education (teacher training)	30%	32%	24%	30%	32%	24%
Theology	28%	32%	24%	28%	33%	23%
Weighted Average	24%	26%	17%	24%	26%	17%

Appendix C

Chapter 4 Appendix

C.1 Identification: A Simple Two-Bin Example

The initial bins contain the salaries of full-time public-school teachers and the salaries of education-program graduates who acquired a position outside the public school system (the outside option). The goal of this procedure is to estimate the number of public-sector teachers within each salary bin and then to subtract them out to reveal the number of people who acquired a job outside the public school system. Once the new bins have been constructed, the salary distributions for the outside-option individuals can be estimated using the maximum likelihood method.

Let x_1 be the range of salaries in bin 1, x_2 be the range of salaries in bin 2 and N be the total number of individuals in the survey. A fraction αN, where $\alpha < 0$, of these individuals will have a job, either as a public-school teacher or through the outside option. Then

$$N^* = \alpha N = N_1 + N_2$$

where N_1 and N_2 represent the numbers of individuals who have a job in bins 1 and 2 respectively. Each of these bins contains the number of individuals $N_{1,T}$, $N_{2,T}$ who receive a teacher salary and the number of individuals $N_{1,O}$, $N_{2,O}$ who receive an the outside-option salary. It therefore follows that

$$N_1 = N_{1,T} + N_{1,O}, N_2 = N_{2,T} + N_{2,O}.$$

The goal is then to estimate,

$$N_{1,O} = N_1 - N_{1,T}$$

$$N_{2,O} = N_2 - N_{2,T}.$$

Furthermore, I assume that individuals have one of two types of qualifications $A1$ and $A2$ (there are four types in the actual data), each of which has a different and known salary distribution that is conditional on having a public-school position. The number of individuals of each type then can be represented by $N_{T,A1}$ and $N_{T,A2}$.

The following probabilities can be directly extracted from the data and are defined in such a way as to correspond with the above-stated definitions:

$$\underbrace{p(T,A1) = \frac{N_{T,A1}}{N},\ p(TC,A2) = \frac{N_{T,A2}}{N},}_{Teacher\ Data}$$

$$\underbrace{p(x_1|T,A1) = \frac{N_{1,T}}{N_{T,A1}},\ p(x_2|TC,A2) = \frac{N_{2,T}}{N_{T,A2}}.}_{Salary\ Grid\ Data}$$

Then the following calculations are used to estimate $N_{1,T}$ and $N_{2,T}$:

$$p(x_1,T,A1) = p(x_1|T,A1)p(T,A1) = \frac{N_{1,T}}{N_{T,A1}}\frac{N_{T,A1}}{N} = \frac{N_{1,T}}{N},$$

$$p(x_2,T,A2) = p(x_2|T,A2)p(T,A2) = \frac{N_{2,T}}{N_{T,A2}}\frac{N_{TC,A2}}{N} = \frac{N_{2,T}}{N}.$$

After rearranging and solving for $N_{1,O} = N_1 - N_{1,T}$ and $N_{2,O} = N_2 - N_{2,T}$:

$$N_{1,O} = N_1 - Np(x_{1,}T, A1),$$

$$N_{2,O} = N_2 - Np(x_2, T, A2).$$

C.2 Data Details

C.2.1 Timing Information

I assume that the teacher job market is in discrete time. Further, I assume that teachers graduate from teachers' college between April and June of their graduation year, and that they acquire their full-time position before September of that year. For example, for the two-year data, if the individual graduated in 2007, then the period in question that indicates whether he had a public-school teaching job would fall between April and June of 2009. Moreover, if this individual was hired for a full-time teaching position, he would have to have received it by September of 2008; therefore, for the calculation requirements of this study, the 2008 salary grid would be used.

C.2.2 Teacher Data

Table C.1 reports the number of graduates in each graduating-year cohort who acquired a teaching ceritifcation in 2014. Similarly to Chapter 1, since data for 2014 was only partially downloaded, I excluded all graduates who acquired a teaching certification in 2014. For example, the exclusion of 1,028 individuals from the 2013 cohort partially explains the decrease in the number of graduates from the 2012 cohort to the 2013 cohort in Table 4.2. Moreover, the decrease in graduates for 2012 and 2013 is also due to the decrease in Ontario teachers' college enrolments for those cohort years. For example, the number of graduates in 2013 is lower relative to the number of graduates in 2012 due to a 7.6 percent drop in confirmed enrolments from 2011 to 2012 (OUAC, 2012) Likewise, the number of

Table C.1: Excluded Observations from the 2014 Certification Year by Graduating-Year Cohort

Year	Sample N
2007	10
2008	7
2009	19
2010	38
2011	74
2012	254
2013	1028
2014	5008
Total	6438

graduates in 2012 is lower relative to the number of graduates in 2011 due to a 6.4 percent drop in confirmed enrolments from 2010 to 2011 (OUAC, 2011).

C.2.3 Inflation Adjusted Bins

Table C.2: Bin Adjustments for Inflation

Year	6 Months	2 Years
2007	1.044763	1.017437
2008	1.009516	1.000000
2009	1.017437	0.970075
2010	1.000000	0.958128
2011	0.970075	0.948010
2012	0.958128	0.928401
2013	0.948010	0.916732

Notes: The year refers to the graduating cohort. Everything was adjusted to 2010 dollars (August CPI). Source: BOC (2019).

C.2.4 Salary-Grid Data Assumption Notes

Several assumptions were made in relation to missing collective agreements. The summary of these assumptions along with the percentage of the observations that were affected are outlined in Table C.3.

Table C.3: Summary of Salary-Grid Assumptions

Assumption Description	Percentage of Observations
No assumptions were needed because all of the values were extracted from the salary grids.	79.55%
There was a wage freeze from 2012 to 2014. The same values were used.	11.86%
If the first and last known years had the same salary-grid values, then the years in between also had the same values.	7.08%
I used the grid of another collective agreement matched from the same union.	1.15%
The values were imputed through the use of similar salary grids, based on the criterion that the same grid values were observed in another year. For example, if two different school boards had the same values in a year when both salary grids were observed, then they should have the same values in all other years.	0.34%
Teachers under the ETFO union did not have a wage freeze for 2013. I assumed the same percentage change from the 2013 and the 2014 salary grids based on the other observed ETFO salary grids.	0.02%
All of the values in the same salary grid increase by the same percentage as in another year. Therefore, one only needs one value in order to calculate the percentage increase; this percentage can be applied to all of the other values in the grid. The values were found in a summary document that includes the maximum and minimum salaries for each qualification category level.	0.01%

C.2.5 OUGS Data

Table C.4 shows the number of bins from which data were missing due to privacy suppression. In Ontario, there is a relatively large number of teachers' college graduates, and therefore only a few bins were missing information; nevertheless, the vast majority had one or two suppressed bins for any group, with a maximum of three bins being suppressed.[1] In general, most of the missing information is at the right tail of the distribution; the data include part-time workers, and so the left tails have no bins with missing information. Refer to Table C.5 for an example of the data format.

Table C.4: Number of Missing Bins Due to Privacy-Based Data Suppression

	Female		Male	
Year	6 Months	2 Years	6 Months	2 Years
2007	2	1	2	2
2008	3	1	2	1
2009	3	1	3	1
2010	2	1	2	2
2011	1	0	0	0
2012	1	0	2	1
2013	0	0	2	0

Table C.5: Example of the OUGS Data Format for Programs (Fictional Data)

Demographic Variables				
Obs.	Graduation Year	Program	Gender	Number of Respondents
1	2007	Education	Female	1304
2	2008	Education	Male	507

(continued below)

Employment Outcome Variables: Six-Month Salary Bins (1-11) and Employment Status															
Obs.	1	2	3	4	5	6	7	8	9	10	11	Q1	Q2	Q3	Q4	Q5
1	89	95	229	389	245	97	54	35	21	*	*	1256	6	12	945	317
2	45	78	95	55	65	54	35	15	11	*	*	454	7	14	391	70

Notes: The numbers in this table are fictional.
Survey Response Choices: Q1 – Employed, Q2 – Offered employment to start at a later date, Q3 – Not employed and not in school, Q4 – Full-time and Q5 – Part-time.

[1] A group refers to a combination of gender, cohort and time since graduation. For example, 2008 females six months after graduation comprise a single group.

C.3 Robustness Results: Other Assumptions

Table C.6: Median Salaries: Assumption 1

A	Median Salary 2010 CDN $: (95% C.I.) Six Months After Graduation: Female		B Median Salary 2010 CDN $: (95% C.I.) Six Months After Graduation: Male	
Year	Outside Option	Teaching	Outside Option	Teaching
2007	29562	46532	37133	47363
	(28632–30522)	(46204–46741)	(34955–39446)	(47131–47806)
2008	26664	46648	34141	47391
	(25774–27584)	(46463–47103)	(32147–36260)	(47105–47865)
2009	25519	48279	31326	49152
	(24710–26354)	(47880–48430)	(29628–33121)	(48556–49625)
2010	26580	48875	31927	49699
	(25777–27408)	(48467–49036)	(30287–33656)	(49066–50295)
2011	25077	48836	30395	49719
	(24312–25866)	(48356–49040)	(28748–32135)	(49045–50197)
2012	23924	48234	29157	49081
	(23227–24642)	(47761–48436)	(27697–30694)	(48406–49794)
2013	23835	47725	28380	48500
	(23181–24508)	(47174–47983)	(27016–29812)	(47735–49511)
C	Median Salary 2010 CDN $: (95% C.I.) Two Years After Graduation: Female		D Median Salary 2010 CDN $: (95% C.I.) Two Years After Graduation: Male	
Year	Outside Option	Teaching	Outside Option	Teaching
2007	34978	47029	45664	47040
	(33825–36171)	(46596–47120)	(43043–48445)	(46158–47571)
2008	32390	47605	38937	47748
	(31326–33490)	(47213–48020)	(36493–41546)	(46954–48425)
2009	29781	47078	35344	47309
	(28821–30774)	(46692–47348)	(33429–37369)	(46473–47986)
2010	29473	47949	35065	47500
	(28610–30361)	(47501–48233)	(33291–36933)	(46999–48134)
2011	30375	48679	34142	49048
	(29519–31257)	(48193–49066)	(32326–36060)	(48109–49751)
2012	29435	48034	34373	48040
	(28667–30222)	(47408–48487)	(32814–36005)	(47106–49038)
2013	27473	46812	33921	46928
	(26767–28198)	(46514–47430)	(32470–35436)	(46207–48152)

Table C.7: Median Salaries: Assumption 3

A	Median Salary 2010 CDN $: (95% C.I.) Six Months After Graduation: Female		B	Median Salary 2010 CDN $: (95% C.I.) Six Months After Graduation: Male	
Year	Outside Option	Teaching		Outside Option	Teaching
2007	29546	47131		37645	47131
	(28618–30504)	(46746–47162)		(35561–39852)	(46677–47363)
2008	26639	47103		34628	47334
	(25752–27556)	(46716–47334)		(32679–36692)	(46878–47777)
2009	25486	48573		31599	49255
	(24681–26318)	(48366–48663)		(29925–33368)	(48660–49852)
2010	26510	49263		32136	49576
	(25713–27331)	(49085–49763)		(30509–33850)	(49020–50231)
2011	25038	49221		30611	49536
	(24277–25823)	(48979–49535)		(28979–32336)	(49010–50190)
2012	23873	48778		29348	48614
	(23181–24586)	(48614–49208)		(27893–30880)	(48095–49450)
2013	23815	42767		28115	48031
	(23162–24486)	(42271–42968)		(26751–29548)	(47117–48978)
C	Median Salary 2010 CDN $: (95% C.I.) Two Years After Graduation: Female		D	Median Salary 2010 CDN $: (95% C.I.) Two Years After Graduation: Male	
Year	Outside Option	Teaching		Outside Option	Teaching
2007	34680	47741		45191	47893
	(33548–35851)	(47405–48038)		(42607–47932)	(47243–48483)
2008	32233	49037		38557	49023
	(31182–33320)	(48439–49609)		(36155–41119)	(48287–49762)
2009	29650	47986		35149	48610
	(28700–30630)	(47592–48431)		(33249–37158)	(47897–49511)
2010	29380	48870		34933	48774
	(28524–30262)	(48563–49452)		(33177–36782)	(48045–49536)
2011	30270	49780		34056	50397
	(29420–31143)	(49422–50397)		(32253–35961)	(49540–51313)
2012	29363	49111		34350	48891
	(28600–30146)	(48678–49734)		(32796–35976)	(47919–50149)
2013	27432	47544		33888	48097
	(26729–28154)	(47198–48109)		(32442–35397)	(46987–49377)

Table C.8: Median Salaries: Assumption 4

A	Median Salary 2010 CDN $: (95% C.I.) Six Months After Graduation: Female		B	Median Salary 2010 CDN $: (95% C.I.) Six Months After Graduation: Male	
Year	Outside Option	Teaching		Outside Option	Teaching
2007	29507	47363		38154	46532
	(28581–30463)	(47195–47363)		(36159–40260)	(46114–47116)
2008	26601	47391		35071	46627
	(25718–27514)	(47334–47799)		(33162–37091)	(46085–47149)
2009	25430	49152		32026	48279
	(24630–26257)	(48660–49409)		(30351–33793)	(47499–48660)
2010	26494	49760		32420	48860
	(25699–27313)	(49261–50019)		(30796–34129)	(48010–49261)
2011	24999	43977		30883	48836
	(24242–25780)	(43762–44156)		(29252–32604)	(48014–49221)
2012	23861	49107		29524	48234
	(23170–24572)	(48614–49431)		(28071–31053)	(47348–48727)
2013	23793	48588		28567	47693
	(23142–24462)	(48101–49047)		(27205–29997)	(46802–48433)
C	Median Salary 2010 CDN $: (95% C.I.) Two Years After Graduation: Female		D	Median Salary 2010 CDN $: (95% C.I.) Two Years After Graduation: Male	
Year	Outside Option	Teaching		Outside Option	Teaching
2007	34461	47029		44922	47040
	(33347–35612)	(46596–47109)		(42360–47640)	(46192–47571)
2008	32044	47627		38548	47764
	(31008–33115)	(47260–48020)		(36166–41087)	(46982–48425)
2009	29550	47078		35088	47312
	(28608–30523)	(46692–47360)		(33200–37084)	(46502–47990)
2010	29315	47942		34842	47500
	(28464–30191)	(47501–48227)		(33090–36686)	(46999–48134)
2011	30213	48689		34019	49048
	(29366–31084)	(48193–49077)		(32219–35919)	(48109–49752)
2012	29334	48034		34290	48034
	(28574–30115)	(47408–48487)		(32742–35911)	(47106–49043)
2013	27399	46812		33854	46927
	(26698–28118)	(46514–47420)		(32409–35363)	(46231–48109)

Curriculum Vitae

Name:	Tomasz Handler
Post-Secondary Education and Degrees:	2013-2019 Ph.D Economics The University of Western Ontario. London, Ontario
	2012 M.A. Economics The University of Western Ontario. London, Ontario
	2010-2012 Hon. B.A. in Economics *Graduated Summa Cum Laude* McMaster University. Hamilton, Ontario
	1997-2001 Hon. B.Sc. in Biology and Psychology McMaster University. Hamilton, Ontario
Honours and Awards:	Dean's Honour List McMaster University 2010-2012
Related Work Experience:	Teaching Assistant The University of Western Ontario 2012-2017