Education-Job Match and the Labour Outcomes of Recent Graduates:

An Empirical Analysis of the National Graduates Survey 2013

by

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Thesis submitted in partial fulfillment of the

requirements for the Degree of

Bachelor of Arts with

Honours in Economics

Acadia University

March 2019

This thesis by Hunter Powell

is accepted in its present form by the

Department of Economics

as satisfying the thesis requirements for the degree of

Bachelor of Arts with Honours

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Acknowledgements

The author would like to thank Dr. Andrew Davis for his role as supervisor for this thesis and for his helpfulness and patience.

This research was funded in part by the Honours Summer Research Awards grant which was awarded to the author during the summer of 2018.

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Abstract

It is well known that the effects of education are significant and positive; however, the dispersion of these effects is very large (Lemieux 2014). One possible cause of this is that recent graduates may have difficulty finding a job that is appropriate for their type of education and level of education. The alignment of the type of education one receives and the skills used at one's job is referred to as qualitative match, whereas the alignment of the quantity of education one receives and the necessary quantity of education is referred to as quantitative match. Using a sample of recent graduates from Canadian post-secondary institutions taken from the National Graduates Survey (2013), the effects of job matching and other factors on income and job satisfaction are estimated using ordinary least squares and logit regressions respectively. The determinants of both types of matching are also estimated using logit and ordered logit regressions. Results show that both types of job matching have significant and large positive effects on wage and job satisfaction. Potential risk factors and causes of education-job mismatch are presented and policy recommendations are given regarding these findings.

CHAPTER 1: Introduction

The topic of returns to education is an evolving question as the amount of people enrolling in university and the demand for skilled labour increases. Human capital theory would suggest a mostly objective return to education based on the skills and experience gained at university, while the signaling model suggests that university acts mostly as a signal to employers. The degree to which someone is adequately suited to their job, however, is a vital component to incorporate into economic theory and modelling regarding the benefits of education. While skills may be transferrable, many are not and thus the labour outcomes of working in an area that does not utilize your specific skills may be inferior to the labour outcomes of working closer to your field all other things being equal.

There are two ways in which education-job match is discussed, qualitatively and quantitatively. Qualitative match refers to the degree of which the skills attained in one's field of study in college or university are similar to the skills necessitated by their job. Quantitative match refers to the match between how much education someone has received and how much is necessitated by their job. An example of qualitative mismatch might be if a biology graduate worked at a bank, whereas an example of quantitative mismatch could be if a master's graduate was employed as a cashier. These two situations could be considered suboptimal both for the individual graduate and society at large, because the implication is that the investment of education is being wasted or misallocated. This matters to the individual as attending post-secondary education sacrifices valuable earning years in addition to the large monetary costs of education.

Society also could be said to operate less efficiently in a world with worse education-job matching, as it means that the investment on behalf of society could be less rewarding overall.

This thesis contributes to the literature by providing analysis and commentary about the determinants and the effects of job matching in both of its forms in the same context. Furthermore, the dataset used in this work is the most recently available version of the National Graduates Survey, which has not been studied in this context before now and gives a Canadian perspective. This thesis also corroborates many findings in related studies regarding the importance of both types of matching in determining labour outcomes.

The results of the empirical analysis are summarized here. Both types of matching have substantial positive effects on income, as well as being a very strong component of job satisfaction. Qualitative match is associated with up to approximately $5,000 more annual earnings compared to no match, while quantitative match is associated with approximately $7,500 per year compared to no match. Recent graduates who report a strong qualitative match are over twice as likely to report a higher level of job satisfaction with a strong qualitative match and recent graduates who report a strong quantitative match are over three times as likely to report a higher level of job satisfaction with a strong quantitative match. These effects are gender specific, as men appear to derive less of their job satisfaction from education-job match relative to women. Meanwhile, women appear to derive less of their job satisfaction from income as compared to men. Different fields of study are shown to have vastly dispersed effects on the likelihood to report a higher degree of qualitative match, with Humanities, Visual Arts, and Physical/Life

Sciences having the lowest rate, and Business and Engineering having the highest rates. On the other hand, field of study has a much lower impact on quantitative match. Qualitative match and quantitative match are shown to be highly correlated, meaning they are usually achieved concurrently.

The presentation of the thesis is as follows. Chapter 2 provides a review of the literature surrounding job matching and labour outcomes, looking specifically at job satisfaction as it is the primary labour outcomes this paper is concerned with. Job satisfaction typically receives less attention than more objective criteria in labour economics, allowing for a more potent contribution to the literature by this research. Chapter 3 presents a detailed description of the dataset, followed by the methodology presented in Chapter 4. Chapter 5 contains the results from the regression analysis along with interpretation, comments, and policy recommendations. Finally, Chapter 6 summarizes the findings of the thesis and suggests further research opportunities in the literature moving forward.

CHAPTER 2: Literature Review

2.1 Qualitative and Quantitative Education-Job Match

In the literature on education and the labour market, education-job matching is defined as the degree to which an individual is appropriately educated for their job. Education-job matching has two nonexclusive forms, quantitative mismatch and qualitative mismatch (Dean, 2018). Quantitative mismatch is measured by the degree of over- or under-education one may have at their job, typically measured using years of study or level of education achieved compared to the years or level of education required by the job. Qualitative mismatch on the other hand is measured by the disparity between the skills needed for one's occupation and the skills taught in their education. Qualitative matching as it is defined here has historically been overlooked in the literature in favor of quantitative matching (Boudarbat and Chernoff, 2010; Robst, 2007; Dean, 2018). This is perhaps in part because one's level of education represents a more easily quantifiable investment by the individual and the educational system and therefore the payoff should rightfully be measured against the costs (Robst, 2007). Another potential factor is that qualitative matching is more subjective than quantitative matching since it is not feasible to assign an exact measure of relatedness that makes reasonable sense for all individuals and jobs. This subjectivity may deter some researchers from including it in their analysis; however, as will be shown here, it does matter a good deal.

While quantitative mismatch literature typically utilizes years of schooling or level of education as its independent variables of interest (Galasi, 2008; Green and Zhu, 2008), qualitative mismatch researchers often rely on subjective criteria. For example, a self-reported measurement from surveys that ask the respondents how much they feel their education relates to their work (Dean, 2018; Boudarbat and Chernoff, 2010; Lee and Sabharwal, 2016). Hartog (2000) argues that a measure of “objective” education-job match conducted by professional job analysts is preferred, however this type of data rarely exists.

Boudarbat and Chernoff (2010) is one of the closest papers in the literature that examines the determinants of qualitative job match. This is in part because they utilize the 2005 Follow-up of Canadian Graduates (FoG) – Class of 2000, which is a previous iteration of the National Graduates Survey (NGS) that this thesis focuses on. The purpose of their research is to assess which factors matter in determining the likelihood of reporting a strong qualitative match between recent Canadian graduates’ employment and education. Their methodology involves estimating a binary logit regression where the dependent variable is whether the respondent reported having a closely related qualitative match. Their results show that different fields of study have strong effects on qualitative match rate, and that the higher the degree achieved, the higher the probability of a match. Unsurprisingly, more job specific majors yielded higher probabilities of a strong qualitative match, with Health Sciences topping the list. Industry, however, was the largest factor in the entire regression and the researchers offer the explanation that some industries may have need of specific labour whereas others may not value specialized labour as much.

Lemieux (2014) also utilizes the NGS 2005 to examine the effects of matching. The focus however is on income differences between those with and without post-secondary education, so he compares the data to the 2006 Census. He decomposes the wage gap of education into the effects of general skills growth, specialized training growth, and the ability to land higher-paying jobs. The effect of the ability to land higher-paying jobs is estimated by comparing the fraction of those in the higher paying occupations for university graduates and high school graduates. The specialized training growth is estimated by the product of the self-assessed qualitative education-job match effect and the fraction of people who claim to work in jobs related to their field of study. What remains of the aggregate gap between university graduates and high school graduates is said to be the “pure” returns to education. The effects of specialized training growth and the ability to land higher-paying jobs are considered by Lemieux to represent a form of qualitative job matching. He concludes from the analysis that the general skills channel makes up half of the wage gap while the other two effects which are related to job matching each make up about a quarter. Additionally, each of the factors is important in explaining the heterogeneity of the returns to education. These results indicate that approximately half of the benefit of post-secondary education is decided by what is being studied and how that leads to a well-suited position.

Dean (2018) examines the effect of qualitative mismatch on immigrants to Canada and finds that 9-14% of the wage discrepancy experienced by immigrants can be explained by their increased risk of mismatch and increased loss from mismatch. This effect was felt more strongly by immigrants from non-English speaking countries. However, the largest cause for the immigrant-native wage gap was found to be the complete discount of foreign work experience. The data here are taken from the Survey of Labour and Income Dynamics (SLID), and thus only provides a Canadian immigrant’s perspective, however the significance of the findings should carry weight for many developed countries. The results of this paper should inform policymakers about the importance of assisting recent Canadian immigrants in finding a job with a strong qualitative match.

In the empirical analysis conducted in this thesis, both quantitative and qualitative mismatch are controlled for. Kim et al. (2012) have found evidence that qualitative mismatch and quantitative mismatch were positively correlated with each other within a cohort of Korean workers. They advise that neither effect be studied without the other as otherwise the effect may be exaggerated. Boudarbat and Chernoff (2010) also find that the higher your level of education, the more likely one is to be matched within their field. This makes intuitive sense as higher levels of education represent more commitment to a certain discipline both in and out of school. While this thesis is more interested in the effect of qualitative matching, the quantitative matching effect will also be fully examined.

2.2 Identification Issues

A chronic issue in analyzing the returns to education in any form is self-selection, which in this context means that people who choose to go to college or choose a specific major may not represent the entire population. Individuals who have a higher aptitude for a specific major or college in general are most likely not going to be affected by the treatment of pursuing higher education the same as an individual with less aptitude. Thus, ability is an omitted variable that could cause endogeneity concerns that may bias the estimated coefficients of the returns to education. Arcidiacono (2004) describes two forms of self-selection. Firstly, those with higher ability are more likely to attend college (or more difficult but rewarding majors) as it will be easier for them to graduate.

Secondly, the returns to college (or specific majors) may be heterogeneous and those who benefit the most are more likely to attend. One way that self-selection can be controlled for is with a proxy variable that represents ability such as grades or SAT scores. A method involving instrumental variables was used by Kirkeboen, Leuven, and Mogstad (2016). They take advantage of the unpredictable admission cutoffs for certain programs in Norway's centralized postsecondary education admission process to effectively randomize students into different fields of study and institutions by discontinuities in admissions. The NGS 2013 does have a question that asks how the graduate ranks in their class, but it is self-assessed and, as an example of how skewed it is, only 2% of respondents report being in the lower half of their class. Despite this, Lemieux (2014) and Boudarbat and Chernoff (2010) include this variable in their respective studies, however in this thesis it has been ignored. This is because the distribution of this variable is so skewed that it does not seem to possess any real information regarding ability. The lack of adequate controls for ability could theoretically create a positive bias in the estimates of the effects of education in this research.

It has been suggested by Lemieux (2014) that the ability bias in OLS estimates of income is small or offset by other measurement factors. In his examination, he uses proxies for ability such as the aforementioned self-reported rank in graduating class and enrollment in co-op programs and found little impact on the effect of qualitative matching. Lamo and Messina (2010) also did not find much evidence that unobserved ability bias was present in their results when looking at quantitative matching effects. Arcidiacono (2004) controls for and examines the effects of ability using SAT scores, while distinguishing between verbal and mathematical ability. He finds that mathematical ability is significant for labour market returns and for selection into different majors, while verbal ability has little effect on either of these. These results suggest that ability is an important factor of labour market returns, however it is not associated with a significant change in qualitative match rate.

2.3 General Returns to Education

In describing the value of education, Heckman et al. (2008) describe the internal rate of return as “the discount rate that equates the present value of two potential income streams”. They assert that under normal conditions, if the marginal internal rate of return is greater than the opportunity cost of funding one’s education, than it is profitable to the individual. Likewise, the same can be said for the social return and opportunity costs. The effect of schooling in Mincer regression is usually said to be an estimate of the internal rate of return to education, however the Mincer equation has been shown to not accurately depict the earnings of U.S workers[1]. Due to this incongruency, Heckman et al. (2008) adopt a more general nonparametric approach to estimate marginal internal rates of return that account for costs of education, and the nonlinear relationship between earnings, schooling, and experience. The exact methodology employed in their estimation is complicated however it essentially involves systematically relaxing the assumptions of Mincer’s model. These assumptions are: no direct or psychic costs of schooling, no income taxes, no loss of working life with additional years of schooling, and marginal returns are equal to average returns. They calculate the marginal internal rates of return to education for black and white men individually with data from the U.S. decennial

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[1] The Mincer earnings equation is typically given as: ln(wages)=β_0+β_1(years of schooling)+ β_2(years of labour experience)+ β_3(years of labour experience)^2. This is the base model that is usually expanded to include more controls. β_1 represents the impact on ln wages when an individual has one more year of schooling all else being equal.

Censuses and the Current Population Survey (CPS). Their findings indicate that the Mincer equation underestimates the returns to college and the returns to having just completed high school compared to the nonparametric estimation, even when considering the present value monetary costs of college. Heckman et al. (2008) conclude that economists must respect the assumptions of the Mincer model, meaning they must be tested empirically, and if they are found to be violated, then those assumptions must be relaxed in estimation procedures. Another consideration put forward in Heckman et al. (2008) is that the *ex ante* returns to schooling are used to determine educational choices, however estimations of the returns to schooling are estimated *ex post*.

Anelli (2016) estimates the returns to attending an elite university compared to "not-selective institutions" using a regression discontinuity design that exploits the difference in admission probability surrounding the unknown admission threshold. The admission threshold is based on a single numeric score; no subjective criteria such as reference letters are considered, making the prediction of being admitted an objective function of this numerical score. The data considered in Anelli (2016) is a group of 30,000 individuals who graduated from high schools in Milan, Italy, between 1985 and 2005. Of those 30,000 individuals, 83% obtained a college degree and of these 83%, 90% attended a college in Milan. He assesses the labour outcomes of those attending the top university in Milan compared to the other four universities in Milan. The estimated returns to admission alone are 40% while the returns to enrollment are 52%. The distinction between these two effects is that the admission effect applies if an individual is admitted but chooses not to enroll at the elite university, while the enrollment effect is the effect of being admitted and subsequently enrolling. The 52% wage premium represents a jump from the 44th percentile of Italy's national income distribution to the 74th percentile. In U.S. dollars, this yearly income premium is shown to be $19,952, as the high school-college gap is estimated to be $23,886 and the high school-elite university gap is estimated to be $43,838.

The dispersion of the returns to education are mostly dependent on the individual, however, as Backman (2013) finds, the returns to education are also dependent on location. She estimates a fixed-effect model to find a partial equilibrium for wages using categorical assignment of Sweden's municipalities into four groups of descending population density and commuting patterns. The data comes from Statistics Sweden, and the time period examined is from 1998 to 2008. Her fixed effect model is an extension of the Mincerian model with added controls for individual characteristics, firm, and municipal effects for where the individual lives and works (separately). With her estimation, Backman finds that the highest returns to education occurs for those living in "metropolitan functional regions", meaning the densest areas such as the municipalities in Stockholm. She asserts that this is likely due to the wider job variety, and increased interaction possibilities which would yield more knowledge and information transfers. The lowest returns to education are as one might expect, in the "peripheral municipalities in small functional regions". These areas typically have homogeneous labour markets, and lack other regional conveniences that firms themselves would desire. Despite this best and worst assessment, the actual difference is only estimated to be about 2% per year of education between their respective returns to education. The finding is still statistically significant, and in a country with such small wage variance, this is still considerable.

Explanations for why the difference is small, however, include that employers must incentivize workers to tolerate less desirable regions with higher wages.

2.4 Job Satisfaction

Job satisfaction is a popular topic in labour economics that is inherently non-objective and therefore harder to analyze than objective criteria such as wages or hours worked. Measuring job satisfaction typically requires self-assessments collected from survey data. The subjective nature of the concept and it being self-assessed may deter some economists from engaging with it, leaving it to sociologists and psychologists, but it is nonetheless necessary to consider when thinking about the consequences of policies. Oswald (1997) asserts that economists should be more concerned than they are with happiness (or job satisfaction) because it really matters to people. He also refers to the fact that psychologists and sociologists have been using self-assessed happiness measures for many years. To motivate its importance, job satisfaction has been found to correlate positively with physical and mental health, and negatively with absenteeism and turnover (Freeman, 1978; Fischer and Sousa-Poza, 2008; Wall et al., 1978; Clegg, 1983).

As determinants of job satisfaction, the effects of education-job match are intuitive. Vila and Garcia-Mora (2005) find that both self-perceived quantitative and qualitative mismatch both negatively impact job satisfaction (the converse is also true) on a cohort of workers in Spain. If one feels that their abilities are under- or mis-utilized, they may be less happy at work and less happy with their compensation. Mavromaras (2009) and Green and Zhu (2008) both explore the idea of overqualification as being different than a term they call “overskilling”, the former being about education level, and the latter dealing with self-reported perception of underutilization of skill. They find that only the latter, “overskilling”, has a significant effect on job satisfaction. This implies that only the internal feeling of being underutilized bears any consequence on job satisfaction, rather than simply being overqualified in a technical sense. They also find that while there are pay penalties for any degree of overeducation, they are much worse for those with “real” overqualification, meaning overeducation coinciding with being “overskilled”.

Lee and Sabharwal (2016) examine the data from the National Survey of Recent College Graduates (NSRCG), taken in the US, for the relation between qualitative education-job match, income, and job satisfaction. Their analysis specifically considers the differences observed in these outcomes between the public, for-profit, and non-profit sectors. They find that the for-profit sector had about a 50% rate for close matches while the public sector reported a 66% match and the non-profit sector reported 63%. The public sector was also found to have the highest rate of job satisfaction. This result has also been demonstrated in previous studies such as Vieira et al. (2004) and Vila and Garcia-Mora (2005). Education-job match had a significant impact on job satisfaction across all sectors. Interestingly, the effect was strongest in the for-profit sector. Salary was found to affect job satisfaction in the for-profit sector exclusively. This point is interesting as Hofmans et al. (2013) similarly discovered using cluster-wise regression that there seems to be a group of people that seemingly do not benefit in job satisfaction from increased salary. Understanding worker preferences is critical in improving retention and creating mutually beneficial incentives for work.

Previous research on the topic of job satisfaction has shown that it is more closely related with people’s relative level of income rather than their absolute income, a phenomenon referred to as relative deprivation in social psychology (Clark and Oswald, 1996). Clark and Oswald (1996) show this effect using a measure of comparison income calculated using the Mincer earnings equation to calculate the ratio between one's income and the predicted income of someone with similar characteristics. This new variable is found to be significant in explaining job satisfaction, yet absolute income is not found to be significant when they are both included together in the model. Brown et al. (2005) take the idea of relative income and push it further, examining the possibility that a worker's rank in the ranking of absolute wage within an institution is more significant than the relative wage models that typically only use the mean earnings of the group in question. The findings indicate that wage rank within an institution also plays a part in determining job satisfaction. They surmise two considerations from this, one being that the skewness of an income distribution matters (distance from mean cannot capture this), and another being that there may be multiple comparisons of income being made that affect job satisfaction (rank and mean individually for example). Bryson et al. (2012) discover a similar effect of wage rank in their study as well. Despite this, Clark et al. (2007) find that within specific reference groups such as a single firm, higher co-worker wages can increase job satisfaction for those earning below the mean. They explain that this could be attributed as a signal of future earnings that higher income coworkers send. Regardless of the exact mechanisms at work, it is clear that understanding the layer of human psychology between income and job satisfaction is of utmost importance in understanding how the two are related.

2.5 Summary

In conclusion, the literature regarding labour outcomes and returns to education is wide and diverse. The effects of education on earnings are consistently estimated as positive and significant; however, the magnitude of these effects depends on estimation methods, controls, and of course on real functional differences such as regional differences. While quantitative education-job match been studied for a relatively longer period of time, qualitative match has received increased attention in the literature recently. The examination of qualitative matching is vital in order to get a proper understanding of the returns to education, especially as the economy continues to develop towards more specialized jobs for higher educated workers.

Job satisfaction has been demonstrated in this literature review to be a relevant labour outcome that is worthy of analysis because of what it represents as well as the known positive effects of having a job that provides higher levels of job satisfaction. While the measurement of job satisfaction is subjective and vulnerable to reporting bias, the underlying variable of true job satisfaction really affects people's lives in important ways such as health.

CHAPTER 3: Dataset Information

3.1 National Graduates Survey Breakdown

The National Graduates Survey is a survey conducted and distributed by Statistics Canada. It is a cross-sectional survey sampling Canadian graduates with public postsecondary education in the reference year of the survey, in this case 2009/2010. The survey was conducted first in 1978 for the class of 1976, then 1984 for the class of 1982. Over a decade later, the survey was conducted again in 2000 for the class of 1995, and in 2005 for the class of 2000. In 2013, the survey was conducted for the class of 2009/2010, and the survey conducted for the class of 2015 at the time of this writing in early 2019.

The NGS 2013 uses a stratified simple random sample design. The variables used for stratification are the thirteen locations (by province/territory) of the institution, five levels of certification, and twelve fields of study. The five levels of certification are: trade/vocational certificate, college diploma, bachelor's degree, master's degree, and doctorate. The twelve fields of study are the twelve primary groupings of the Classification of Instructional Programs (CIP) 2000. These fields of study are: "Education", "Visual and Performing Arts, and Communications Technologies", "Humanities", "Social and Behavioural Sciences and Law", "Business, Management and Public Administration", "Physical and Life Sciences and Technologies", "Mathematics, Computer and Information Sciences", "Architecture, Engineering, and Related Technologies", "Agriculture, Natural Resources and Conservation", " Health, Parks, Recreation and Fitness", "Resources and Conservation", and "Other". Out of 636 possible strata only 434 were created.

The NGS 2013 has a response rate of 49.1%. The respondents were interviewed using a computer-assisted telephone interviewing method. Multiple attempts were made to contact the selected graduates. There were no proxy responses accepted. The survey was weighted in two phases, the first phase involved selecting the sample and weighting them by the inverse probability of having selected that graduate, and then that weight was further adjusted using response homogeneous groups to account for non-respondents.

This thesis utilizes the public use microdata file (PUMF) for the NGS 2013. The major differences in the PUMF and the master file are that all continuous variables were converted to categorical variables and certain categorical variables were reduced to have fewer categories. The Master file also contains 28,715 observations while the PUMF which contains only 14,745 observations. As well, respondents who took trade/vocational programs are omitted in the data. Information regarding the details of graduates who moved to the United States is also omitted. The same weighting procedure used for non-respondents was used to redistribute the weights of the omitted respondents onto the respondents that were kept in. The selection of the respondents that remain in the PUMF was chosen by random sampling within each stratum. More details regarding the NGS, its survey design, included variables, and the differences in the PUMF, can be found on the Statistics Canada website included in the references section.

3.2 Variable Explanations and Descriptive Statistics

In this subsection, the different variables included in the empirical analysis of the NGS 2013 are explained. The dependent variables are given more detail and justification. Weighted descriptive statistics for the subset of interest (employed recent graduates) are presented in Table 1.

3.2.1 Qualitative education-job match

Respondents were asked "How closely is the [job/main job] you held last week related to your certificate, diploma or degree?" Respondents were given three choices: closely related, somewhat related, and not related at all. The three choices of this variable are considered to be ordered but non-linear.

3.2.2 Quantitative education-job match

There are three variables in the data that are relevant to this effect. One asks the respondents how their level of education compares to the required level of education of the job (or if it even has one). One of the other two variables asks, "Considering your experience, education and training, do you feel that you are overqualified for the (main) job you held last week?". The last question is the same as the overqualification question but replaced with underqualification. However, the underqualification question has a high rate of skips in the questionnaire. This is because those who felt overqualified were not asked if they felt underqualified. Regardless, as in Lemieux (2014), and justified by Mavromaras (2009) and Green and Zhu (2008), this thesis estimates quantitative match using the self-reported assessment of being overqualified for one's job[2].

[2] In section 2.4, justification for using this self-reported overqualification question as opposed to the objective measure of having more education than the job requires is provided. The effects of

3.2.3 Field of study

Respondents were asked “What was your major field of study or specialization for your [certificate/diploma/degree] program?”. This exact variable is the dependent variable in both Boudarbat and Chernoff (2010) and Lemieux (2014), as well as being very similar to the survey answers taken from the U.S. National Survey of College Graduates used by Robst (2007). This question does not allow for two majors so any individuals with two equally relevant majors were only labelled with one. This should not create problems as the number of cases where the respondent has a double major that influences the respondents’ matching response should be relatively small. The ten fields of study are taken from the CIP 2000 as defined above, except “Personal, Protective and Transportation Services” and “Other” were merged into the “Health, Parks, Recreation, and Fitness” group for the PUMF derived variable. Figure 1 provides the distribution of graduates in each field of study in the sample of employed individuals from the NGS 2013.

3.2.4 Level of study

This variable measures what the highest known level of education achieved by the graduate was at the time of their graduation in 2009/2010. In the PUMF, Ph. D. graduates are aggregated with master’s graduates, so the levels for this variable are “College or CEGEP diploma or certificate”, “Bachelor’s degree, first professional degree, university diploma/ certificate below bachelor’s level”, and “Master’s degree, doctorate, university diploma/certificate above bachelor’s level”.

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overqualification are mostly experienced when the individual possesses more skills than the job requires, rather than just having a higher level of education which may not always be applicable.

3.2.5 Income

As mentioned above, in the PUMF income data was turned from a continuous variable to a categorical one with bins of $10,000 annual salary, from $0 to $9,999 per annum, $10,000 to $19,999, and so on until $90,000 or more. Apart from the last bin, each bin is of equal width, however it can be safely assumed that the distribution of income within each bin is not uniform. The final bin likely has a very long tail that is completely obfuscated by the aggregation. Despite this, in my regression all respondents in one bin will be assigned an income of the middle value in the interval. The $90,000 or more bin will be coded to be $95,000 per annum. The variable will be treated as continuous for our purposes as a dependent variable only even though there are only ten possible numeric values it assumes. This may bias the coefficients, but on average across the income distribution the disturbance should be mild. Even so, estimating the income effects of education is not the primary focus of this research. Figure 2 provides the distribution of graduates' incomes from the NGS 2013.

3.2.6 Job satisfaction

Respondents were asked, "Considering all aspects of the job you held last week, how satisfied were you with the job?" and then given the choices: "Very satisfied", "Satisfied", "Dissatisfied", and "Very dissatisfied". "Neither satisfied or dissatisfied" was available as a response but it was not read to the respondents. Respondents were also asked, "Considering the duties and responsibilities of this job, how satisfied were you with the money you made?" with the same four choices read to them and "Neither satisfied or dissatisfied" still available as a response, however this question will not be considered as the goal is to determine total job satisfaction rather than just pay satisfaction. These responses are treated as ordered but non-linear in the same way as the qualitative match variable. Only 1% of the graduates reported feeling neither satisfied or dissatisfied, since it was not read to the respondents explicitly as a choice. Extremely low counts of data make ordered logit hard to estimate so they will be dropped when this is used as a dependent variable.

3.2.7 Labour market characteristics

Labour market characteristics are included primarily as controls. These include whether the recent graduate works part-time (< 30 hrs/week), has a permanent job, what occupation and industry they work in, and if they have co-op experience. These labour market characteristics controls are included in each specification presented in the next section. The main method used to find one's job is included only when estimating the determinants of job matching, and whether one's job provides any benefits is included only when estimating job satisfaction.

Part-time workers are going to be paid less for their jobs as they work fewer hours, and the supply of part-time jobs is less specialized, thus there is a higher expected degree of mismatch for part-time workers. Workers in a permanent job are expected to be matched better and paid better as well as possibly experience higher job satisfaction due to having less stress of job loss. Occupation and industry are included to prevent them from biasing the effects of different fields of study and job matching, as certain fields of study produce graduates that are more likely to work in certain jobs, and some industries and occupations naturally demand more specialized labour that will affect the matching response of the respondent and their annual income. Co-op experience is included as it may affect recent graduates' ability to find a good match, as it at the very least removes one or more jobs from their future career considerations, and at best it could help to start a career that is matched and compensated well.

The main method used to find one's job is included as it is expected to be impactful in determining a good job match, since being approached directly for a job suggests you are more likely what the company is looking for, whereas answering a job ad suggests that the job requirements are less strict and therefore less likely to produce a strong match comparatively. Whether a job offers benefits is included in the job satisfaction specification as it is expected to positively impact job satisfaction since it represents non-pecuniary compensation from work.

3.2.8 Demographic controls

The demographic controls included in each specification are: age, gender, minority status, disability, marital status, immigrant status, language spoken most at home, region of institution, and having dependent children. Age is included as income is known to increase until around middle age and then decline until retirement. Gender is included to control for the different experiences that men and women may have. These differences are examined further as each specification is also estimated using the male and female subsets separately. Minority status is included to examine any possible racial differences in outcomes.

Those with long-term disabilities are controlled for as it could be asserted that these individuals may have a harder time finding a well-matched job, and their disability may result in decreased job satisfaction and lower wage due to having fewer employment opportunities available to them. Married individuals are controlled for as it may be that those with higher incomes are more likely to be married since they have achieved a higher level of financial stability. Immigrant status is included to examine the expected difficulties faced by the immigrant population in finding a good job match and the effects of being an immigrant on their other labour outcomes. Language spoken most at home is included to control for the expected negative labour market outcomes that are associated with primarily speaking a language besides English or French, since the labour market where most of these recent graduates work is within Canada.

Region of institution is included as a control both for the labour market status of the region that graduate works in (if they stayed in the area of the institution that they graduated from), and as an average difference between different regions' schools. The magnitude of the regional labour market effect is likely to be the larger proportion of the total magnitude of this control. Debt at graduation is included in the income specification as it is possible that those with more debt may seek higher income jobs to be able to pay off student loans. Finally, having dependent children is included as it is expected that those with higher income will be more able to raise children. This effect may also depend on whether you are the mother or father of the dependent children, since women are typically required to sacrifice work to raise children.

Table 1 - Descriptive Statistics

<table>
<tr><td>Good Quantitative Match:</td><td>69.0%</td><td>Qualitative Match:
• Closely related: 58.2%
• Somewhat related: 21.6%
• Not related at all: 20.2%</td></tr>
<tr><td>Part-time workers:</td><td>13.3%</td><td>Level of Education:
• College: 30.13%
• Bachelor’s degree: 54.2%
• Master’s or higher: 15.66%</td></tr>
<tr><td>Permanent job:</td><td>80.4%</td><td rowspan="2">Job Satisfaction:
• Very satisfied: 45.2%
• Satisfied: 45.9%
• Neither satisfied or dissatisfied: 1.0%
• Dissatisfied: 6.0%
• Very dissatisfied: 1.9%</td></tr>
<tr><td>Co-op experience:</td><td>17.98%</td></tr>
<tr><td>Job provides benefits:</td><td>86.8%</td><td rowspan="5">Method Used to Find Job:
• Referred by family, friends or teachers: 24.1%
• Answered job ad (Internet): 31.3%
• Answered job ad (Newspaper, etc.): 3.3%
• Contacted employer directly: 12.2%
• Campus placement office: 4.0%
• Employment agency: 2.6%
• Approached or contacted directly by employer: 5.6%
• Other: 8.4%</td></tr>
<tr><td>Female:</td><td>59.02%</td></tr>
<tr><td>Minority:</td><td>23.29%</td></tr>
<tr><td>Disabled:</td><td>4.33%</td></tr>
<tr><td>Married:</td><td>47.8%</td></tr>
<tr><td colspan="2">Region of Institution:
• Atlantic provinces: 6.84%
• Quebec: 24.82%
• Ontario: 40.17%
• Western provinces, territories: 28.15%</td><td>Age at graduation:
• Less than 25: 51.03%
• 25 to 29: 23.67%
• 30 to 39: 14.55%
• 40 or more: 10.73%</td></tr>
<tr><td colspan="2" rowspan="2">Debt at graduation:
• No debt: 55.49%
• Less than $5,000: 5.87%
• $5,000 to less than $10,000: 7.25%
• $10,000 to less than $25,000: 16.45%
• $25,000 or more: 14.91%</td><td>Immigrant Status:
• Citizen by birth: 82.44%
• Citizen by naturalization: 14.43%
• Landed immigrant: 3.12%</td></tr>
<tr><td>Language Spoken Most at Home:
• English only: 63.42%
• French only: 20.12%
• English and French: 7.18%
• Other only: 2.71%
• None of the above: 6.54%</td></tr>
<tr><td colspan="2">Father’s Education:
• Below high school: 14.3%
• High school: 25.54%
• Trade certificate: 8.79%
• College: 14.85%
• Bachelor’s degree: 23.0%
• Above bachelor’s degree: 13.48%</td><td>Mother’s Education:
• Below high school: 9.97%
• High school: 31.3%
• Trade certificate: 4.77%
• College: 21.95%
• Bachelor’s degree: 23.71%
• Above bachelor’s degree: 8.27%</td></tr>
</table>

Figure 1 - Field of Study Distribution

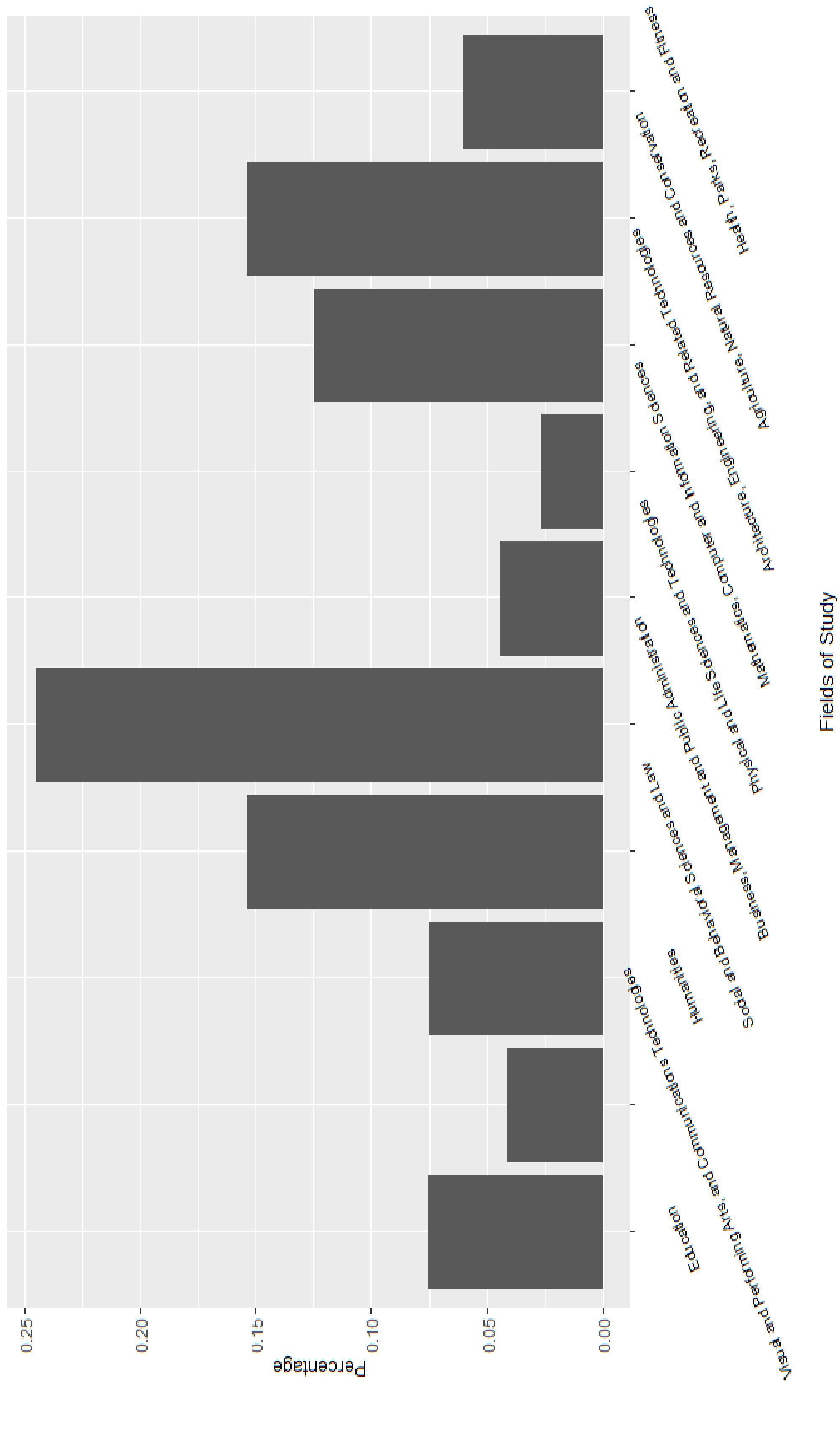
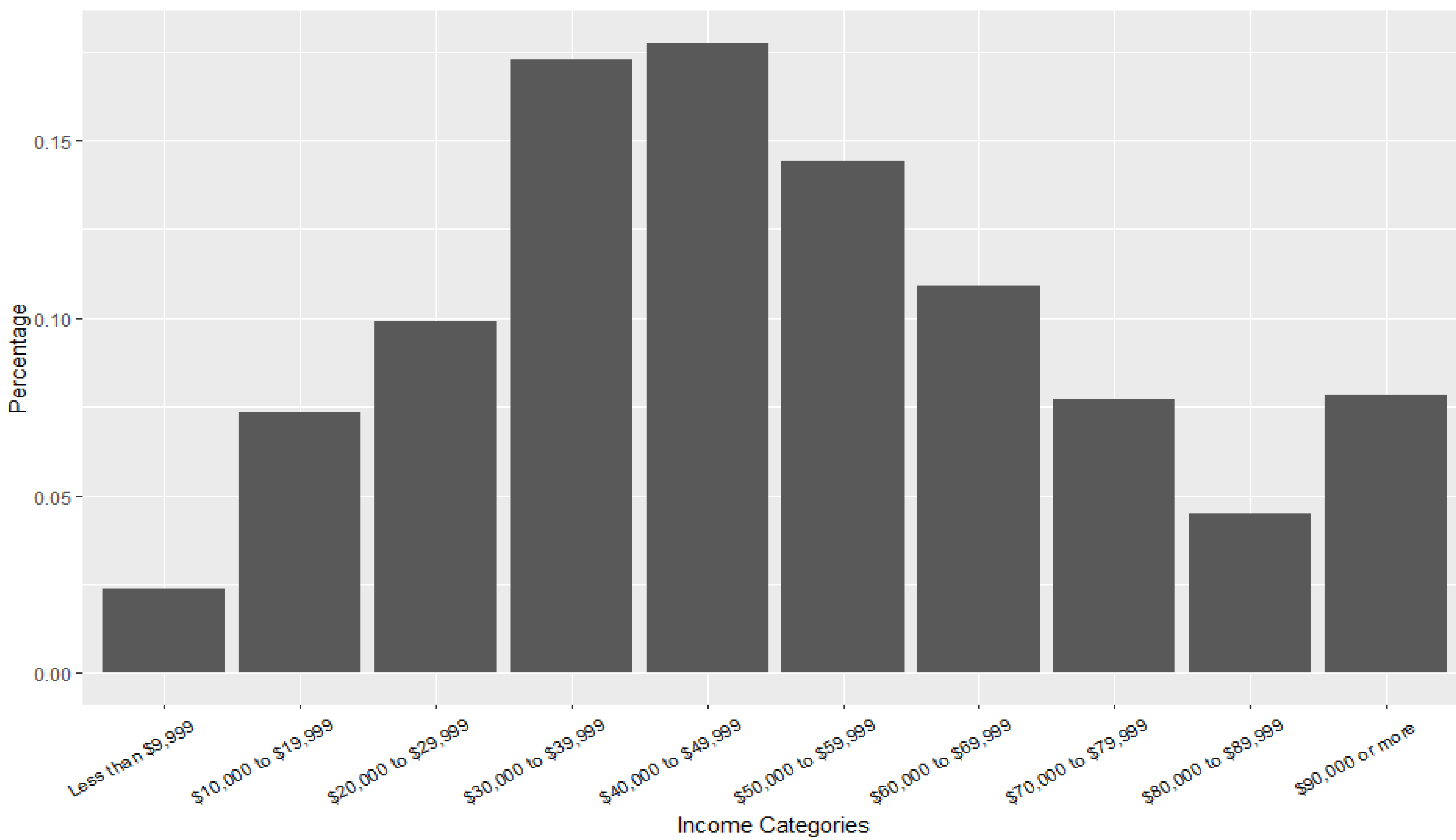


Figure 2 - Income Distribution



CHAPTER 4: Methodology

As mentioned before, this thesis includes four separate regressions. The dependent variables considered are annual income, job satisfaction, qualitative match, and quantitative match. Qualitative match is measured by respondents' self-assessment of whether their job is "not related at all", "somewhat related", or "closely related" to their education. Quantitative match is measured by respondents' self-assessment of being overqualified for their job or not. The subset of the survey being examined are those who reported their labour force status as "Employed". In this section the exact specifications of the estimating equations will be provided, with reasoning behind which variables are included and how the results are to be interpreted.

Each specification in this thesis is ran on the full sample including a female dummy, and again on the male and female subsets individually to examine possible gender specific effects beyond what the female dummy would be able to express in each regression. Besides exclusion of the female dummy, the variables included in each stratified regression are exactly the same as the full sample regression. For some variables, this sheds light on some key differences that can be observed from the data. For example, since the full sample regression coefficient is essentially a weighted average of the male and female subsets, some coefficients that are close to zero in the full sample regression may actually be positive for men and negative for women or vice versa.

4.1 Income Specification

The income specification utilizes ordinary least squares (OLS) regression, with annual income as the dependent variable. OLS is appropriate for this specification because income is treated as continuous even though the variable used in the regression was derived from categorical data. Since every variable in the dataset is a categorical variable, all coefficients represent relative difference between the reference group and the base group. Note that in each specification, vectors are in bold. The total specification is given as:

$$income = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{qual.match}) + \beta_2(quant.match) + \boldsymbol{\beta_3}(\boldsymbol{education\ controls}) + \boldsymbol{\beta_4}(\boldsymbol{employment\ controls}) + \boldsymbol{\beta_5}(\boldsymbol{personal\ controls}) + \boldsymbol{\varepsilon}$$

[Equation 1]

β_1 is a vector because qualitative match has two levels in the sample. The controls are split up into three groups for convenience. Education controls in this specification include field of study, level of study, and whether someone did co-op during their education.

Employment controls include the industry and occupation classifications, as well as whether the respondent's job was part-time, and whether the respondent's job was permanent. Industry and occupational effects are likely some of the largest in the specification as different jobs demand vastly different pay even if the worker in the job has the same characteristics. Part-time and non-permanent jobs need to be accounted for as they are guaranteed to pay less ceteris paribus by the nature of the job.

Personal controls in the income specification include demographic controls as well as background, which is derived using the parent's education, and total debt at graduation which could theoretically act as a motivator for finding a higher paying job. The demographic controls in this vector are gender, age at graduation, region of institution, minority status, immigration status, language spoken most at home, disability status, marital status, and if the respondent has any dependent children. Disability status, region of institution, and language spoken most at home are not included in the main regression table however they are present in the appendix tables.

4.2 Job Satisfaction Specification

The job satisfaction specification utilizes ordered logistic regression (ordered logit), with job satisfaction as the dependent variable. Ordered logit is appropriate here because the dependent variable has levels with a clear ordering however it cannot be asserted that the difference between "Very satisfied" and "Satisfied" is the same as the difference between "Dissatisfied" and "Satisfied". As mentioned in the data section, the respondents who answered "Neither satisfied or dissatisfied" are not included because this response was not explicitly read to respondents during the survey. While the interpretation of this response is still understood to be between satisfied and dissatisfied, the fact that it was not read to respondents meant that only 1% of respondents gave this answer, which is a very small number of observations to estimate with ordered logit.

The ordered logit model produces coefficients that represent additive increases in log odds ratios. Odds ratios are ratios that represent the odds of observing a higher level of the dependent variable when that variable is increased by one unit, or in this context, when the dummy is active compared to the base category. For example, an odds ratio of three for the female dummy would mean that women are three times more likely than men on average to report a higher category of job satisfaction all else being equal. The derivation of the coefficients is as follows (where y is the dependent variable and Y is any higher level of y, for all levels of y):

$$\frac{\partial \ln(\frac{P(y \leq Y)}{1 - P(y \leq Y)})}{\partial X} = \beta \qquad \textbf{[Equation 2]}$$

An implicit assumption of ordered logit is that for each level of the dependent variable, the log odds ratio remains the same for each independent variable. This assumption is usually referred to as the assumption of proportional odds and gives ordered logit another name as the proportional odds model. The functional form of this specification is given as:

$$ln\left(\frac{P(job\ satisfaction \leq X)}{1-P(job\ satisfaction \leq X)}\right) = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}(qual.match) + \beta_2(quant.match) + \boldsymbol{\beta_3}(\boldsymbol{education\ controls}) + \boldsymbol{\beta_4}(\boldsymbol{employment\ controls}) + \boldsymbol{\beta_5}(\boldsymbol{personal\ controls}) \qquad \textbf{[Equation 3]}$$

Note that β_0 is a vector because ordered logit has multiple intercepts for each threshold between levels of the dependent variable used to make predictions. The matching variables remain as our key variables of interest. The education controls in this specification are field of study and level of study. The employment controls are industry and occupation classifications, income, whether the respondent's job was part-time, whether the respondent's job was permanent, and whether the job included any benefits. Income and job satisfaction are predicted to be positively correlated, while non-permanent and part-time jobs are expected to give less job satisfaction overall. As well, benefits are non-pecuniary rewards from labour that should be accounted for in estimating job satisfaction.

The personal controls in this specification are gender, age at graduation, region of institution, minority status, immigration status, disability status, marital status, whether the respondent has any dependent children, and language spoken most at home. These are the same demographic controls employed in the income specification minus the respondent's parents' education controls. Many of these variables carry similar concerns of inequity for job satisfaction as they do for income, so they deserve to be addressed.

4.3 Job Matching Specifications

The job matching specifications utilize two related regression methods. Qualitative match has three levels in this dataset, so as a dependent variable the specification utilizes ordered logit as described in the job satisfaction specification. The proportional odds assumption is again invalid in this specification; however, the same argument applies regarding the assumed preservation of interpretation of the results. The quantitative match variable only has two levels, so a regular logit regression is estimated. The interpretation of logit is simpler than ordered logit as the log odds ratios in this context represent the odds of reporting feeling adequately qualified rather than reporting feeling overqualified. There is no proportional odds assumption that could be violated so this specification has increased fidelity compared to the ordered logit regressions. The derivation of coefficients in the logit model is:

$$\frac{\partial \ln\left(\frac{P(event)}{1 - P(event)}\right)}{\partial X} = \beta \qquad \textbf{[Equation 4]}$$

With qualitative match as the dependent variable, quantitative match is included among the regressors, and when quantitative match is the dependent variable, qualitative match is included among the regressors as well. It has been shown that the two types of matching are correlated so they must be included together to avoid biasing other coefficients in the estimation (Kim et al. 2012). This also allows measuring the degree to which they occur together in the sample. The specifications are as follows:

$$ln(\frac{P(qual.\ match \leq X)}{1-P(qual.\ match \leq X)}) = \boldsymbol{\beta_0} + \beta_1(quant.match) + \boldsymbol{\beta_2(field\ of\ study)} + \boldsymbol{\beta_3(education\ controls)} + \boldsymbol{\beta_4(employment\ controls)} + \boldsymbol{\beta_5(personal\ controls)} \quad \textbf{[Equation 5]}$$

$$ln(\frac{P(quant.\ match)}{1-P(quant.\ match)}) = \beta_0 + \boldsymbol{\beta_1}(qual.match) + \boldsymbol{\beta_2(field\ of\ study)} + \boldsymbol{\beta_3(education\ controls)} + \boldsymbol{\beta_4(employment\ controls)} + \boldsymbol{\beta_5(personal\ controls)} \quad \textbf{[Equation 6]}$$

Both models use the exact same regressors besides flipping qualitative match and quantitative match as dependent variable and regressor. Field of study is expressed on its own outside of the rest of the education controls here to emphasize that field of study is a variable of interest regarding the propensity to find a match or not. Level of study and having done co-op remain in the education controls vector though they are still reported in the regression table. Employment controls in this specification include industry and occupation classifications, whether the respondent's job was part-time, whether the respondent's job was permanent, and what the main method used to find the job was. The method used to find the job is included because different methods of getting a job may be more or less conducive with appropriate matching.

Demographic controls in these specifications are identical to the demographic controls present in the job satisfaction specification. The controls are gender, age at graduation, region of institution, minority status, immigration status, disability status, marital status, whether the respondent has any dependent children, and language spoken most at home.

CHAPTER 5: Empirical Results and Discussion

5.1 Income Specification

Table 2: Income Regression

	Dependent variable:		
	Annual Income		
	Full	Male	Female
	(1)	(2)	(3)
Qualitative Match: (Base: Not related at all) | Closely related	5,099.829***	7,016.969***	3,543.346***
	(801.879)	(1,292.355)	(978.568)
Somewhat related	3,329.847***	4,613.351***	2,342.197***
	(805.492)	(1,317.562)	(997.920)
Quantitative Match: (Base: Overqualified) | Adequately qualified	7,572.043***	8,098.278***	7,288.437***
	(581.627)	(1,024.890)	(668.630)
Level of education: (Base: College) | Bachelor's degree	10,603.910***	9,998.896***	10,811.210***
	(632.596)	(1,101.736)	(727.648)
Master's degree or greater	19,682.610***	18,847.240***	20,388.730***
	(823.617)	(1,474.925)	(965.246)
Field of Study: (Base: Education) | Visual/Performing Arts and Communications	-3,869.422***	-7,179.643***	-2,508.404***
	(1,183.287)	(2,708.746)	(1,248.647)
Humanities	-2,332.157*	-5,419.508*	-1,001.701*
	(1,191.543)	(2,370.531)	(1,369.284)
Social/Behavioural Sciences and Law	-1,369.858	-2,858.839	-1,116.601
	(980.613)	(2,251.495)	(1,061.313)
Business, Management, and Public Administration	1,767.371*	341.079*	2,110.463*
	(1,055.334)	(2,172.538)	(1,145.783)
Physical and Life Sciences Technologies	-5,487.239***	-7,824.003***	-4,386.687***
	(1,236.959)	(2,348.838)	(1,484.410)
Computer/Information Sciences and Mathematics	-408.155	-3,258.309	2,265.327
	(1,266.516)	(2,195.471)	(1,868.189)
Architecture, Engineering, and Related Technologies	3,210.989**	326.571**	3,066.463**
	(1,276.634)	(2,169.852)	(1,987.859)
Agriculture, Natural Resources, and Conservation	303.532	-798.133	883.367
	(1,199.916)	(2,859.660)	(1,261.687)

Health, Parks, Recreation, and Fitness	-874.572	-2,678.143	-599.800
	(1,208.597)	(2,336.405)	(1,476.934)
Co-op: (Base: Didn't do co-op) | Did co-op	599.783	1,385.394	143.351
	(733.165)	(1,218.676)	(871.946)
Job status: (Base: Full-time) | Part-time	-22,081.130***	-22,905.820***	-21,935.030***
	(683.647)	(1,283.579)	(777.429)
Job tenure: (Base: Permanent) | Not permanent	-5,442.710***	-8,291.254***	-3,963.235***
	(617.398)	(1,127.055)	(702.125)
Gender: (Base: Male) | Female	-4,597.864***		
	(580.146)		
Minority Status: (Base: Not a visible minority) | Visible minority	548.267	-84.205	637.347
	(816.117)	(1,349.141)	(971.979)
Immigration Status: (Base: Native citizen) | Citizen by naturalization	-1,489.277	-771.527	-1,762.402
	(1,028.258)	(1,762.629)	(1,211.576)
Landed immigrant	-7,228.292***	-4,278.796***	-10,179.170***
	(1,627.410)	(2,623.312)	(1,819.861)
Marital Status: (Base: Single) | Married/Common-law	1,895.383***	2,287.896***	1,559.164***
	(566.511)	(1,072.085)	(638.920)
Children: (Base: No dependent children) | 1 or more dependent children	-2.785	2,215.555	-1,177.870
	(663.558)	(1,208.025)	(768.452)
Constant	29,185.050***	33,737.750***	22,545.790***
	(1,685.765)	(2,979.329)	(1,930.465)
Observations	9,357	3,738	5,619
R^2	0.532	0.485	0.558
Adjusted R^2	0.529	0.476	0.553
Residual Std. Error	80,549.690 (df = 9294)	86,054.810 (df = 3676)	75,634.460 (df = 5557)
F Statistic	170.351*** (df = 62; 9294)	56.689*** (df = 61; 3676)	114.895*** (df = 61; 5557)
Note:			*p<0.1; **p<0.05; ***p<0.01
			SE's and significance are using Huber/White heteroscedasticity robust errors (as used in Stata)

The effect of qualitative match and quantitative match on income are positive and significant, both statistically and economically. Most of the benefit from qualitative matching seems to come when respondents feel their education was somewhat related to their occupation, an increase in wages of about $3,300 per year. The difference between somewhat and closely related is significant and is estimated to be around $1,700 per year. Examining the stratified regression coefficients, it can be observed that men seem to experience about double the benefit from qualitative match than women experience. It is beyond the scope of this paper to discern to how much of this disparity is derived from simply perceiving match differently between the genders, however it may be that women are more adaptable (i.e. less penalty with mismatch), or that they are rewarded less for specializing appropriately (i.e. less reward with match). The magnitude of the quantitative matching effect is slightly higher than the qualitative effect, yielding about $7,500 more annual income on average ceteris paribus, and unlike the qualitative effect it does not seem to vary between the genders as much.

Unsurprisingly there is a steep benefit for having completed a bachelor’s degree, and again for having completed a master’s degree or more relative to having just completed a college degree. The pay increase for these credentials does not vary much between men and women, which suggests that there is little difference between the wage premiums of each gender for having more post-secondary education.

There is a wide disparity in expected earnings for different fields of study as well. The difference between the highest paying field of study, Engineering, Architecture and Related, and the lowest paying field of study, Physical and Life Sciences Technologies, is estimated to be just under $8,700 in annual earnings. The list of highest to lowest paying fields of study is estimated to be (program names shortened): Engineering, Business and Public Administration, Agriculture and Conservation, Education, Computer Science and Mathematics, Health and Fitness, Social Sciences and Law, Humanities, Visual Arts, and finally Physical/Life Sciences. It should be noted that Business and Public Administration is only significantly higher than the base group Education at the 10% level of significance. Similarly, Humanities is only significantly lower than Education at the 10% level of significance. All other fields of study in the list above between Agriculture and Conservation and Social Sciences and Law are not significantly different from Education.

The co-op dummy is not significant at any level in the full sample, so it does not seem to be a particularly good predictor of income. This seems to suggest that the benefits of doing a co-op program are felt elsewhere such as by helping fund one's education or by aiding in finding a good match (as reported in the matching results). Job status acts as expected with very little difference in the stratified regressions. Job tenure, however, seems to have a much larger effect on income for men than women, which may have to do with career advancement or the types of jobs that are being worked by men and women.

Turning attention to the demographic variables, the female dummy is significantly negative both statistically and economically. Keeping in mind that as many relevant job characteristics as possible are included in the dataset, a roughly $4,500 disparity in annual income between recent female graduates and male graduates is concerning. The visible minority dummy is not significant which is as we hope to see. The naturalized citizen dummy is negative in the full and stratified results, but it is insignificant at all significance levels. Conversely, permanent residents, especially women, appear to earn much less per year. Married people seem to earn a couple thousand more on average per year which suggests that higher income workers are more likely to be married. There appears to be a gender disparity for having dependent children, however it is not statistically significant for either gender.

5.2 Job Satisfaction Specification

Table 3: Job Satisfaction Regression

	Dependent variable:		
	Job Satisfaction		
	Full	Male	Female
	(1)	(2)	(3)
Qualitative Match: (Base: Not related at all) | Closely related	0.812^{***}	0.477^{***}	1.028^{***}
	(0.013)	(0.020)	(0.017)
Somewhat related	0.259^{***}	-0.136^{***}	0.546^{***}
	(0.013)	(0.021)	(0.018)
Quantitative Match: (Base: Overqualified) | Adequately qualified	1.214^{***}	1.111^{***}	1.339^{***}
	(0.010)	(0.016)	(0.013)
Level of education: (Base: College) | Bachelor's degree	-0.290^{***}	-0.316^{***}	-0.258^{***}
	(0.011)	(0.017)	(0.014)
Master's degree or greater	-0.429^{***}	-0.406^{***}	-0.411^{***}
	(0.016)	(0.026)	(0.020)
Co-op: (Base: Didn't do co-op) | Did co-op	-0.020^{*}	0.092^{***}	-0.102^{***}
	(0.011)	(0.018)	(0.015)
Annual Income: (Base: Under 10,000) | Under 20,00	0.042	0.016	0.129^{***}
	(0.032)	(0.072)	(0.037)
Under 30,00	-0.027	-0.031	-0.013
	(0.033)	(0.074)	(0.038)
Under 40,00	0.138^{***}	0.462^{***}	0.092^{**}
	(0.034)	(0.075)	(0.039)
Under 50,00	0.276^{***}	0.578^{***}	0.204^{***}
	(0.035)	(0.075)	(0.041)
Under 60,00	0.280^{***}	0.543^{***}	0.232^{***}
	(0.036)	(0.076)	(0.042)
Under 70,000	0.436^{***}	0.771^{***}	0.342^{***}
	(0.037)	(0.077)	(0.043)
Under 80,00	0.635^{***}	1.165^{***}	0.398^{***}
	(0.038)	(0.078)	(0.045)
Under 90,000	0.751^{***}	0.877^{***}	0.830^{***}
	(0.040)	(0.080)	(0.051)

90,000 or more	0.837***	1.334***	0.478***
	(0.039)	(0.078)	(0.049)
Job status: (Base: Full-time) | Part-time	-0.058***	0.170***	-0.225***
	(0.017)	(0.034)	(0.020)
Job tenure: (Base: Permanent) | Not permanent	-0.053***	-0.027	-0.003
	(0.011)	(0.020)	(0.014)
Benefits: (Base: Job does not have benefits) | Job has benefits	0.239***	0.364***	0.149***
	(0.014)	(0.024)	(0.018)
Gender: (Base: Male) | Female	0.062***		
	(0.009)		
Minority Status: (Base: Not a visible minority) | Visible minority	-0.194***	-0.065***	-0.274***
	(0.012)	(0.019)	(0.015)
Immigration Status: (Base: Native citizen) | Citizen by naturalization	-0.035**	0.056**	-0.080***
	(0.015)	(0.024)	(0.020)
Landed immigrant	-0.289***	-0.454***	-0.128***
	(0.026)	(0.037)	(0.038)
Marital Status: (Base: Single) | Married/Common-law	0.037***	0.253***	-0.112***
	(0.009)	(0.016)	(0.012)
Children: (Base: No dependent children) | 1 or more dependent children	-0.032***	0.049**	-0.061***
	(0.012)	(0.020)	(0.015)
Observations	9,905	3,978	5,927
Log Likelihood	-227,251.300	-89,611.650	-135,065.000
Note:			*p<0.1; **p<0.05; ***p<0.01

In discussing the coefficients from the logistic models, this thesis will be using the odds ratios rather than the log odds ratios posted in the regression table. These are obtained by simply exponentiating the posted coefficients with the base *e*. The effects of our matching variables display high magnitudes as expected. Respondents are 2.25 times as likely to report a higher category of satisfaction when they feel a close qualitative match relative to no match, however they are only about 29.6% more likely to report a higher category of satisfaction from a somewhat related job relative to no match. This suggests that the somewhat related criteria has a relatively weak impact on job satisfaction compared to the impact of having a closely related job. Quantitative match has an even higher magnitude of importance, with an odds ratio of 3.367 for those who do not feel overqualified compared to those who do. The fact that quantitative match appears to impact job satisfaction more than qualitative match is not surprising, as quantitative match is also associated with a higher income premium than qualitative match and being overqualified is more likely to cause one to dislike their job than working in a field that they didn't study for. There are significant differences in the odds ratios between men and women for these variables. Women appear to derive much more of their total job satisfaction from a good qualitative and quantitative match than men do on average. In fact, men that report having a somewhat related qualitative match on average report less job satisfaction than men who report having no match whatsoever. It is unclear as to why this coefficient is negative, however it may be that men only experience benefits to their job satisfaction when the match is strong. When the match is only weak, men may be better off just finding a job that offers a higher degree of implicit job satisfaction outside of qualitative matching effects.

Level of education appears to detract from job satisfaction. This is likely caused by the result presented in the next results subsection that bachelor's degrees are associated with higher qualitative and quantitative mismatch relative to a college diploma, and that possessing a master's degree increases the likelihood of reporting a quantitative mismatch even further. As both types of matching positively affect job satisfaction, this could explain why higher levels of education are associated with lower levels of job satisfaction. This effect is not particularly gendered in the sample. Income has an approximately monotonic relationship with job satisfaction, as the odds ratios climb slowly from 1.043 to 2.308 across the income distribution for the full sample coefficients. This is consistent with the understanding that as wages increase ceteris paribus, that one should be happier at their job because they are being compensated better. However, the effects for men are consistently higher than for women, which suggests that men derive more job satisfaction from higher income than women on average.

The part-time job and tenure dummies are negative, and the benefits dummy is positive, which is again as was predicted. The female dummy is slightly positive, but this only corresponds with a 6.4% higher likelihood in reporting a higher category of satisfaction. Visible minorities are about 21.3% more likely to report a lower level of job satisfaction, however this ignores the difference in genders. Male members of a visible minority are about 6.7% more likely to report a lower level of job satisfaction than non-minority men, while female members of a visible minority are 31.4% more likely to report a lower level of job satisfaction than non-minority women. The cause of this racial effect is beyond the scope of this paper; however, it is significant that female members of a visible minority in particular experience lower job satisfaction in particular compared to male members of a visible minority. Naturalized citizens are only 3.6% more likely to report a lower level of job satisfaction than native citizens, however permanent residents are about 33.5% more likely to report a lower level of job satisfaction. These effects are fairly expected since naturalized citizens have been in the country long enough to not suffer the same magnitude of difficulty that more recent immigrants face. The stratified regressions show a gendered effect that married men are 28.7% more likely to report a higher level of job satisfaction than single men, while married women are 11.8% more likely to report a lower level of job satisfaction at their jobs than single women. This difference may be due to men in society having higher expectations to succeed in the workplace while married than married working women. Having dependent children has a slightly negative impact on job satisfaction but only for women, which may have to do with having more expectations at home as the primary caregiver for the children.

5.3 Matching Specifications

Table 4: Education-Job Match Regressions

	Dependent variable:					
	Qualitative Match *cumulative link*			Quantitative Match *logistic*		
	Full	Male	Female	Full	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Qualitative Match: (Base: Not related at all) | Closely related				1.361***	1.426***	1.346***
				(0.013)	(0.021)	(0.017)
Somewhat related				0.337***	0.498***	0.242***
				(0.013)	(0.021)	(0.018)
Quantitative Match: (Base: Overqualified) | Adequately qualified	1.037***	1.042***	1.036***			
	(0.009)	(0.014)	(0.012)			
Level of education: (Base: College) | Bachelor's degree	-0.222***	-0.106***	-0.317***	-0.104***	-0.358***	0.060***
	(0.011)	(0.017)	(0.014)	(0.012)	(0.019)	(0.015)
Master's degree or greater	-0.021	0.169***	-0.133***	-0.291***	-0.555***	-0.195***
	(0.016)	(0.026)	(0.021)	(0.017)	(0.028)	(0.021)
Field of Study: (Base: Education) | Visual/Performing Arts and Communications	-1.054***	-0.661***	-1.183***	0.308***	0.686***	0.188***
	(0.028)	(0.051)	(0.035)	(0.031)	(0.056)	(0.038)
Humanities	-1.200***	-1.258***	-1.157***	0.078***	0.449***	-0.051*
	(0.023)	(0.044)	(0.028)	(0.025)	(0.048)	(0.030)
Social/Behavioural Sciences and Law	-0.583***	0.031	-0.838***	0.080***	0.302***	-0.026
	(0.021)	(0.041)	(0.025)	(0.023)	(0.044)	(0.027)
Business, Management, and Public Administration	0.339***	0.882***	0.090***	0.013	0.032	0.072***
	(0.022)	(0.041)	(0.026)	(0.023)	(0.043)	(0.027)
Physical and Life Sciences Technologies	-0.979***	-0.370***	-1.293***	-0.178***	-0.004	-0.218***
	(0.026)	(0.046)	(0.033)	(0.029)	(0.050)	(0.036)

Computer/Information Sciences and Mathematics	-0.097***	0.561***	-0.529***	-0.075**	-0.078	0.363***
	(0.032)	(0.049)	(0.054)	(0.035)	(0.052)	(0.062)
Architecture, Engineering, and Related Technologies	0.266***	0.908***	-0.288***	-0.055**	0.052	0.131***
	(0.025)	(0.043)	(0.039)	(0.027)	(0.045)	(0.044)
Agriculture, Natural Resources, and Conservation	-0.048*	0.148***	-0.145***	0.101***	0.190***	0.098***
	(0.025)	(0.050)	(0.030)	(0.026)	(0.052)	(0.031)
Health, Parks, Recreation, and Fitness	0.183***	0.635***	-0.003	-0.140***	0.145***	-0.270***
	(0.027)	(0.046)	(0.035)	(0.028)	(0.049)	(0.035)
Co-op: (Base: Didn't do co-op) | Did co-op	0.204***	0.312***	0.114***	0.053***	-0.381***	0.380***
	(0.012)	(0.019)	(0.016)	(0.013)	(0.021)	(0.018)
Job status: (Base: Full-time) | Part-time	-0.626***	-0.799***	-0.561***	-0.592***	-0.679***	-0.564***
	(0.013)	(0.026)	(0.016)	(0.014)	(0.028)	(0.016)
Job tenure: (Base: Permanent) | Not permanent	-0.284***	-0.181***	-0.317***	-0.233***	-0.148***	-0.294***
	(0.011)	(0.018)	(0.014)	(0.012)	(0.021)	(0.015)
Gender: (Base: Male) | Female	-0.090***			0.001		
	(0.009)			(0.011)		
Minority Status: (Base: Not a visible minority) | Visible minority	-0.032***	-0.155***	0.002	-0.415***	-0.464***	-0.370***
	(0.012)	(0.019)	(0.016)	(0.013)	(0.021)	(0.017)
Immigration Status: (Base: Native citizen) | Citizen by naturalization	-0.088***	-0.075***	-0.084***	-0.196***	0.141***	-0.460***
	(0.015)	(0.023)	(0.021)	(0.016)	(0.026)	(0.022)
Landed immigrant	-0.057**	-0.011	-0.094**	0.054*	0.350***	-0.138***
	(0.026)	(0.038)	(0.038)	(0.030)	(0.043)	(0.042)
Marital Status: (Base: Single) | Married/Common-law	-0.025***	0.149***	-0.107***	-0.029***	-0.104***	0.016
	(0.009)	(0.016)	(0.012)	(0.011)	(0.018)	(0.014)

Children: (Base: No dependent children) | 1 or more dependent children	-0.008	-0.051^{**}	0.009	-0.032^{**}	0.037	-0.055^{***}
	(0.012)	(0.021)	(0.016)	(0.013)	(0.023)	(0.017)
Constant				-0.749^{***}	-0.777^{***}	-0.791^{***}
				(0.034)	(0.057)	(0.042)
Observations	10,646	4,299	6,347	10,646	4,299	6,347
Log Likelihood	-220,970.000	-92,567.560	-126,482.100	-146,076.900	-58,048.100	-86,251.760
Akaike Inf. Crit.				292,267.800	116,208.200	172,615.500
Note:						*p<0.1; **p<0.05; ***p<0.01

From Table 3, it is quickly observed that qualitative and quantitative match are highly correlated. The two are much more likely to be reported alongside each other: we expect 40.1% more quantitative matches with a somewhat close qualitative match (Col. 4) and 389.8% more quantitative matches with a close qualitative match (Col. 4) relative to having no match. Graduates are 2.822 times as likely to report a higher category of qualitative match when they have a quantitative match (Col. 1). This agrees with previous findings that the two types of match occur alongside each other more often than not.

Regarding qualitative match alone, it appears that there is some degree of gender disparity in most fields of study (Col.2 and Col. 3), however this is heavily obfuscated by the fact that the regression coefficients are not treating the likelihood of being in these fields of study as the summary statistics for males and females being in those fields. The list of majors that are most likely to be matched for the full sample from highest to lowest is as follows (program names shortened): Business, Engineering, Health and Fitness, Education, Agriculture and Conservation, Computer Science and Mathematics, Social Sciences and Law, Physical/Life Sciences, Visual Arts, and finally Humanities (Col. 1). This ranking loosely follows the ranking that exists within Boudarbat and Chernoff

(2010), however some of the coefficients of these fields of study are not significantly different from each other such as Agriculture and Conservation and Education. What is also of note regarding this ranking is that it is quite similar to the one derived from the income results posted above. Most fields of study have considerably less impact on one's ability to find a good quantitative match than for qualitative match (Col. 4). This is unsurprising as field of study determines what the respondent assesses their qualitative match with. Some majors offer more specialized skills than others, and some majors may have fewer job opportunities that truly utilize that type of education.

Bachelor's degrees appear to decrease the likelihood of reporting either type of match relative to college diplomas, but particularly the qualitative match is affected (Col. 4). As mentioned in the previous results subsection, the negative effects of matching with level of education can likely explain the lower job satisfaction associated with higher levels of education. The odds ratio for qualitative match is close to 1 (0.979) when a master's degree is considered which suggests that one is more likely to be matched qualitatively with further study (Col. 1) which follows Boudarbat and Chernoff (2010). The reason college diplomas have higher rates of qualitative match is likely since they typically offer more applied and job specific skills. Conversely, a master's degree further increases the likelihood of feeling overqualified (Col. 4), which makes sense as increasing the level of qualification is more likely to make one feel overqualified than it is to get one to feel only adequately qualified.

Co-op experience appears to have positive consequences for qualitative match with 22.6% more respondents reporting a higher level of match (Col. 1), however men appear to benefit more in this regard. Conversely, the effect of co-op on quantitative match is very gendered, as men are about 46.4% more likely than other men to report feeling overqualified if they have done co-op (Col. 5), while women are about 46.2% less likely than other women to report feeling overqualified if they have done co-op (Col. 6). Such a high disparity is hard to explain, but it may be caused by differences in reporting between men and women conditionally on having done co-op. Part-time workers are about 86.9% more likely to report a lower degree of match (Col. 1) and about 80.8% more likely feel overqualified (Col. 4). Part-time work rarely rewards workers with specialized skills or advanced education so this appears to be appropriate. Workers with jobs that are not permanent are about 32.8% more likely to report a lower degree of qualitative match (Col. 1) and 26.2% more likely to feel overqualified (Col. 4). The cause of this likely follows a similar reasoning to part-time work, that non-permanent jobs are less likely to be require advanced skills.

Women appear to report lower levels of qualitative match 9.4% more than men (Col. 1) and there is no substantive difference between men and women for quantitative match (Col. 4). Members of a visible minority do not seem to report much of a substantive difference in qualitative job match (Col. 1); however, they do report feeling overqualified about 51.5% more than non-minorities (Col. 4). Immigrants report that they are qualitatively matched well less often than native citizens (Col. 1), however, immigrants' reports of quantitative match are quite gendered, as the male immigrants' odds ratios are consistently greater than 1 while the female immigrants' odds ratios are consistently lower than 1 (Col. 5 and Col. 6). What is a little surprising is that landed immigrants report higher rates of quantitative job match than naturalized citizens (Col. 4);

however, this may have to do with reporting bias due to lower expectations of quantitative match.

Marital status appears to have a gendered effect; however, it is reversed between the two different types of match. Married men compared to single men report more qualitative match with an odds ratio of 1.161 (Col. 2), but report less quantitative match with an odds ratio of 0.901 (Col. 5). Conversely, married women compared to single women report less qualitative match with an odds ratio of 0.899 (Col. 3), but report more quantitative match with an odds ratio of 1.016 (Col. 6). The effect of having children or not on having a good qualitative and quantitative match is very small however (Col. 1 and Col. 4).

5.4 Policy Suggestions

The first and foremost policy suggestion by this thesis is that attention be given by the government into possible ways of assisting people to find a job that suits them. The wage effects of qualitative and quantitative match are about $5,000 per year for qualitative match and about $7,500 per year for quantitative match, and job satisfaction is similarly strongly affected by education-job matching. Providing services and information that would reduce the risk of job mismatch would be greatly beneficial both to the individual and to society, if the individual in question is truly misallocated in the labour market. This is intrinsically linked to helping people escape from underemployment in general, because, as this research finds, the likelihood of being unable to utilize your education appropriately is about 86% higher when one works part-time and about 32% higher when one works at a non-permanent job. Regarding quantitative match specifically, the creation of skilled labour jobs should be a priority as the more high skill jobs there are, the less likely it will be that high skill workers will be unable to find an appropriate job for their level of education.

The second policy suggestion proposed here is that findings such as those present within this work are made readily available for both prospective university and college students, as well as to universities themselves. While there is likely not going to be a huge surge of jobs that necessitate Humanities experience, the understanding of which fields of study are more or less likely to yield a good qualitative education-job match should be valuable to students when making decisions about their education if they would otherwise hold unfounded expectations of being able to find suitable work in their field. The supply of graduates in a given field of study is important in determining the likelihood of finding a good match since the availability of employment is a function of both supply and demand. While it is not in the interest of universities to drive people away from any programs, nor is it necessarily a social good if all education is only valued for its labour market implications, knowledge of the field of study effects on qualitative matching may be useful in aiding campus placement agencies should they exist. Ultimately, the accessibility of results such as those in this thesis would reduce the possible information asymmetry faced by students, who are mostly vulnerable young people, who may not know what the actual expectations are regarding their educational choices.

A nominal suggestion put forward by this thesis is to further examine the causes and possible solutions to potential negative effects experienced by immigrants, women, and minorities. While it is beyond the scope of this work to assert any claims of discrimination, there are fairly substantive gender, minority, and immigrant effects that are estimated here. All else being equal, recently graduated members of visible minorities report feeling overqualified almost 51.5% more often than recently graduated people who are not members of any visible minority. Women are estimated to earn about $4,500 less per year than men on average, ceteris paribus. Compared to native citizens, permanent residents earn about $7,200 less on average, after controls.

Conclusion

In this thesis, the labour outcomes of recent graduates with respect to their education and specifically their education-job match were estimated. Considerable positive wage effects were attributed to the presence of a good education-job match. The magnitudes of the effect of qualitative and quantitative match separately were found to be fairly close on average. As well, the determinants of education-job match were estimated. This has revealed which fields of study and which demographic groups are more likely to experience education-job mismatch. Policy suggestions were made to address the findings of this research, such as the creation of more high skill jobs.

One of the more interesting results from this paper is that women seemingly derive less of their job satisfaction from income and more from a good match than men. This suggests that women may be more incentivized by the non-pecuniary benefits of work such as the feeling of doing what one is good at. A different story could be that women have less faith in getting promoted so they instead seek out appropriate matches.

This thesis corroborates many findings from previous studies about the effects of education-job match as well as the determinants of it. Field of study was extremely relevant in predicting whether a good qualitative match was reported, which follows Boudarbat and Chernoff (2010). Previous literature has agreed that the effects of education-job match are both statistically significant and substantive and that qualitative match and quantitative match often occur together, both of which are conclusions that this research also reaches. This thesis also estimates wage penalties and/or job satisfaction penalties for women, visible minorities, and immigrants, however the estimation of these effects was not a major focal point of this work. There is a very large literature that examines discrimination that does a much better job at estimating and explaining these effects.

There is still a lot of room for more research into this topic. There is a lack of studies that find a causal relationship between education-job match and earnings or job satisfaction or a causal relationship from the apparent determinants of education-job match (Lemieux 2014). Studies seeking to find causality would probably require data that measures labour outcomes before and after changing jobs with different degrees of education-job match. As well, there are different populations that could be studied, as this research only focuses on recent Canadian graduates. While we still fully expect to observe the same positive wage and job satisfaction effects from matching, it would be interesting to see the differences in the effects of education-job match on wage and job satisfaction between populations. In general, this thesis strongly advocates that education-job match always be considered when estimating returns to education. Qualitative match has been underappreciated compared to quantitative match, but as we find here, they both effect wage in similar magnitudes. As well, both types of matching should be addressed when looking at job satisfaction. Once the National Graduates Survey (2018) is released for public analysis, it would be very interesting to examine it in a similar light as this research so that comparisons across time can be made.

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Appendix: Full Regression Results

Table 5 - Full Income Regression

	Dependent variable:		
	Annual Income		
	Full	Male	Female
	(1)	(2)	(3)
Qualitative Match: (Base: Not related at all) | Closely related	5,099.829***	7,016.969***	3,543.346***
	(801.879)	(1,292.355)	(978.568)
Somewhat related	3,329.847***	4,613.351***	2,342.197***
	(805.492)	(1,317.562)	(997.920)
Quantitative Match: (Base: Overqualified) | Adequately qualified	7,572.043***	8,098.278***	7,288.437***
	(581.627)	(1,024.890)	(668.630)
Level of education: (Base: College) | Bachelor's degree	10,603.910***	9,998.896***	10,811.210***
	(632.596)	(1,101.736)	(727.648)
Master's degree or greater	19,682.610***	18,847.240***	20,388.730***
	(823.617)	(1,474.925)	(965.246)
Field of Study: (Base: Education) | Visual and Performing Arts, and Communications Technologies	-3,869.422***	-7,179.643***	-2,508.404***
	(1,183.287)	(2,708.746)	(1,248.647)
Humanities	-2,332.157*	-5,419.508*	-1,001.701*
	(1,191.543)	(2,370.531)	(1,369.284)
Social and Behavioural Science and Law	-1,369.858	-2,858.839	-1,116.601
	(980.613)	(2,251.495)	(1,061.313)
Business, Management and Public Administration	1,767.371*	341.079*	2,110.463*
	(1,055.334)	(2,172.538)	(1,145.783)
Physical and Life Sciences and Technologies	-5,487.239***	-7,824.003***	-4,386.687***
	(1,236.959)	(2,348.838)	(1,484.410)
Computer/Information Sciences and Mathematics	-408.155	-3,258.309	2,265.327
	(1,266.516)	(2,195.471)	(1,868.189)

Architecture, Engineering, and Related Technologies	3,210.989**	326.571**	3,066.463**
	(1,276.634)	(2,169.852)	(1,987.859)
Agriculture, Natural Resources, and Conservation	303.532	-798.133	883.367
	(1,199.916)	(2,859.660)	(1,261.687)
Health, Parks, Recreation, and Fitness	-874.572	-2,678.143	-599.800
	(1,208.597)	(2,336.405)	(1,476.934)
Co-op: (Base: Didn't do co-op) | Did co-op	599.783	1,385.394	143.351
	(733.165)	(1,218.676)	(871.946)
Father's education level: (Base: Less than high school) | High school diploma	-1,263.184	-4,325.496	119.785
	(932.654)	(1,681.393)	(1,057.162)
Trade certificate or diploma	-829.436	-3,545.312	499.207
	(1,032.987)	(1,909.932)	(1,182.976)
College or CEGEP diploma	-883.916	-2,670.178	-215.156
	(1,074.218)	(1,877.682)	(1,235.278)
Bachelor's degree	227.001	-1,459.212	663.697
	(1,024.695)	(1,727.790)	(1,217.061)
Greater than bachelor's degree	-622.590	-3,350.789	750.693
	(1,109.931)	(1,780.315)	(1,383.733)
Mother's education level: (Base: Less than high school) | High school diploma	1,899.489*	3,926.547*	678.835*
	(982.676)	(1,740.001)	(1,158.790)
Trade certificate or diploma	981.366	5,453.768	-1,078.666
	(1,424.407)	(2,975.938)	(1,530.817)
College or CEGEP diploma	748.955	1,277.826	395.214
	(1,079.590)	(1,921.613)	(1,273.891)
Bachelor's degree	3,109.354***	4,383.364***	1,900.883***
	(1,114.965)	(1,887.384)	(1,334.754)
Greater than bachelor's degree	3,354.619**	5,581.596**	1,895.005**
	(1,316.138)	(2,159.869)	(1,662.201)
Job status: (Base: Full-time) | Part-time	-22,081.130***	-22,905.820***	-21,935.030***
	(683.647)	(1,283.579)	(777.429)

Job tenure: (Base: Permanent) | Not permanent	-5,442.710***	-8,291.254***	-3,963.235***
	(617.398)	(1,127.055)	(702.125)
Industry Classification: (Base: Trade, transportation and warehousing) | Goods-producing industries	5,332.100***	3,431.199***	6,867.546***
	(1,291.612)	(1,827.683)	(1,740.793)
Finance, insurance, real estate, public administration	3,982.489***	1,018.800***	6,488.048***
	(1,121.351)	(1,760.406)	(1,361.106)
Professional, scientific and technical services	-776.965	-1,750.745	145.953
	(1,359.108)	(2,032.056)	(1,684.871)
Education services	-1,927.557	-6,397.352	1,328.518
	(1,309.311)	(2,098.865)	(1,570.552)
Health care and social assistance	-3,697.016***	-5,989.645***	-1,845.168***
	(1,117.606)	(1,861.888)	(1,317.380)
Other services	-4,897.220***	-7,077.916***	-2,377.530***
	(1,295.340)	(2,467.561)	(1,482.337)
Occupation Classification: (Base: Sales and service occupations) | Management occupations	13,195.680***	14,237.120***	12,109.510***
	(1,434.013)	(2,282.804)	(1,485.080)
Business, finance and administrative occupations	3,827.743***	3,689.127***	4,195.092***
	(1,031.080)	(1,810.151)	(1,102.489)
Natural and applied sciences and related occupations	7,664.961***	7,202.402***	8,835.099***
	(1,268.915)	(1,906.199)	(1,485.035)
Health occupations	15,654.350***	14,861.550***	15,811.410***
	(1,453.087)	(3,025.692)	(1,569.081)
Social science, education, government service and religion	6,334.640***	6,740.641***	6,122.180***
	(1,166.091)	(1,926.264)	(1,310.812)
Occupations in art, culture, recreation and sport	1,731.745	4,795.547	653.733
	(1,496.733)	(3,268.075)	(1,395.048)
Trades, transport and equipment operators	8,032.181***	8,013.642***	11,255.680***
	(1,993.915)	(2,433.131)	(4,092.530)

Primary industry, processing, manufacturing and utilities	8,197.239***	9,344.844***	5,045.195***
	(2,528.045)	(2,926.587)	(5,093.120)
Gender: (Base: Male) | Female	-4,597.864***		
	(580.146)		
Minority Status: (Base: Not a visible minority) | Visible minority	1,577.588**	608.754**	2,169.529**
	(690.256)	(1,142.565)	(838.319)
Age at graduation: (Base: Less than 25) | 25 to 29	7,063.349***	6,115.245***	7,076.235***
	(840.775)	(1,455.821)	(1,013.944)
30 to 39	8,709.176***	6,285.578***	9,579.461***
	(1,036.725)	(1,940.264)	(1,188.116)
40 or more	548.267	-84.205	637.347
	(816.117)	(1,349.141)	(971.979)
Immigration Status: (Base: Native citizen) | Citizen by naturalization	-1,489.277	-771.527	-1,762.402
	(1,028.258)	(1,762.629)	(1,211.576)
Landed immigrant	-7,228.292***	-4,278.796***	-10,179.170***
	(1,627.410)	(2,623.312)	(1,819.861)
Marital Status: (Base: Single) | Married/Common-law	1,895.383***	2,287.896***	1,559.164***
	(566.511)	(1,072.085)	(638.920)
Children: (Base: No dependent children) | 1 or more dependent children	-2.785	2,215.555	-1,177.870
	(663.558)	(1,208.025)	(768.452)
Region of institution: (Base: Atlantic provinces) | Quebec	-1,793.491*	-3,759.163*	-751.410*
	(1,007.008)	(1,614.069)	(1,269.911)
Ontario	1,523.769**	792.331**	1,931.092**
	(682.824)	(1,139.295)	(840.341)
Western provinces, territories	3,494.991***	3,143.665***	3,559.133***
	(611.564)	(1,076.267)	(737.664)

Language spoken at home: (Base: English only) | French only	-1,506.224	-1,602.203	-1,282.272
	(1,053.929)	(1,646.471)	(1,334.817)
Other only	-2,632.513*	-4,196.132*	-795.282*
	(1,409.327)	(1,988.579)	(1,985.847)
English and French only	-2,642.051	-957.526	-3,134.630
	(1,807.073)	(2,565.948)	(2,246.946)
None of the above	-1,738.549	-2,396.208	-1,129.640
	(1,172.405)	(1,856.052)	(1,451.913)
Disability Status: (Base: No long-term disability) | Has a long-term disability	-5,064.036***	-3,880.318***	-4,793.981***
	(952.915)	(1,776.416)	(1,106.025)
Debt at graduation: (Base: No debt) | Less than 5,000	-1,380.643	-861.690	-1,721.777
	(975.791)	(1,777.924)	(1,075.267)
5,000 to less than 10,000	-2,825.978***	-2,793.136***	-2,775.453***
	(819.443)	(1,347.430)	(964.895)
10,000 to less than 25,000	-1,830.896***	-1,397.552***	-1,849.141***
	(673.637)	(1,160.090)	(748.672)
25,000 or more	-277.649	-918.409	12.378
	(740.149)	(1,185.261)	(918.050)
Constant	29,185.050***	33,737.750***	22,545.790***
	(1,685.765)	(2,979.329)	(1,930.465)
Observations	9,357	3,738	5,619
R^2	0.532	0.485	0.558
Adjusted R^2	0.529	0.476	0.553
Residual Std. Error	80,549.690 (df = 9294)	86,054.810 (df = 3676)	75,634.460 (df = 5557)
F Statistic	170.351*** (df = 62; 9294)	56.689*** (df = 61; 3676)	114.895*** (df = 61; 5557)
Note:			*p<0.1; **p<0.05; ***p<0.01
			SE's and significance are using Huber/White heteroscedasticity robust errors (as used in Stata)

Table 6 - Full Job Satisfaction Regression

	Dependent variable:		
	Job Satisfaction		
	Full	Male	Female
	(1)	(2)	(3)
Qualitative Match: (Base: Not related at all) | Closely related	0.812***	0.477***	1.028***
	(0.013)	(0.020)	(0.017)
Somewhat related	0.259***	-0.136***	0.546***
	(0.013)	(0.021)	(0.018)
Quantitative Match: (Base: Overqualified) | Adequately qualified	1.214***	1.111***	1.339***
	(0.010)	(0.016)	(0.013)
Level of education: (Base: College) | Bachelor's degree	-0.290***	-0.316***	-0.258***
	(0.011)	(0.017)	(0.014)
Master's degree or greater	-0.429***	-0.406***	-0.411***
	(0.016)	(0.026)	(0.020)
Field of Study: (Base: Education) | Visual and Performing Arts, and Communications Technologies	0.264***	-0.120**	0.372***
	(0.027)	(0.050)	(0.033)
Humanities	0.351***	-0.012	0.426***
	(0.022)	(0.043)	(0.026)
Social and Behavioural Science and Law	0.113***	-0.353***	0.262***
	(0.020)	(0.040)	(0.023)
Business, Management and Public Administration	0.069***	-0.047	-0.003
	(0.020)	(0.040)	(0.023)
Physical and Life Sciences and Technologies	0.271***	-0.140***	0.450***
	(0.025)	(0.045)	(0.032)
Mathematics, Computer and Information Sciences	0.132***	-0.261***	0.132**
	(0.031)	(0.047)	(0.052)
Architecture, Engineering, and Related Technologies	-0.058**	-0.458***	0.227***
	(0.024)	(0.041)	(0.037)
Agriculture, Natural Resources, and Conservation	-0.118***	-0.737***	0.102***
	(0.023)	(0.047)	(0.026)
Health, Parks, Recreation, and Fitness	0.256***	-0.040	0.311***
	(0.025)	(0.044)	(0.032)

Co-op: (Base: Didn't do co-op) | Did co-op	-0.020*	0.092***	-0.102***
	(0.011)	(0.018)	(0.015)
Annual Income: (Base: Under 10,000) | Under 20,00	0.042	0.016	0.129***
	(0.032)	(0.072)	(0.037)
Under 30,00	-0.027	-0.031	-0.013
	(0.033)	(0.074)	(0.038)
Under 40,00	0.138***	0.462***	0.092**
	(0.034)	(0.075)	(0.039)
Under 50,00	0.276***	0.578***	0.204***
	(0.035)	(0.075)	(0.041)
Under 60,00	0.280***	0.543***	0.232***
	(0.036)	(0.076)	(0.042)
Under 70,000	0.436***	0.771***	0.342***
	(0.037)	(0.077)	(0.043)
Under 80,00	0.635***	1.165***	0.398***
	(0.038)	(0.078)	(0.045)
Under 90,000	0.751***	0.877***	0.830***
	(0.040)	(0.080)	(0.051)
90,000 or more	0.837***	1.334***	0.478***
	(0.039)	(0.078)	(0.049)
Job status: (Base: Full-time) | Part-time	-0.058***	0.170***	-0.225***
	(0.017)	(0.034)	(0.020)
Job tenure: (Base: Permanent) | Not permanent	-0.053***	-0.027	-0.003
	(0.011)	(0.020)	(0.014)
Industry Classification: (Base: Trade, transportation and warehousing) | Goods-producing industries	0.214***	0.021	0.405***
	(0.019)	(0.026)	(0.030)
Finance, insurance, real estate, public administration	0.382***	0.545***	0.196***
	(0.017)	(0.026)	(0.023)
Professional, scientific and technical services	0.084***	0.035	0.083***
	(0.019)	(0.027)	(0.026)
Education services	0.601***	0.777***	0.519***
	(0.021)	(0.036)	(0.027)

Health care and social assistance	0.358***	0.162***	0.494***
	(0.017)	(0.027)	(0.023)
Other services	0.209***	0.034	0.255***
	(0.019)	(0.036)	(0.024)
Occupation Classification: (Base: Sales and service occupations) | Management occupations	0.015	0.022	0.020
	(0.021)	(0.029)	(0.030)
Business, finance and administrative occupations	0.071***	0.030	0.077***
	(0.015)	(0.025)	(0.020)
Natural and applied sciences and related occupations	0.285***	0.560***	-0.088***
	(0.020)	(0.028)	(0.030)
Health occupations	0.406***	0.887***	0.147***
	(0.024)	(0.047)	(0.030)
Social science, education, government service and religion	0.391***	0.374***	0.366***
	(0.018)	(0.029)	(0.024)
Occupations in art, culture, recreation and sport	0.103***	0.335***	-0.070**
	(0.026)	(0.044)	(0.032)
Trades, transport and equipment operators	0.079***	0.318***	-0.393***
	(0.027)	(0.032)	(0.090)
Primary industry, processing, manufacturing and utilities	0.429***	0.598***	0.427***
	(0.035)	(0.042)	(0.068)
Benefits: (Base: Job does not have benefits) | Job has benefits	0.239***	0.364***	0.149***
	(0.014)	(0.024)	(0.018)
Gender: (Base: Male) | Female	0.062***		
	(0.009)		
Age at graduation: (Base: Less than 25) | 25 to 29	0.052***	-0.136***	0.151***
	(0.010)	(0.016)	(0.014)
30 to 39	0.001	-0.348***	0.161***
	(0.015)	(0.024)	(0.019)
40 or more	0.333***	0.001	0.465***
	(0.016)	(0.029)	(0.020)
Minority Status: (Base: Not a visible minority) | Visible minority	-0.194***	-0.065***	-0.274***
	(0.012)	(0.019)	(0.015)

Immigration Status: (Base: Native Citizen) | Citizen by naturalization	-0.035**	0.056**	-0.080***
	(0.015)	(0.024)	(0.020)
Landed immigrant	-0.289***	-0.454***	-0.128***
	(0.026)	(0.037)	(0.038)
Marital Status: (Base: Single/widowed/separated/divorced) | Married/Common-law	0.037***	0.253***	-0.112***
	(0.009)	(0.016)	(0.012)
Children: (Base: No dependent children) | 1 or more dependent children	-0.032***	0.049**	-0.061***
	(0.012)	(0.020)	(0.015)
Region of institution: (Base: Atlantic provinces) | Quebec	-0.185***	-0.056	-0.262***
	(0.021)	(0.034)	(0.028)
Ontario	-0.046***	-0.116***	-0.003
	(0.017)	(0.027)	(0.021)
Western provinces, territories	-0.134***	-0.178***	-0.099***
	(0.017)	(0.028)	(0.022)
Language spoken at home: (Base: English only) | French only	0.144***	0.125***	0.193***
	(0.017)	(0.028)	(0.023)
Other only	-0.295***	-0.132***	-0.470***
	(0.020)	(0.029)	(0.029)
English and French only	0.090***	0.418***	-0.101***
	(0.025)	(0.041)	(0.033)
None of the above	0.113***	0.081***	0.077***
	(0.019)	(0.030)	(0.025)
Disability Status: (Base: No long-term disability) | Has a long-term disability	-0.202***	-0.316***	-0.046*
	(0.020)	(0.032)	(0.027)
Observations	264,399	103,104	161,294
Log Likelihood	-227,251.300	-89,611.650	-135,065.000
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7 - Full Education-Job Match Regressions

	Dependent variable:					
	Qualitative Match *cumulative link*			Quantitative Match *logistic*		
	Full	Male	Female	Full	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Qualitative Match: (Base: Not related at all) Closely related				1.361***	1.426***	1.346***
				(0.013)	(0.021)	(0.017)
Somewhat related				0.337***	0.498***	0.242***
				(0.013)	(0.021)	(0.018)
Quantitative Match: (Base: Overqualified) | Adequately qualified	1.037***	1.042***	1.036***			
	(0.009)	(0.014)	(0.012)			
Level of education: (Base: College) | Bachelor's degree	-0.222***	-0.106***	-0.317***	-0.104***	-0.358***	0.060***
	(0.011)	(0.017)	(0.014)	(0.012)	(0.019)	(0.015)
Master's degree or greater	-0.021	0.169***	-0.133***	-0.291***	-0.555***	-0.195***
	(0.016)	(0.026)	(0.021)	(0.017)	(0.028)	(0.021)
Field of Study: (Base: Education) | Visual/Performing Arts and Communications	-1.054***	-0.661***	-1.183***	0.308***	0.686***	0.188***
	(0.028)	(0.051)	(0.035)	(0.031)	(0.056)	(0.038)
Humanities	-1.200***	-1.258***	-1.157***	0.078***	0.449***	-0.051*
	(0.023)	(0.044)	(0.028)	(0.025)	(0.048)	(0.030)
Social/Behavioural Sciences and Law	-0.583***	0.031	-0.838***	0.080***	0.302***	-0.026
	(0.021)	(0.041)	(0.025)	(0.023)	(0.044)	(0.027)
Business, Management, and Public Administration	0.339***	0.882***	0.090***	0.013	0.032	0.072***
	(0.022)	(0.041)	(0.026)	(0.023)	(0.043)	(0.027)
Physical and Life Sciences Technologies	-0.979***	-0.370***	-1.293***	-0.178***	-0.004	-0.218***
	(0.026)	(0.046)	(0.033)	(0.029)	(0.050)	(0.036)

Computer/Information Sciences and Mathematics	-0.097***	0.561***	-0.529***	-0.075**	-0.078	0.363***
	(0.032)	(0.049)	(0.054)	(0.035)	(0.052)	(0.062)
Architecture, Engineering, and Related Technologies	0.266***	0.908***	-0.288***	-0.055**	0.052	0.131***
	(0.025)	(0.043)	(0.039)	(0.027)	(0.045)	(0.044)
Agriculture, Natural Resources, and Conservation	-0.048*	0.148***	-0.145***	0.101***	0.190***	0.098***
	(0.025)	(0.050)	(0.030)	(0.026)	(0.052)	(0.031)
Health, Parks, Recreation, and Fitness	0.183***	0.635***	-0.003	-0.140***	0.145***	-0.270***
	(0.027)	(0.046)	(0.035)	(0.028)	(0.049)	(0.035)
Co-op: (Base: Didn't do co-op) | Did co-op	0.204***	0.312***	0.114***	0.053***	-0.381***	0.380***
	(0.012)	(0.019)	(0.016)	(0.013)	(0.021)	(0.018)
Method used to find job: (Base: Referred) | Answered job ad (internet)	0.275***	0.340***	0.221***	0.008	0.040**	-0.028*
	(0.011)	(0.017)	(0.015)	(0.012)	(0.020)	(0.016)
Answered job ad (newspaper, etc.)	0.307***	-0.040	0.425***	-0.264***	-0.657***	-0.122***
	(0.025)	(0.044)	(0.031)	(0.026)	(0.049)	(0.032)
Contacted employer directly	0.002	-0.048**	0.110***	0.065***	0.200***	-0.024
	(0.015)	(0.024)	(0.020)	(0.016)	(0.027)	(0.021)
Held job before	0.495***	0.322***	0.570***	0.282***	0.259***	0.328***
	(0.027)	(0.041)	(0.037)	(0.029)	(0.046)	(0.039)
Campus placement office	0.414***	0.136***	0.662***	0.254***	0.319***	0.240***
	(0.023)	(0.032)	(0.034)	(0.026)	(0.039)	(0.037)
Employment agency (public or private)	-0.197***	0.224***	-0.492***	0.335***	0.319***	0.388***
	(0.026)	(0.042)	(0.035)	(0.030)	(0.047)	(0.039)
Approached or contacted directly by employer	0.309***	0.316***	0.290***	0.616***	0.631***	0.640***
	(0.020)	(0.029)	(0.028)	(0.024)	(0.035)	(0.033)
Networking, job fair	0.201***	0.095***	0.323***	0.299***	0.323***	0.226***
	(0.019)	(0.029)	(0.027)	(0.023)	(0.035)	(0.030)

Other	0.283***	0.229***	0.328***	0.217***	0.185***	0.242***
	(0.017)	(0.026)	(0.022)	(0.018)	(0.029)	(0.024)
Job status: (Base: Full-time) | Part-time	-0.626***	-0.799***	-0.561***	-0.592***	-0.679***	-0.564***
	(0.013)	(0.026)	(0.016)	(0.014)	(0.028)	(0.016)
Job tenure: (Base: Permanent) | Not permanent	-0.284***	-0.181***	-0.317***	-0.233***	-0.148***	-0.294***
	(0.011)	(0.018)	(0.014)	(0.012)	(0.021)	(0.015)
Industry Classification: (Base: Trade, transportation and warehousing) | Goods-producing industries	0.565***	0.336***	0.820***	0.694***	0.852***	0.493***
	(0.019)	(0.025)	(0.030)	(0.021)	(0.029)	(0.033)
Finance, insurance, real estate, public administration	0.357***	0.143***	0.549***	0.519***	0.448***	0.550***
	(0.016)	(0.025)	(0.023)	(0.018)	(0.027)	(0.025)
Professional, scientific and technical services	0.799***	0.442***	1.183***	1.157***	1.159***	1.119***
	(0.018)	(0.027)	(0.026)	(0.022)	(0.031)	(0.031)
Education services	1.163***	1.174***	1.289***	0.978***	1.019***	0.964***
	(0.021)	(0.036)	(0.027)	(0.023)	(0.039)	(0.030)
Health care and social assistance	0.322***	0.070***	0.553***	0.254***	0.197***	0.251***
	(0.017)	(0.025)	(0.023)	(0.018)	(0.028)	(0.024)
Other services	1.047***	0.673***	1.282***	0.354***	0.417***	0.280***
	(0.019)	(0.037)	(0.024)	(0.021)	(0.040)	(0.027)
Occupation Classification: (Base: Sales and service occupations) | Management occupations	0.457***	0.190***	0.716***	0.763***	0.584***	1.061***
	(0.020)	(0.027)	(0.029)	(0.022)	(0.031)	(0.033)
Business, finance and administrative occupations	0.553***	0.438***	0.685***	0.362***	0.625***	0.273***
	(0.015)	(0.024)	(0.020)	(0.016)	(0.026)	(0.021)

Natural and applied sciences and related occupations	1.088***	0.816***	1.456***	0.804***	0.822***	0.777***
	(0.019)	(0.026)	(0.031)	(0.022)	(0.030)	(0.034)
Health occupations	1.973***	1.946***	2.044***	1.390***	1.903***	1.388***
	(0.025)	(0.052)	(0.030)	(0.027)	(0.061)	(0.032)
Social science, education, government service and religion	1.572***	1.309***	1.743***	0.675***	0.558***	0.776***
	(0.018)	(0.029)	(0.024)	(0.019)	(0.031)	(0.026)
Occupations in art, culture, recreation and sport	1.974***	1.964***	2.025***	0.525***	-0.020	0.819***
	(0.025)	(0.044)	(0.032)	(0.028)	(0.046)	(0.036)
Trades, transport and equipment operators	0.250***	-0.038	1.023***	0.703***	0.590***	0.558***
	(0.026)	(0.031)	(0.083)	(0.029)	(0.034)	(0.093)
Primary industry, processing, manufacturing and utilities	0.035	-0.220***	0.463***	0.448***	0.369***	0.181***
	(0.031)	(0.038)	(0.069)	(0.035)	(0.043)	(0.070)
Gender: (Base: Male) | Female	-0.090***			0.001		
	(0.009)			(0.011)		
Age at graduation: (Base: Less than 25) | 25 to 29	0.110***	-0.052***	0.225***	0.039***	0.005	0.046***
	(0.011)	(0.017)	(0.015)	(0.012)	(0.019)	(0.017)
30 to 39	0.321***	0.127***	0.459***	-0.155***	-0.205***	-0.095***
	(0.015)	(0.025)	(0.020)	(0.017)	(0.027)	(0.022)
40 or more	0.124***	0.037	0.131***	-0.270***	-0.336***	-0.204***
	(0.016)	(0.028)	(0.021)	(0.018)	(0.031)	(0.022)
Minority Status: (Base: Not a visible minority) | Visible minority	-0.032***	-0.155***	0.002	-0.415***	-0.464***	-0.370***
	(0.012)	(0.019)	(0.016)	(0.013)	(0.021)	(0.017)
Immigration Status: (Base: Native Citizen) | Citizen by naturalization	-0.088***	-0.075***	-0.084***	-0.196***	0.141***	-0.460***
	(0.015)	(0.023)	(0.021)	(0.016)	(0.026)	(0.022)

Landed immigrant	-0.057**	-0.011	-0.094**	0.054*	0.350***	-0.138***
	(0.026)	(0.038)	(0.038)	(0.030)	(0.043)	(0.042)
Marital Status: (Base: Single) | Married/Common-law	-0.025***	0.149***	-0.107***	-0.029***	-0.104***	0.016
	(0.009)	(0.016)	(0.012)	(0.011)	(0.018)	(0.014)
Children: (Base: No dependent children) | 1 or more dependent children	-0.008	-0.051**	0.009	-0.032**	0.037	-0.055***
	(0.012)	(0.021)	(0.016)	(0.013)	(0.023)	(0.017)
Region of institution: (Base: Atlantic provinces) | Quebec	0.334***	0.353***	0.302***	-0.120***	-0.155***	-0.122***
	(0.022)	(0.034)	(0.030)	(0.025)	(0.039)	(0.032)
Ontario	-0.014	0.033	-0.057**	-0.078***	-0.058*	-0.116***
	(0.017)	(0.026)	(0.023)	(0.019)	(0.031)	(0.026)
Western provinces, territories	0.080***	0.217***	-0.030	0.096***	0.068**	0.129***
	(0.018)	(0.027)	(0.024)	(0.020)	(0.032)	(0.027)
Language spoken at home: (Base: English only) | French only	-0.066***	-0.095***	-0.012	-0.304***	-0.514***	-0.234***
	(0.020)	(0.031)	(0.028)	(0.022)	(0.034)	(0.029)
Other only	0.335***	0.454***	0.268***	0.081***	0.284***	-0.033
	(0.018)	(0.028)	(0.025)	(0.020)	(0.032)	(0.026)
English and French only	-0.001	0.069**	-0.026	-0.150***	-0.304***	-0.035
	(0.020)	(0.029)	(0.029)	(0.022)	(0.032)	(0.031)
None of the above	-0.165***	-0.171***	-0.152***	0.281***	0.295***	0.313***
	(0.026)	(0.039)	(0.035)	(0.029)	(0.045)	(0.041)
Disability Status: (Base: No long-term disability) | Has a long-term disability	0.112***	-0.054*	0.159***	-0.283***	-0.174***	-0.379***
	(0.019)	(0.030)	(0.026)	(0.020)	(0.033)	(0.026)

Constant				-0.749***	-0.777***	-0.791***
				(0.034)	(0.057)	(0.042)
Observations	10,646	4,299	6,347	10,646	4,299	6,347
Log Likelihood	-220,970.000	-92,567.560	-126,482.100	-146,076.900	-58,048.100	-86,251.760
Akaike Inf. Crit.				292,267.800	116,208.200	172,615.500
Note:						*p<0.1; **p<0.05; ***p<0.01