Is Enough Better than Too Much? Research on Returns to Education:

Sector and Occupational Level Analysis of Wage with Education in Canada

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Abstract

This paper uses census data to estimate the effects of education on wage. The data are divided according to industrial sector and the occupation, and the returns to education are estimated for each sector and occupation in order to estimate the effects of education, and to find the optimal education level. The results show that the returns to education depend greatly on sector and occupation. In most sectors and occupations, the marginal returns to the doctorate degree are low, suggesting that having a doctorate degree does not lead to higher wages. However, obtaining a bachelor's degree or master's degree does lead to higher wages for workers in most sectors and occupations. Thus, the returns to education appear to have been diminishing in some sectors and occupations. Over-education may be one explanation for the diminishing returns to education. This paper examines such cases at the levels of industrial sector and occupation and tries to assess the potential causes of diminishing returns to education.

1. Introduction

It is widely believed that the overall increasing educational attainments of the labour force of a nation substantially favour growth of its economy. These effects of education are remarkable and sustainable in both developing and developed countries. A complete and universal education system not only accelerates the growth of individual and family earnings, but also reduces the degree of inequality of the distribution of income by narrowing the overall wage gap. As a country with a high aggregate income level and a relatively low Gini coefficient, Canada benefits from high enrolment rates in post-secondary and tertiary education compared to some nother countries in the Organization for Economic Co-operation and Development (OECD). The OECD Education Statistics for 2014 show that 53.6% of the Canadian population between 25 and 64 years old have tertiary education, the highest among the 34 OECD countries. The Canadian government invests an enormous amount of resources to education annually. Without a doubt, this expenditure on education is a wise investment for the nation.

The effects of education on wages for individuals can be tied to several economic developments. Since 1980, technological changes and globalization have diminished job opportunities for many workers in Canada, but investment in education remains a good strategy to reduce the high adjustment costs that have been occasioned by displacement. Research regarding the returns to education is well-developed, and most studies conclude that education has a significant positive effect on wages. However, the marginal returns to education can vary dramatically, and typically they diminish as the level of education rises. If a worker is over-qualified for his/her occupation, or the job does not require a high degree of skill, having more education will not lead to a higher wage, ceteris paribus.

Although evidence supporting the existence of diminishing returns to education has been found in previous studies, these studies mostly estimate overall returns to education regardless of industrial sector and occupation. Yet, education-related effects on wages depend heavily on the characteristics of the industrial sector and occupation under consideration. I therefore argue that aggregate estimates cannot represent the true values of returns to education, and that we lack a complete picture of the returns to education. Here, I re-examine the effects of education by estimating the returns to education at the sectoral level as well as occupational level in order to assess optimal education level. The optimal education level is that level where workers have the highest estimated returns to education, regardless of the investment costs of education. In other words, the marginal return is equal to zero at the optimal level. I also consider explanations for the varied results associated with different sectors and occupations.

Based on data from Statistics Canada, I select two identical samples for the analysis. According to the 2011 census, one is divided into 19 groups according to industrial sector; the other is divided into 10 groups according to occupation. Educational attainments are classified into six levels in order to estimate returns to education along a range of education levels. Descriptive statistics on yearly earnings provide a preliminary picture. I then apply Ordinary Least Squares (OLS) regression analysis in order to assess the significance and magnitude of the effects. Other individual characteristics such as gender, experience and home language are also included in the regression to control for these effects.

The results of regression analysis are numerous. In general, results from both samples show discernable traces of the existence of overeducated workers in the Canadian labour market, indicating that the returns to education do diminish past a certain level. The marginal returns to education can be low or even negative in some sectors and occupations, indicating that some workers have educational attainments above the optimal education level. The optimal education level varies across industrial sectors and occupations. Overall, a bachelor's degree and master's degree show positive returns in most sectors and occupations, while the returns to a PhD degree are low. Control variables for individual characteristics, including gender, work experience and home language also affect wages earned, and the role of these factors should not be underestimated. As hypothesized, the effects of education and other factors depend on the industrial sector and the occupation of the worker.

The rest of the paper is structured as follows. Section 2 provides a literature review of previous studies on the returns to education and the phenomenon of over-education. Section 3 introduces the dataset used, describes the restrictions on the sampling of the data and presents some descriptive statistics. Section 4 explains the methodology employed and the econometric model. The results of the estimation are represented in Section 5. Section 6 presents the conclusions.

2. Literature Review

2.1 Studies about Returns to Education

The literature on the returns to education is quite developed, with most studies focusing on the returns to university degrees. Bar-Or, Burbidge, Magee and Robb (1995) conducted an early study investigating the wage premium for a university education relative to obtaining 11-13 years of schooling over the period from 1971 to 1991 in Canada. The data used are from the Canadian Public Use Sample Tapes, including 15 waves of the Survey Consumer Finances (SCF) between 1971 and 1991. The main empirical approach is to compare mean and median earnings between the two groups (university educated versus no university), and most of the results are depicted in figures. Bar-Or et al. (1995) further investigate the data by dividing the sample according to the amount of work experience, and compare the means, medians and log differences that are generated from OLS regressions for earnings. They find that the wage premium between men with a university education and men with 11-13 years of schooling generally declined during the 1970s. For those with little work experience, the wage premium increased significantly since 1979. For women, no trend is found due to the noisiness in the data, and the only discernable trend is a decline in the university wage premium during the 1970s for some experience groups. Bar-Or et al. also find that for workers with less than 6 years of work experience and regardless of gender, the university premium recovered between 1979 and 1985. Nevertheless, when all experience groups are taken together, the university premium in 1985 was not as large as that in the early 1970s.

Burbidge, Magee and Robb (2002) challenge the prevailing belief at the time that the wage premium between university graduates and high school graduates had risen in Canada and the United Sates during the period from 1981 to 1999. Various datasets are used to compare the trends in the two countries, including the US current Population Survey (CPS) and the SCF in Canada. In order to extend the interval of analysis, the Panel Study on Income Dynamics (PSID) and the Labour Force Survey (LFS) are also utilized. They divide the sample into six groups according to education level, and compare the weekly earnings for women and men separately. The evolution of the earnings ratios for workers with and without university degrees is emphasized. The descriptive summary points out that the trends in the university-high school wage premium are completely different in the two countries. The ratio of the earnings of university graduates to the earnings of high school graduates was 1.40 for men in Canada in 1999, which was almost the same as that in 1981. This number was approximately 1.34 for men in 1981 in the US and 1.77 in 1999. For women, this number in Canada falls from 1.65 to 1.50 during the period from 1981 to 1999, while it rises from 1.50 to 1.75 in the US. Burbidge et al. (2002) attribute the different behaviours of the education premium to the institutional differences between the US and Canada.

In order to reconcile the divergent conclusions of previous studies, Boudarbat, Lemieux and Riddell (2010) attempt to provide a comprehensive examination of the evolution of the returns to human capital from 1980 to 2005 in Canada. Observable human capital consists of experience and education, and formal education is given emphasis in the paper. Using census data from 1981 to 2006, including the waves of 1981, 1986, 1991, 1996, 2001, and the master file data from the 2006 census, they compare the returns to education based on both median and mean earnings and calculate the wage gap between the workers with university bachelor's degrees and workers who are high school graduates. They report the evolution of both the unadjusted wage gap and the regression-adjusted wage gap and suggest that most of the rise in returns to education occurred in the early 1980s, after which growth in the gap became modest. For men, during the period from 1980 to 2005, the wage gap between those with a bachelor's degree and high school graduates rose from 32 percent to 40 percent. The returns to education are larger for women than for men, but the increase over the 25-year interval is less dramatic; the wage gap between the holders of a bachelor's degree and high school graduates rose by only 6 percent for women.

Bourbeau, Lefebvre and Merrigan (2012) investigate a similar issue at the provincial level. The observations are restricted to young adults aged 21 to 35 years from 1990 to 2005. The dataset consists of census data carried out in 1991, 1996, 2001 and 2006. They apply an OLS regression analysis to estimate the wage equation; four different specifications are estimated for each of the four censuses. The differences between the specification lie in the different interaction terms, including education interacted with age, work experience and province. As the paper reports, the returns to higher education increased considerably for both male and female graduates from 1991 to 2006, and the estimates are larger than those found by Boudarbat, Lemieux and Riddell (2010) for the same time period using a sample of 16 to 65 year olds. Another finding is that the differentials in the returns to education also differed significantly across provinces, with returns to higher education higher in western Canada. More recent studies similarly report that wage differentials, as well as income inequality, differ across provinces (Morissette, Picot, and Lu, 2013; Fortin and Lemieux 2015).

Lemieux (2014) provides several possible channels of how education affects wages. He believes that the disconnect between the public's perception of low returns to university degrees and the scientific findings of high returns to education occurs through a failure to recognize channels. The three behavioural channels that he sets out are the following. First, education can make workers more productive when given a specific task to perform. Second, if the production technology is skill-intensive, more-educated workers are more likely to be assigned to high-paid occupations. Third, workers can be more productive when assigned to the occupations related to their own field. Lemieux (2014) concludes that the first channel is the general productivity effect that creates returns regardless of occupation, and that the remaining two effects of the second and third channels depend on the matching between education, skills and occupation. He uses two datasets, the National Graduates Survey of 2005 and the census of 2006, to estimate the three effects on earnings, and performs a decomposition analysis to quantify the contribution of each. He accomplishes this by applying the wage equation with the matching variable included, where the matching variable is the measurement of "relatedness" between occupation and field of study in his paper. He finds that the second and third channels i.e., the two matching effects each account for a quarter of the conventional return to education, while the first channel i.e., the general productivity effect, accounts for half. Another main finding of his study is that the return to education also varies greatly depending on occupation, field of study, and the match between these two factors.

Frenette (2014) examines the long-term labour market premiums for the individuals with college certificates and bachelor's degrees compared to those with high school diplomas.

Individuals are examined using longitudinal data over a 20-year period, following them from their mid-30s to their mid-50s. The creation of the new linked file that consists of the 1991 Census of the Population and the Longitudinal Worker File (LWF) makes the examination feasible. The estimating sample used contains 7,951 individuals who have appeared in the file in at least 18 out of 20 years in order to eliminate those that left Canada to work abroad. Mean total earnings over the 20-year period are calculated according to three education levels, namely high school, college and university, and the relationship between labour market outcomes and educational attainments is estimated separately for men and women. He concludes that individuals who have bachelor's degrees or college certificates have more favourable labour market outcomes over their working lives compared to individuals with only high school diplomas. Denominated in 2010 constant dollars, for bachelors the premiums are $728,000 for men and $442,000 for women on the average, while for college graduates which are $248,000 for men and $180,000 for women on the average.

2.2 Studies about Over-education and Mismatch

A mismatch between workers and their occupations can diminish the education premium, as can the event of being over-educated for a job. Over-education refers to the situation in which the workers' educational attainments exceed the posted requirements for their jobs. Note that less-educated workers are less likely to be employed in the occupations with high skill requirements, yet more-educated workers may accept jobs whose requirements for education are lower than their education levels. In such cases, a predictable result is that the marginal returns of higher education tend to be lower relative to normal level.

The concept of "over-education" derives from the book by Richard Freeman, "The Overeducated American" (1976). This book subsequently inspired certain Canadian researchers. Dooley (1986) has examined this issue using individual data from six waves of the SCF from 1971 to 1981. He confirms that a decline had occurred in relative earnings differentials during the ten-year period, particularly between men with university degrees and men with only secondary education, and attributes it to the phenomenon of over-education.

To date, propositions regarding over-education in Canada have not been sufficiently supported with evidence, while the topic are well-developed in some other countries. McGuinness and Doyle (2007) have explored the incidence and impact of over-education among Northern Ireland graduates. Ghignoni and Verashchagina (2014) have analysed the influence of both demand and supply factors on educational mismatch. However, the relevant studies concerning Canada are limited in number. Card and Lemieux (2001) suggest that the college premium for younger workers had risen in UK and the US, but the rise for younger workers is less dramatic than for older workers, and the college premium for older workers even decreased over the 1980s in Canada. This result may be a signal of the possible existence of over-education.

Most of the existing studies regarding over-education are theoretical in nature and give little in the way of empirical evidence. One example is Skott (2006), in which the author defines workers to be overeducated if they have education in excess of that required for their jobs. In his view, a high-skill worker who is unable to obtain a high-skill job may accept a low wage in a low-skill job, while a low-skill worker does not have the analogous option of getting a high-skill job. In his model, he considers three conditions: high-skill workers in high-skill jobs, high-skill workers in low-skill jobs, and low-skill workers in low-skill jobs. His model predicts the existence and persistence of over-education based on an efficiency wage framework in which workers' productivity levels depend on wages. He uses several numerical examples to show that the wage premium paid to the workers in high-skill jobs, induced by the relative supply of high-skill workers, provides an incentive for workers to acquire the high skill, even though they face a risk of spending at least part of their working life in low-skill jobs. Therefore, Skott believes that over-education cannot be eliminated in such cases. Yet, no empirical tests are carried out in this paper.

Frenette (2004) investigates the role of the academic program on the incidence, persistence, and economic returns to over-qualification among Canadian post-secondary graduates. The data reflect three cohorts (1982, 1986, and 1990) of the National Graduates Survey (NGS). Frenette (2004) defines the trait of over-qualification based on a comparison of educational attainment and job-hiring criteria. The paper finds that about approximately one third of Canadian graduates were overqualified for their job shortly after graduation in the early 1980s, and this rate diminished between 1980s and 1990s. Yet, more than half of graduates with a master's degree remain overqualified for their jobs, even 5 years after graduation. Frenette (2014) concluded that master's graduates are more prone to being overqualified, while co-op graduates at both the master's level and bachelor's level do not have this problem. This indicates that the event of being overqualified is highly related to the educational program attended, and that on-the-job training is very important.

Wald and Fang (2016) found that recent immigrants are more likely to be over-educated than Canadian-born workers. They examine the impacts of over-education on immigrants' earnings in the Canadian labour market using data from the Canadian Workplace and Employee Survey (WES) from 1999. To assess the degree of over-education, they compare actual educational attainment with the education level that the workers believe is required. Using this definition, nearly half of the immigrants arriving between 1989 and 1997 are found to be overeducated in 1999. They emphasize that these immigrants suffer a large disadvantage in earnings due to mismatches.

Wald (2005) uses data from the Changing Employment Relationship Survey (CERS) designed by the Canadian Policy Research Networks in 2000 to test the hypothesis that overqualified workers are less committed because they are more likely to engage in job search. He analyzes the relationship between over-qualification and job search activities by estimating job search decisions with a maximum likelihood probit model, where indicators of job search, over-qualification and other control variables are included. He defines searchers as those who either looked for a job or had plans to become self-employed in the past 12 months, and determines whether the workers are overeducated according to their perceptions. As a result, overqualified workers are found to be more actively engaged in job search, and thus employers may deliberately shun overqualified applicants based on the belief that they will quit when a better job becomes available. However, he also finds that if workers have positive perceptions about their current jobs, searching for new jobs can be reduced.

Only a few of the existing articles are interested in whether over-education diminishes the wage premium received by the worker. Vahey (2000) is one of the earliest studies to do so, drawing on data from the National Survey of Class Structure and Labour Process in Canada (NSCS), which was conducted in 1982 and contained approximately 3000 respondents. One advantage of this survey is that individuals are classified as over-educated or under-educated by comparison of their educational attainments and the requirements of their jobs in the survey records. Vahey finds in his sample, about 57% of males and 33% of females under 26 are overeducated, and estimates wage equations using over-education and under-education as two dummy variables. The results indicate that being over-educated does not reduce the wage relative to workers who are not over-educated for their jobs. For males whose jobs require bachelor's degrees, over-education has positive effects on wage, but for other required education levels, the effect of over-education is insignificant. Those who are undereducated receive lower wages than their counterparts, even if the jobs require only low education. However, for females, no significant result is found. The author suggests that family considerations can account for a part of the differences in returns by gender, yet the returns for females who are less tied by families are not prone to a higher level.

3. Data

The dataset I use is the Canadian Census Public Use Microdata File (PUMF): Individuals File from the 2011 National Household Survey (NHS). The NHS was introduced for the first time in 2011 to replace the mandatory long-form census. NHS is a voluntary questionnaire designed to collect demographic, social and economic information on the Canadian population. It covers all persons who usually live in Canada. The individual is the unit of the observation in PUMF, which contains 133 variables and 887,012 observations representing 2.7% of the target population.

I use NHS data because census data provides the best estimate of the degree of income inequality due to its coverage and detailed information (Frenette, Green and Milligan, 2007), and it can be applied to estimating returns to education. Another advantage of the NHS data is that the level of education is very detailed. The variable reflecting the highest level of education an individual received ranges from no certificate to a doctorate degree, indicating a total of 13 different levels. The information on the industrial sectors where individuals work is sorted very clearly based on the 2007 North American Industry Classification System (NAICS) in the PUMF; it covers 19 sectors. The occupations are sorted into 10 classes based on the 2006 National Occupational Classification for Statistics (NOC-S).

Even so, several statistical disadvantages may undermine the validity of the estimation results. For example, the information of age is not accurate. For instance, two individuals aged 47 and 45 respectively are both given the value of 13 for their ages in the PUMF 2011; such data errors induce measurement error. However, other datasets also have this drawback. Another shortcoming of the PUMF is the lack of a weekly wage; only total earnings for the year of 2010 are available. As many previous studies indicate, annual earnings cannot reflect lifetime income. In order to estimate the education effects, weekly wages or hourly wages are better measures. However, after restrictions are imposed on the data, part-time workers are removed from the sample that I include in my analysis. 89.58% of the individuals worked more than 40 weeks in 2010, thus annual earnings can reasonably be used as a proxy for weekly wages.

The sample that I use includes individuals aged 25 to 69, who had full-time jobs in 2010 and excludes those who are self-employed. The age-related restrictions aim to exclude students who are in the process of obtaining higher education without a full-time job, as well as older individuals who have retired or are about to retire from the labour force. I choose to include only full-time workers because their earnings are relatively more stable, which, in turn, will reflect the effects of education more accurately. I exclude the self-employed because their incomes derived from working are unlikely to be reflected in earnings, as a significant portion of their incomes stems from capital or entrepreneurship. After all of the sampling restrictions are imposed, the unavailable, inapplicable and missing values are removed. Finally, the sample size is reduced from 887,012 to 277,208; approximately one-third of original observations are preserved. The final sample includes information on workers who are active participants in the labour market. Most of the observations with no stable income source are excluded from the sample because they are not full-time workers.

As Figure 1 shows, the proportion of the workers who have full-time jobs but earn less than \$20,000 is not small. It represents about 15.9% of the workers in the sample. More than half of the workers earned between \$21,000 and \$60,000 in 2010, which represents the majority of the workers. However, the distribution of the earnings variable is severely right-skewed, implying that a relative small group of the workers earn extremely high wages.

Figure 1 shows that approximately 3.3% of workers earned more than $140,000 in 2010, excluding any investment income.

In the PUMF 2011, the industrial sectors and occupations where individuals work are recorded. There are 19 sectors and 10 occupational groups, ranging from agriculture, construction to finance and education. Table 1 provides the cross-tabulated means and medians across industrial sectors. It is noteworthy that in every industrial sector, the mean wage is greater than the median wage, indicating a right-skewed distribution. The same pattern can be found in Table 2 as well, which shows the means and medians cross-tabulated across occupations. In sectors such as mining, quarrying, and oil and gas extraction, the mean-median gap is very large, with the mean value exceeding the median value by 22.4%. These gaps indicate that the severely right-skewed distributions of wages present in the overall labour market also exist at the sectoral and occupational levels. The workers in mining, quarrying, and oil and gas extraction sectors earn the highest wages; their mean wage is almost three times higher than the mean wage earned by the workers in accommodation and food services sectors. The mean wages of workers in 11 sectors are less than the overall mean wage, and the remaining 8 sectors have higher mean wages. Among the 11 relatively low-earnings sectors, several, such as construction and retail trade, are regarded as labour-intensive sectors. Conventional knowledge-intensive sectors, such as information and cultural industries, tend to have higher mean wages, as expected. Similar conclusions apply at the occupational level.

The 2011 census reports 13 different levels of educational attainments of the workers.

For the convenience of the interpretation and presentation, I aggregate the educational attainments into six education levels. The first level (*NoEdu*) includes those with no certificate, diploma or degree; it is the lowest education level. The second level includes individuals who graduate from high school but never enter college. The workers with trades certificates or apprenticeship certificates are also included in this level. The third level (*college*) includes the workers who graduated from college rather than from university. The fourth level (*university*) is for university graduates without a master's degree or higher degree, where the workers with a degree in medicine, dentistry, veterinary medicine or optometry are also included. As the individuals with a bachelor's degree account for the majority at this level, it can be regarded equivalent to a bachelor level. The fifth level (*master*) is for those that have earned a master's degree, while the last level (*PhD*) is for PhDs.

Table 3 and Table 4 show the proportions of individuals with different education levels across the 19 industrial sectors and the 10 occupations, respectively. Approximately 91.4% of the workers have completed elementary education, 57.8% have completed some post-secondary education, and only 1.1% have obtained a PhD. High school graduates or the equivalent are the largest group, accounting for about one third of the sample, while PhDs account for the lowest share. In 13 of the 19 sectors, high school graduates have the largest proportion, while in the other five sectors those with the bachelor's degrees make up the largest group. Only in the sector of health care and social assistance do college graduates account for the largest proportion. At the occupation level, only in five of the 10 occupational classes do the high school graduates account for the largest proportion; the remaining five classes of occupations are dominated by those with a bachelor's degree.

The overall proportion of PhDs is 1.1%, and the proportion is higher than this in only three sectors, namely professional, scientific & technical services, educational services, and public administration. These three sectors also have the highest proportions of master's degree holders, especially in the sector of education services (16.0% and 6.2% for master's degrees and PhDs, respectively). Sectors such as construction and transporting & warehousing tend to employ less-educated workers, as more than 80% of their workers have not graduated from a university. In the sector of agriculture, forestry, fishing & hunting, out of a total of 3345 workers, only five have obtained a PhD degree, and 26 have obtained a master's degree. At the occupational level, in three classes of occupation, namely the natural & applied sciences & related occupations, the health occupations, and the occupations in social science, education, government service & religion, the proportion of PhDs exceeds the overall mean proportion. The proportion of more-educated workers tends to be low in some labour-intensive occupations. One example is the occupations unique to primary industry, where only three PhDs and 35 with a master's degree out of a total 4746 workers are employed.

As classic economic theories suggest, the labour market can reach its equilibrium by the interaction of demand and supply forces. Thus, the proportion of more-educated workers and less-educated workers in each industrial sector is also determined by the market. However, this does not mean that workers are suitably qualified for the positions that they hold. For example, if the five PhDs in the sector of agriculture, forestry, fishing & hunting were unable to earn higher wages than their coworkers in that sector, it appears that the marginal return of obtaining a PhD degree on wages is zero for this group.

Table 5 and Table 6 show the mean wages of the workers with different education levels cross-tabulated by sector and occupation, respectively. For example, in the sector of agriculture, forestry, fishing & hunting, the mean wage increases as the education level increases up to the master's level, yet for those who have earned doctorate degrees, the mean wage falls rapidly. The PhD workers’ mean wage is lower than those who merely attended high school. This seems implausible because workers with doctorate degrees must have earned bachelor’s degrees, so the lower bound of the mean wage should be at least close to the mean wage of the workers with a bachelor’s degree. With only five observations, I attribute this to a statistical anomaly. The same pattern is seen in the occupations unique to primary industry. In the sector of real estate & rental & leasing, the mean wage of PhD workers is just a little higher than the mean wage of workers with a bachelor’s degree, and it is far lower than the mean wage of workers with a master’s degree. A similar pattern arises in a number of other sectors, where it appears that the return to doctorate degrees is very low or even negative. However, whether higher education brings negative marginal returns requires deeper examination.

Another noteworthy feature is the increasing relationship between the standard deviation and the wage level, indicating that higher levels of education tend to be associated with a greater degree of earnings dispersion. In Table 5, most of the standard deviations grow as the mean wages increase, and sometimes they are very close to each other in value. For instance, in the sector of manufacturing, the growth rate of the standard deviation as the level of education rises is larger than the growth rate of mean wage. This pattern suggests that the returns to education tend to be more variable as the level of education increases. Nonetheless, in sectors such as retail trade, a maximum point appears at the master's level. It seems that in the sector of retail trade, a doctorate degree has the marginal effects of reducing the variance of the wage rather than increasing the level of the wage. A similar pattern appears in the sector of utilities, where the mean wage of PhD workers is slightly lower than the mean wage of the workers with a master's degree, but the standard deviation is half as much (shown in Figure 2). However, these conclusions do not apply at the occupational level, where mean wage increases with education level (Table 6), as previous studies predict.

The summary of the descriptive statistics shows that the returns to education can be low or even zero in certain sectors or occupations, at least over a certain range of educational attainment. However, this phenomenon is not apparent unless the analysis is done by disaggregating the data separately by sectors and occupations. An econometric model is needed to control for related factors for a deeper analysis.

4. Econometric Model

The econometric model employed in this paper is based on the well-known theory of human capital. The estimating equation is the Mincer equation:

$$lnW_{ij} \;=\; \beta_0 + \sum_{k=1}^{5} \beta_k edu_{ijk} + X_{ij}\gamma \;+\; \varepsilon_{ij},$$

where W_{ij} is the wage income of the individual in 2010, which is included in the 2011 census. edu_{ijk}s is specified by the five dummy variables representing the highest education levels attained by the individual. *NoEdu* represents those who have no certificates, *college* represents college or equivalent, followed by the variables *university*, *master* and *PhD*, which have been described in the data section. The omitted category is those with a high school diploma or equivalent. This category is frequently treated as the reference group in previous studies because it serves as a suitable benchmark for examining the returns to higher education. X_{ij} is a vector containing several control variables, ε_{ij} is the error term, which represents the influence of unknown factors, sampling errors, and purely random factors. The subscript i identifies different individuals, j identifies the 19 industrial sectors or the 10 occupations, and k is the index for the education dummy variables.

The control variables consist of three sets of variables. The first set of variables represents work experience. Since data on work experience and schooling years are not available in the census 2011, age is used as a proxy for work experience. According to the human capital model and the Mincer equation, the relationship between wages and experience is not linear, thus *age* and age^2 are both included in the vector X_{ij}. The second type of variable is the gender variable *sex*, which is a dummy variable equal to 1 if the individual is female and 0 if male. The third set of variables includes two dummy variables regarding language. The variable *Eng* is equal to 1 if the individual speaks English at home and 0 otherwise. The variable *Fre* is equal to 1 if the individual speaks French at home and 0 otherwise. Individuals whose home languages are neither of these two languages are treated as the reference group. The reason for choosing the home language rather than office language as the independent variables is that home language is more closely related to the first language of the individual.

The equation is estimated by the OLS method based on two sets of samples. The first set consists of data disaggregated by sector, the second set consists of data disaggregated by occupation. There are 19 sectors and 10 occupations each having their own estimating equation. In addition to these 29 equations, there is also an aggregated equation. Each group of regression results is displayed in each column of the tables.

5. Regression Results

The OLS regression results are displayed in Table 7 and Table 8. For convenience, each sector has been labeled from 1 to 19 in Table 7. The concordance between these numbers and the sectors is shown in the preceding tables. Each column in Table 7 shows one set of regression results for the corresponding industrial sector, and the last column contains the pooled regression results. Similarly, each occupation has been labeled from 1 to 10 in Table 8, and the regression results are displayed in each corresponding column.

The pooled regression result indicates that all included variables have statistically significant coefficients. It suggests that experienced workers and native speakers of both English and French earn wage premiums, while the overall gender wage premium in favour of men is 21.6%. The estimated coefficients of educational variables are -0.386, 0.243, 0.547, 0.776 and 0.635, respectively. All of them have the expected signs, indicating positive returns to education. It is noteworthy that the estimated coefficient of *PhD* is smaller than that of *master*, which represents a negative wage gap between the workers with a master's degree and those with doctorate degrees. This indicates that the marginal returns to education start to diminish here. However, the results are more complicated when sector and occupational levels are assessed separately.

5.1 Sector Level Regression Results

5.1.1. Control Variables

The regression results of each sector differ. In general, all of the estimated coefficients of *age* and age^2 have the expected signs, and most of them are significant. Three exceptions occur in the sectors of mining, quarrying & oil & gas extraction, real estate & rental & leasing, and administrative & support, waste management & remediation services. The relationship between work experience and wage is quadratic and concave (a 'inverted U' shape) rather than linear, as expected. The effect of work experience on earnings is positive when the value of work experience is located on the first, ascending half of the "inverted U" curve. Once the effect reaches its peak, it begins to decline as work experience grows, although the overall effect is still positive. However, if the value of work experience exceeds a certain threshold, the effect will become negative. In practice, work experience itself never has an overall negative effect, but the marginal returns to age may be negative. Although slightly different across sectors, the absolute values of the estimated coefficients of *age* are around 90 times the magnitude of those of age^2, indicating the threshold for an overall negative effect is about 90, and the peak is about 45 (Table 9), both exceeding all the values of age recorded in census. Therefore, the overall effect associated with work experience for a normal individual can never be negative.

The effects of gender and home language on earnings vary across sectors. In most sectors, the estimated coefficients of the two language variables are significant and have positive signs, as expected. The regression results support the conjecture that having neither English nor French as a home language will reduce one's wage. In the sectors of agriculture, forestry, fishing & hunting, utilities, and arts, entertainment & recreation, no evidence is found to support the notion that native English speakers or native French speakers have any wage advantages. Only in the other sectors is a positive effect found for either or both of them. This advantage is estimated to be extremely large in the sector of transportation & warehousing, where the values of both estimated coefficients exceed 1. In most of the 16 sectors where home language matters, English is the dominant language. Only in the sectors of construction, transportation & warehousing, real estate & rental & leasing, and administrative & support, waste management & remediation services, do French speakers have a slight advantage over English speakers.

Gender discrepancies are very common in most sectors. Women and men have similar wages in only four sectors, namely construction, transportation & warehousing, finance & insurance/management of companies & enterprises, and real estate & rental & leasing. In other sectors, men's wages are statistically higher than women's. The wage gaps vary from 10.2% to 42.7% across sectors. The largest wage gap occurs in the sector of other services except public administration, where women earn 42.7% less than men do. The sector of agriculture, forestry, fishing & hunting comes next with 34.8%, and the wage gap in the sector of educational services is relatively smaller at 10.2%.

5.1.2. Education Variables

The significance of the estimated coefficients of the five education variables and the magnitudes of their estimated coefficients vary across sectors. To ease interpretation of the results, I summarize them into six groups. The first group includes five sectors: manufacturing, wholesale trade, information & cultural industries, finance & insurance/management of companies & enterprises, and professional, scientific & technical services. All the estimated coefficients of the five education variables are statistically significant, and they have the expected signs for these five sectors, where holding no certificate or diploma has negative effects on wage, while holding a college education or above have positive effects. For example, for the sector of manufacturing, the estimated coefficients are -0.0284, 0.231, 0.599, 0.754 and 0.793. The value of the estimated coefficient increases as the education level gets higher, indicating that the marginal returns to education are persistently positive. For this group of sectors, the highest education level is the optimal education level as defined in my research paper.

The second group includes three sectors: educational services, other services (except public administration), and public administration. The regression results for the education variables for these three sectors are similar to the results for the pooled regression. The estimated coefficients of the education variables are significant, and they have the expected signs. The estimated coefficients of the pooled regression are -0.386, 0.243, 0.547, 0.776 and 0.635, which have been stated before. Though the returns to education remain positive, note that the magnitude of the coefficient for *PhD* is smaller than that of *master*, meaning the marginal return of the doctorate degree is negative. A similar pattern applies to all the sectors in this group, and is especially prominent for the sector of other services (except public administration), where the estimated coefficients of the variables *university*, *master* and *PhD* are 0.674, 0.992 and 0.645, respectively. The PhD-masters wage gap is slightly larger than the bachelor-master wage gap. Since the wage gap for workers with a master's degree compared to those with doctorate degrees is negative, earning a doctorate degree does not lead to higher wages. Therefore, in this group, the master's degree is the optimal education level.

The third group has five sectors: utilities, construction, retail trade, transportation & warehousing, and administrative & support, waste management & remediation services. The estimated coefficients of the education variables are all significant except for the variable *PhD*. This implies that the return to the doctorate degree is not statistically different from zero, and thus there is no statistical evidence of the existence of a wage gap between the workers with high school diplomas and those with doctorate degrees. All other estimated coefficients have the expected signs and magnitudes. For example, for the sector of construction, the estimated coefficients are -0.428, 0.144, 0.311 and 0.423, which are monotonic and increasing in education levels. The economic implication is that compared to the workers with high school diplomas, those with no diplomas or certificates earn a 34.8% lower wage, while those who have higher educational attainments earn 26.0%, 36.5% and 52.7% higher wages, respectively. It seems implausible that the workers with doctorate degrees do not benefit from high returns. One cause may be that there are very few PhD workers in these sectors. Considering they are working in the labour-intensive sectors, over-education may be another possible explanation.

The fourth group consists of only one sector: health care and social assistance. It is the only sector where a negative return to the doctorate degrees is statistically significant. The estimated coefficients are -0.390, 0.501, 0.642, 0.920 and -0.327, which are all statistically significant, yet the estimated coefficient for the variable *PhD* is very much unexpected. It suggests that the workers with doctorate degrees earn 27.9% less than those with high school diplomas or certificates. There are 294 workers with doctorate degrees working in this sector, thus I do not believe that small sample size causing a statistical anomaly is the cause. One reasonable explanation may be that medical doctors do not have doctorate degrees. However, this also implies that if one's major field is not related to health, the master's degree is the optimal education level in the sector of health care and social assistance, and that obtaining a PhD is penalized in this sector.

The fifth group is quite different from the previous groups; its returns to education are unstable and discontinuous. It includes four sectors: agriculture, forestry, fishing & hunting, mining, quarrying & oil & gas extraction, arts, entertainment & recreation, and accommodation & food services. Two of these sectors are natural resources industries, and the other two belong to the service industry. For the sector of agriculture, forestry, fishing & hunting, only the variable *master* is statistically significant. The value of its estimated coefficient 1.473 is extremely large, meaning workers with a master's degree earn 336.2% more than do those with high school diplomas or certificates. For the sector of mining, quarrying, and oil and gas extraction, the estimated coefficient of the variable *college* is not significant, but other variables and their estimated coefficients are in line with expectations. For the sector of arts, entertainment & recreation, the regression results are confusing. Only the returns to the college diplomas or certificates and the master's degrees are positive. For the sector of accommodation & food services, the estimated coefficients of the variables *NoEdu*, *college* and *university* are statistically significant, the values of which are -0.294, 0.295 and 0.291, respectively, suggesting that college education is optimal for these workers. Note that although the regression results in this group of sectors are diverse, no evidence can support the assertion that the returns to education are negative.

The only sector in the last group is real estate & rental & leasing. For this sector, negative returns to education are prevalent. The variables *NoEdu*, *college* and *university* are all statistically significant, yet none of their estimated coefficients have the predicted signs or magnitudes. The estimated coefficients are 0.630, -0.786 and -0.308, which are completely contrary to the theory of human capital. It suggests that the optimal education level is no formal education, because workers with no diploma or certificates earn on average 87.8% higher wages than those with high school diplomas or certificates, while workers with college diplomas or certificates or bachelor's degrees earn even less. One possible explanation is that in the sector of real estate & rental & leasing, sales and marketing skills are the most influential determinants of wages. A worker who has never advanced in formal education may be a master in communication and interpersonal skills.

Diminishing returns to education are found in some sectors, and some of these can be explained by the phenomenon of over-education and industrial sector characteristics.

Nonetheless, examination by pooling sectors with blue-collar and white-collar workers may lead to omitted variable bias stemming from aggregation and wage determination processes. Aggregation bias may be introduced when blue-collar and white-collar workers whose wages are very different are put into the same group for estimation. Since estimating by the sector cannot separate these workers, regression results by the occupation are necessary for a more accurate conclusion.

5.2 Occupational Level Regression Results

5.2.1 Control Variables

Regression results vary across occupations, as was the case for the results across sectors, and they are easier to interpret because the workers' skills are more homogenous with an occupation. For the ten occupations, the estimated coefficients of the variables of work experience are all significant, and they have the expected signs and exhibit the same quadratic form. As shown in Table 10, the concave relationship seen in the previous analysis (disaggregated by sector) is maintained, as are the thresholds and peaks at about 90 and 45, respectively. Therefore, the same interpretation applies to the results at the occupational level that were presented for the sector level (section 5.1.1).

The coefficients of the variables for the home language are significant, except in the occupation unique to primary industry, and they are all positive. For the occupations unique to primary industry, neither *English* nor *French* has a significant effect on workers' wages. In contrast, for the trades, transport & equipment operators & related occupations, the estimated coefficients of the home language indicators are 0.930 and 0.939 for English and French, respectively. The high values indicate that the native English and French speakers earn about 153.4% and 155.7% higher wages, respectively. In general, English is still the dominant language, with French speakers having a slight advantage only for occupations in art, culture, recreation & sport, and trades, transport & equipment operators & related occupations.

Gender discrepancies are also common in most occupations. Except for occupations in art, culture, recreation and sport, the gender effect is statistically significant in all occupations. The estimated coefficients for gender are negative for all occupations. This wage gap is the largest in the occupations unique to primary industry, where the estimated coefficient is -0.921. This suggests that women in these occupations earn 60.2% less than men do. In the business, finance and administrative occupations and health occupations, the gaps narrow to 7.92% and 8.50%. The regression results suggest that the gender wage gap tends to be wider among blue collar workers and narrower among white collar workers.

5.2.2 Education Variables

Regression results are divided into five groups according to the same scheme, which is based on the empirical patterns of the returns to education, arranging the groups from the most conventional to the least conventional.

The first group includes two classes of occupations: management occupations and natural & applied sciences & related occupations. For natural & applied sciences & related occupations, the estimated coefficients of the education variables are significant, and their values are -0.412, 0.183, 0.332, 0.423, and 0.443. As might be expected according to human capital theory, the signs are positive, and the magnitudes are increasing. The results for management occupations are similar: -0.535, 0.142, 0.522, 0.785 and 0.994. It seems that the wage becomes more sensitive to the education level in management occupation, because the marginal returns to higher education are larger and strictly increasing. The doctorate degree remains the optimal education level in this group.

The second group consists of the occupations in social science, education, government service & religion. The stable returns to education are confirmed for this group of occupations, but the marginal return to doctorate degree is negative. Workers with a master's degree earn a little more than those with the doctorate degrees, and thus the master's degree is optimal here.

The third group also contains only one class of occupation: business, finance & administrative occupations. The workers with a master's degree earn the highest wages, while the estimated coefficient of the variable *PhD* is not statistically significant.

The fourth group has two classes of occupations, namely the health occupations and occupations in art, culture, recreation & sport. For the latter, the estimated coefficients are -0.734, 0.273, 0.458, 0.695 and -1.037, revealing a strongly negative return to the doctorate degree. Although for the health occupations, the estimated coefficient of the variable *NoEdu* is not significant, the same pattern applies. However, the underlying causes discerned may differ. I suggest that over-education is one of the reasons for the negative return to doctorate degrees for the latter occupations, but that for health occupations, the negative return may due to that medical doctors are classified into the education level of *university* because they do not have doctorate degrees.

I put the remaining four classes of occupations in the last group. Only a portion of the education variables have statistically significant estimated coefficients, but none have unexpected signs. In the sales & service occupations, a bachelor's degree is sufficient for workers aiming to get high wages. In the trades, transport & equipment operators & related occupations and the occupations unique to processing, manufacturing & utilities, a college diploma or certificate is optimal. In the occupations unique to primary industry, no evidence of positive returns to education is found. Note that these four classes of occupation are intensive in physical skills, making it likely for the well-educated worker to be over-qualified.

Most of the results at the occupational level are similar to those at the sectoral level. Both sets of results generally indicate diminishing returns to education as well as cases of over-education in Canadian labour market.

5.3 Bias

Several factors which influence the level of wage are omitted due to the inaccessibility of data. Researchers suggest that the omitted factors such as ability are highly correlated with the level of education, and bias may arise in such cases. It is believed that there is a positive relationship between ability and education, thus the estimates of education variables are likely biased up. However, recent studies such as Lemieux (2014) suggest that the ability bias in OLS regression is either small or being offset by other omitted factors. On balance, I do not think that it will violate my results about over-education.

A real drawback is the measurement error. In 2011 census data, variables like age are not recorded precisely. Yet at this aspect, other datasets do no better than census, the choices are quite limited. Fortunately, though not precise, the group values of ages are highly related with real ages, and the number of age groups are enough.

6. Conclusion

I estimate the returns to education across sectors and occupations to obtain a full picture of the phenomenon of diminishing returns to education. Inspired by the concept of over-education, I estimate the optimal education levels where the marginal returns to education are equal to zero by sector and by occupation at a high level of aggregation. Several findings were unexpected.

The first unexpected finding is about the returns to education at the sector level. In most sectors, the estimated returns to PhD degrees are quite low, and the marginal returns to PhD degrees are negative in some cases. Workers with a master’s degree tend to have higher wage earnings. The returns to education depend heavily on the industrial sector. For the sector of real estate & rental & leasing, education-related returns are abnormal, as all of the empirical results are contrary to the theory of human capital, while those results are more sensible for the sectors such as information and cultural industries.

At the occupational level, it is difficult to know to what extent blue collar workers are separated from white collar workers, but the pattern of results is similar to those obtained at the sector level. Over-education and mismatching may be the main causes, yet more empirical evidence based on more complete regression models is required to fully assess this.

Pooling all the groups together, the result of the regression indicates that the overall returns to education are stable and significantly positive. It indicates that the overall positive returns to education are not eliminated. However, the overall marginal return to the PhD degree remains unexpectedly low. Perhaps PhDs have unobservable characteristics that reduce their wages. The more plausible reason I believe is that the skills and knowledge obtained by PhDs are not rewarded in their jobs. This is a probable result of over-education.

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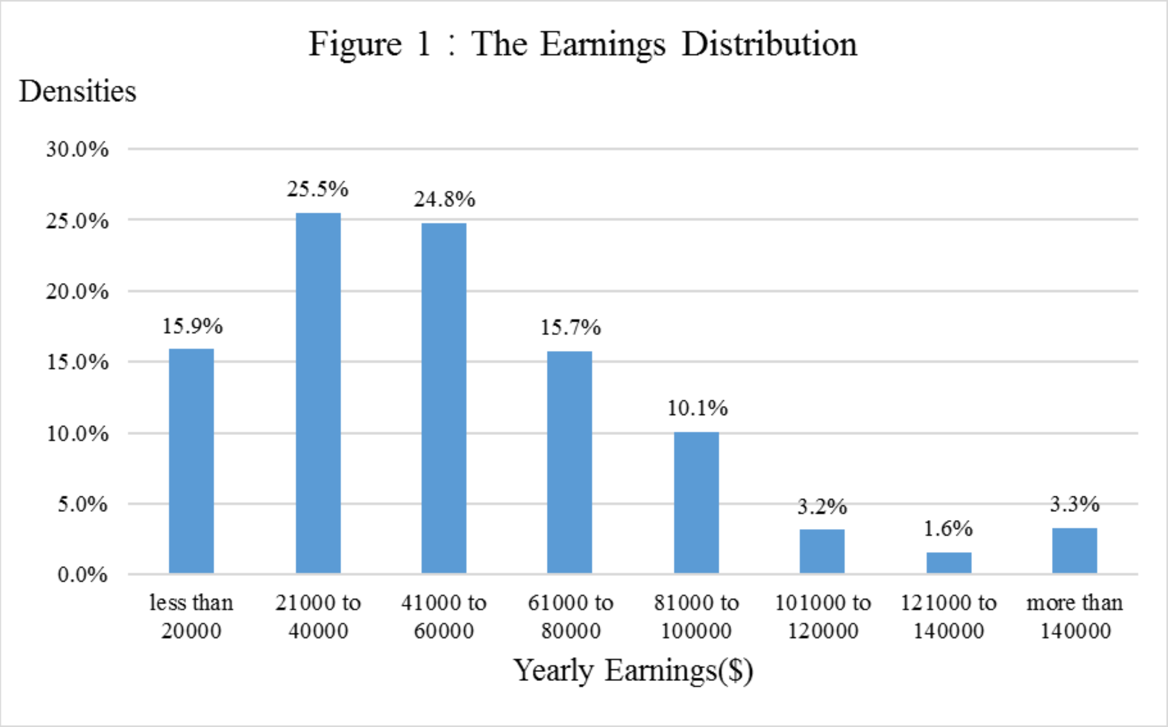
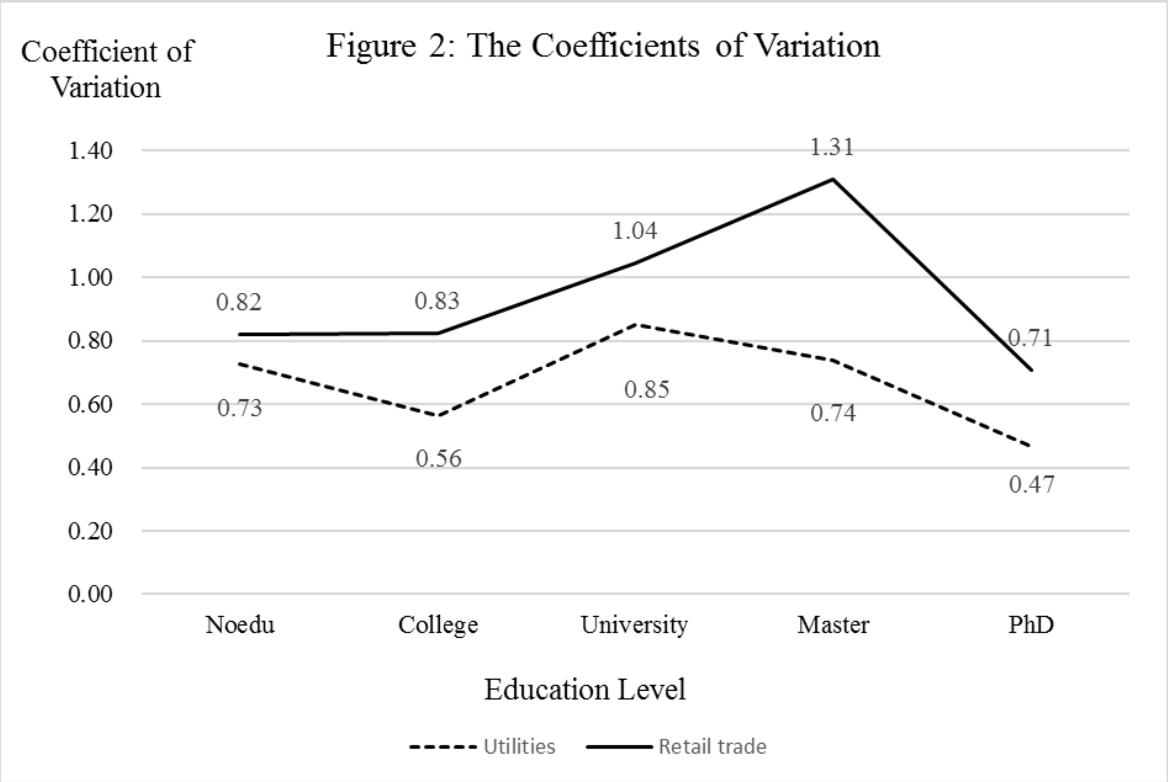


Source: Census 2011, Statistic Canada



Source: Census 2011, Statistic Canada

Table 1: Means and Medians Cross-Tabulated Across Industrial Sectors

	Number of observations	Mean wage ($)	Median wage ($)
(1) Agriculture, forestry, fishing & hunting	3345	35869	30000
(2) Mining, quarrying, & oil & gas extraction	4834	105222	86000
(3) Utilities	3266	87050	79000
(4) Construction	16211	52797	46000
(5) Manufacturing	32924	54567	46000
(6) Wholesale trade	14564	62255	48000
(7) Retail trade	24017	41046	34000
(8) Transportation & warehousing	14657	50661	47000
(9) Information & cultural industries	7527	66659	56000
(10) Finance & insurance/ Management of companies & enterprises	15988	72282	51000
(11) Real estate & rental & leasing	4750	47671	39000
(12) Professional, scientific & technical services	19409	67461	54000
(13) Administrative & support, waste management & remediation services	9014	37377	31000
(14) Educational services	24144	59600	56000
(15) Health care & social assistance	30949	48866	42000
(16) Arts, entertainment & recreation	3389	40872	36000
(17) Accommodation & food services	10495	28706	24000
(18) Other services (except public administration)	10850	42644	37000

Table 1: Means and Medians Cross-Tabulated Across Industrial Sectors (continued)

(19) Public administration	26875	65465	61000
Total	277208	55175	46000

Table 2: Means and Medians Cross-Tabulated Across Occupations

	Number of observations	Mean wage ($)	Median wage ($)
(1) Management occupations	33520	86431	68000
(2) Business, finance & administrative occupations	56816	49305	43000
(3) Natural & applied sciences & related occupations	26130	71536	65000
(4) Health occupations	17593	56883	50000
(5) Occupations in social science, education, government service & religion	29634	60539	57000
(6) Occupations in art, culture, recreation & sport	5871	49160	45000
(7) Sales & service occupations	46994	38904	31000
(8) Trades, transport & equipment operators & related occupations	41206	49363	46000
(9) Occupations unique to primary industry	4746	44872	33000
(10) Occupations unique to processing, manufacturing & utilities	14698	42784	38000
Total	277208	55175	46000

Table 3: Educational Attainment Shares Cross-Tabulated Across Industrial Sectors (%)

	NoEdu	HS	College	Bachelor	Master	PhD	Total
(1) Agriculture, forestry, fishing & hunting	27.0%	44.3%	17.1%	10.8%	0.7%	0.1%	100.0%
(2) Mining, quarrying, & oil & gas extraction	10.7%	42.7%	21.6%	20.1%	4.1%	0.7%	100.0%
(3) Utilities	2.8%	33.2%	30.6%	26.8%	6.2%	0.5%	100.0%
(4) Construction	14.8%	55.4%	19.2%	9.5%	1.1%	0.0%	100.0%
(5) Manufacturing	15.2%	43.3%	20.0%	17.7%	3.3%	0.4%	100.0%
(6) Wholesale trade	10.3%	39.6%	21.6%	24.2%	3.9%	0.4%	100.0%
(7) Retail trade	12.6%	48.1%	20.3%	16.9%	1.9%	0.2%	100.0%
(8) Transportation & warehousing	14.4%	48.6%	20.8%	14.3%	1.8%	0.1%	100.0%
(9) Information & cultural industries	2.5%	24.6%	27.8%	36.8%	7.8%	0.5%	100.0%
(10) Finance & insurance/ Management of companies & enterprises	2.1%	25.4%	24.6%	39.5%	7.9%	0.3%	100.0%
(11) Real estate & rental & leasing	8.8%	34.6%	26.5%	26.5%	3.3%	0.2%	100.0%
(12) Professional, scientific & technical services	1.8%	15.7%	24.3%	44.4%	12.1%	1.7%	100.0%
(13) Administrative & support, waste management & remediation services	13.6%	39.7%	22.7%	20.4%	3.5%	0.2%	100.0%
(14) Educational services	1.9%	11.4%	13.3%	51.2%	16.0%	6.2%	100.0%

Table 3: Educational Attainment Shares Cross-Tabulated Across Industrial Sectors (%) (continued)

(15) Health care & social assistance	3.9%	21.6%	34.8%	32.8%	5.9%	0.9%	100.0%
(16) Arts, entertainment & recreation	8.9%	35.8%	24.3%	26.9%	4.0%	0.2%	100.0%
(17) Accommodation & food services	18.2%	45.1%	18.8%	15.9%	1.8%	0.1%	100.0%
(18) Other services (except public administration)	8.6%	40.2%	21.9%	22.5%	6.2%	0.5%	100.0%
(19) Public administration	3.3%	26.0%	27.1%	34.0%	8.6%	1.1%	100.0%
Total	8.6%	33.6%	23.1%	27.7%	6.0%	1.1%	100.0%

Notes: the numbers in brackets are standard deviations.

Table 4: Educational Attainment Shares Cross-Tabulated Across Occupations (%)

	Noedu	HS	College	University	Master	PhD	Total
(1) Management occupations	4.7%	27.1%	21.3%	35.8%	10.2%	0.9%	100.0%
(2) Business, finance & administrative occupations	5.0%	35.0%	27.8%	27.9%	4.2%	0.2%	100.0%
(3) Natural & applied sciences & related occupations	1.5%	14.0%	28.2%	42.7%	11.6%	2.1%	100.0%
(4) Health occupations	2.0%	16.2%	35.9%	39.3%	5.3%	1.2%	100.0%
(5) Occupations in social science, education, government service & religion	1.1%	7.2%	14.7%	54.2%	17.0%	5.7%	100.0%
(6) Occupations in art, culture, recreation & sport	2.2%	16.9%	27.7%	41.9%	10.6%	0.6%	100.0%
(7) Sales & service occupations	13.7%	43.8%	23.4%	17.4%	1.7%	0.1%	100.0%
(8) Trades, transport & equipment operators & related occupations	16.8%	59.1%	17.9%	5.6%	0.6%	0.1%	100.0%
(9) Occupations unique to primary industry	25.5%	49.7%	16.3%	7.8%	0.7%	0.1%	100.0%
(10) Occupations unique to processing, manufacturing & utilities	24.2%	50.2%	14.7%	9.6%	1.2%	0.1%	100.0%
Total	8.6%	33.6%	23.1%	27.7%	6.0%	1.1%	100.0%

Table 5: Mean Wages by Education Level Cross-Tabulated with Industrial Sector ($)

	NoEdu	HS	College	Bachelor	Master	PhD
(1) Agriculture, forestry, fishing & hunting	29920 (30774)	34498 (30983)	40116 (43365)	48838 (52883)	72836 (64882)	32200 (45735)
(2) Mining, quarrying, & oil & gas extraction	71434 (53986)	90771 (67832)	98710 (75655)	142921 (144916)	193568 (217223)	271205 (305191)
(3) Utilities	56638 (40376)	75688 (45958)	82544 (46631)	103571 (87917)	117241 (86710)	99815 (46443)
(4) Construction	41581 (32541)	51012 (41810)	57205 (54076)	68702 (80328)	91421 (102773)	57970 (26182)
(5) Manufacturing	37467 (24332)	49019 (34837)	57511 (44109)	73244 (69408)	92325 (92614)	107531 (112884)
(6) Wholesale trade	41524 (31190)	52198 (43489)	60843 (61410)	83197 (92949)	101654 (116452)	109737 (95154)
(7) Retail trade	32153 (26327)	38367 (31449)	40958 (33799)	53922 (56296)	61989 (81046)	54641 (38697)
(8) Transportation & warehousing	41918 (30431)	47713 (34239)	54332 (44331)	60717 (62503)	81633 (90582)	154803 (244275)
(9) Information & cultural industries	51316 (54387)	54955 (44177)	59532 (47115)	75784 (81793)	90109 (97729)	118721 (163026)
(10) Finance & insurance/ Management of companies & enterprises	46837 (39098)	52999 (55594)	54961 (46782)	85717 (105236)	132322 (165392)	130915 (151722)
(11) Real estate & rental & leasing	38830 (31455)	42615 (42662)	43438 (47586)	57790 (74749)	82785 (134067)	62427 (80970)
(12) Professional, scientific & technical services	43311 (37486)	51273 (45477)	55014 (42096)	73405 (70203)	92262 (108923)	103475 (121874)
(13) Administrative & support, waste management & remediation services	28759 (30681)	33641 (26693)	38128 (31688)	46459 (51443)	57094 (71810)	87249 (152498)

Table 5: Mean Wages by Education Level Cross-Tabulated with Industrial Sector ($) (continued)

(14) Educational services	32754 (18964)	40553 (25785)	41984 (22928)	61705 (32613)	70854 (43704)	99157 (76430)
(15) Health care & social assistance	29113 (18906)	34537 (20523)	45848 (26278)	59767 (52949)	72401 (67239)	77724 (85798)
(16) Arts, entertainment & recreation	29187 (20793)	36607 (33041)	43552 (35699)	47070 (47357)	50732 (33572)	36857 (35149)
(17) Accommodation & food services	22373 (155146)	27000 (21916)	32939 (29975)	35045 (39523)	38988 (45945)	39056 (43737)
(18) Other services (except public administration)	32086 (23816)	38587 (29512)	41054 (29143)	49799 (53327)	63254 (49575)	87575 (104903)
(19) Public administration	45946 (24014)	56391 (29522)	61436 (31588)	72786 (44206)	82905 (45964)	92707 (61461)
Total	36520 (29367)	46113 (37990)	52045 (41446)	67935 (67308)	84576 (90896)	98690 (97595)

Notes: the numbers in brackets are standard deviations.

Table 6: Mean Wages by Education Level Cross-Tabulated with Occupation ($)

	Noedu	HS	College	University	Master	PhD
(1) Management occupations	54617 (51669)	66756 (64544)	74061 (69986)	100856 (102128)	129409 (130308)	149881 (139455)
(2) Business, finance & administrative occupations	38480 (25753)	42382 (31278)	44756 (31039)	60151 (63809)	81567 (106499)	82952 (133329)
(3) Natural & applied sciences & related occupations	50862 (34930)	60403 (39697)	65021 (40778)	76567 (63966)	81256 (63315)	99443 (111367)
(4) Health occupations	32791 (18438)	36316 (20659)	51866 (28167)	68811 (62510)	76458 (75727)	79803 (108407)
(5) Occupations in social science, education, government service & religion	31567 (25916)	41577 (39493)	41762 (25939)	62311 (43246)	70538 (62106)	96116 (76430)
(6) Occupations in art, culture, recreation & sport	35193 (27736)	43062 (35951)	45102 (29554)	52448 (47928)	60066 (43843)	67261 (122870)
(7) Sales & service occupations	27877 (23235)	35629 (29524)	43643 (38620)	48803 (53546)	52073 (71877)	63165 (80182)
(8) Trades, transport & equipment operators & related occupations	40258 (27034)	50320 (33174)	55037 (37480)	49056 (37156)	50936 (45221)	74274 (67680)
(9) Occupations unique to primary industry	36947 (39979)	47489 (50053)	49078 (50175)	43688 (45496)	65074 (67610)	30667 (52252)
(10) Occupations unique to processing, manufacturing & utilities	34344 (22117)	44044 (31347)	50185 (33569)	45788 (36447)	47977 (48014)	47339 (36081)
Total	36520 (29367)	46113 (37990)	52045 (41446)	67935 (67308)	84576 (90896)	98690 (97595)

Table 7: OLS Regression Results of the Wage Equation Across Industrial Sectors

	Part 1: First five sectors				
	(1)	(2)	(3)	(4)	(5)
NoEdu	-0.0144 (0.148)	-0.540*** (0.113)	-0.771*** (0.235)	-0.428*** (0.661)	-0.0284*** (0.0379)
college	0.0540 (0.173)	0.142 (0.0892)	0.231** (0.102)	0.144** (0.0607)	0.231*** (0.0344)
university	0.254 (0.209)	0.584*** (0.0950)	0.493*** (0.106)	0.311*** (0.0822)	0.559*** (0.0368)
master	1.473** (0.729)	0.617*** (0.186)	0.798*** (0.186)	0.423** (0.222)	0.754*** (0.0746)
PhD	-1.230 (1.696)	1.117*** (0.429)	0.860 (0.610)	0.990 (1.285)	0.793*** (0.215)
age	0.227*** (0.0431)	0.0433 (0.0269)	0.108*** (0.0337)	0.0646*** (0.0168)	0.0859*** (0.0103)
age2	-0.00289*** (0.000478)	-0.000470 (0.000309)	-0.00123*** (0.00382)	-0.000745*** (0.000193)	-0.000889*** (0.000115)
sex	-0.459*** (0.140)	-0.327*** (0.0903)	-0.179* (0.0928)	-0.0749 (0.0715)	-0.368*** (0.0292)
Eng	0.0464 (0.237)	0.545*** (0.180)	0.148 (0.214)	0.847*** (0.0861)	0.433*** (0.0377)
Fre	0.224 (0.250)	0.318 (0.206)	0.0384 (0.223)	0.883*** (0.0950)	0.395*** (0.226)
Constant	4.967*** (0.962)	9.379*** (0.594)	8.233*** (0.741)	7.836*** (0.360)	7.88*** (0.226)
Number of observations	3345	4834	3266	16211	32924
R squared	0.0263	0.0214	0.0197	0.012	0.0251
F-Statistic	9.02	10.56	6.55	19.72	84.79

Table 7: OLS Regression Results of the Wage Equation Across Industrial Sectors (continued)

	Part 2: Second five sectors				
	(6)	(7)	(8)	(9)	(10)
NoEdu	-0.263*** (0.0660)	-0.348*** (0.0467)	-0.415*** (0.0717)	-0.326** (0.165)	-0.390*** (0.132)
college	0.231*** (0.0510)	0.0285 (0.0397)	0.163*** (0.0637)	0.205*** (0.0702)	0.0587 (0.0536)
university	0.520*** (0.0502)	0.272*** (0.0435)	0.319*** (0.0747)	0.374*** (0.0672)	0.403*** (0.0506)
master	0.770*** (0.105)	0.382*** (0.114)	0.756*** (0.193)	0.543*** (0.106)	0.724*** (0.351)
PhD	1.123*** (0.305)	0.242 (0.368)	0.554 (0.732)	0.871** (0.370)	0.785** (0.351)
age	0.0713*** (0.0148)	0.0952*** (0.0110)	0.107*** (0.0190)	0.184*** (0.0211)	0.158*** (0.0151)
age2	-0.000759*** (0.000166)	-0.00104*** (0.000124)	-0.00126*** (0.000210)	-0.00199*** (0.000245)	-0.00178*** (0.000172)
sex	-0.242*** (0.0413)	-0.266*** (0.0299)	-0.0143 (0.0574)	-0.175*** (0.0517)	-0.0581 (0.0410)
Eng	0.524*** (0.0619)	0.623*** (0.0526)	1.374*** (0.0810)	0.610*** (0.0919)	0.467*** (0.0635)
Fre	0.361*** (0.0721)	0.405*** (0.0582)	1.366*** (0.0924)	0.463*** (0.102)	0.384*** (0.0732)
Constant	8.216*** (0.326)	7.490*** (0.240)	6.473*** (0.420)	5.797*** (0.445)	6.493*** (0.324)
Number of observations	14564	24017	14657	7527	15988
R squared	0.021	0.0172	0.0273	0.0262	0.0193
F-Statistic	31.21	42.12	41.04	20.26	31.47

Table 7: OLS Regression Results of the Wage Equation Across Industrial Sectors (continued)

	Part 3: Third five sectors				
	(11)	(12)	(13)	(14)	(15)
NoEdu	0.630*** (0.212)	-0.645*** (0.140)	-0.293*** (0.0913)	-0.769*** (0.0965)	-0.390*** (0.0760)
college	-0.786*** (0.150)	0.119** (0.0582)	0.279*** (0.0776)	0.252*** (0.0515)	0.501*** (0.0390)
university	-0.308** (0.154)	0.277*** (0.0539)	0.502*** (0.0818)	0.775*** (0.0422)	0.642*** (0.0402)
master	-0.551 (0.341)	0.423*** (0.0706)	0.573*** (0.168)	0.794*** (0.0496)	0.920*** (0.0676)
PhD	0.179 (1.308)	0.489*** (0.150)	-0.733 (0.621)	0.732*** (0.0650)	-0.327** (0.152)
age	0.00464 (0.0411)	0.127*** (0.0137)	0.00604 (0.0211)	0.148*** (0.0102)	0.0849*** (0.0111)
age2	-0.000483 (0.000448)	-0.001415*** (0.000158)	-0.0000733 (0.000238)	-0.00145*** (0.000115)	-0.000852*** (0.000125)
sex	0.0699 (0.118)	-0.220*** (0.0369)	-0.209*** (0.0598)	-0.108*** (0.0277)	-0.286*** (0.0377)
Eng	0.521*** (0.188)	0.425*** (0.0564)	0.347*** (0.0867)	0.668*** (0.0561)	0.493*** (0.0532)
Fre	0.585** (0.231)	0.371*** (0.0659)	0.556*** (0.102)	0.613*** (0.0601)	0.238*** (0.0577)
Constant	9.477*** (0.926)	7.178*** (0.296)	9.068*** (0.454)	5.836*** (0.229)	7.502*** (0.246)
Number of observations	4750	19409	9014	24144	30949
R squared	0.0228	0.0134	0.0126	0.0448	0.0238
F-Statistic	11.07	26.29	11.47	113.3	75.43

Table 7: OLS Regression Results of the Wage Equation Across Industrial Sectors (continued)

	Part 4: Last four sectors and pooled result				
	(16)	(17)	(18)	(19)	Pooled (entire sample)
NoEdu	-0.232 (0.164)	-0.294*** (0.0649)	-0.355*** (0.0965)	-0.311*** (0.0645)	-0.386*** (0.0178)
college	0.329*** (0.118)	0.295*** (0.0643)	0.322*** (0.0689)	0.166*** (0.0309)	0.243*** (0.0128)
university	0.0521 (0.117)	0.219*** (0.0698)	0.674*** (0.0696)	0.403*** (0.0298)	0.547*** (0.0123)
master	0.535** (0.245)	0.197 (0.186)	0.992*** (0.116)	0.587*** (0.0450)	0.776*** (0.0214)
PhD	-0.726 (1.056)	0.422 (0.680)	0.645* (0.363)	0.488*** (0.111)	0.635*** (0.0480)
age	0.136*** (0.0324)	0.0726*** (0.0175)	0.0741*** (0.0188)	0.0842*** (0.00921)	0.111*** (0.00361)
age2	-0.00147*** (0.000366)	-0.000791*** (0.000203)	-0.000734*** (0.000211)	-0.000921*** (0.000104)	-0.00121*** (0.000409)
sex	-0.204** (0.0906)	-0.198*** (0.0473)	-0.557*** (0.0526)	-0.265*** (0.0227)	-0.243*** (0.0957)
Eng	0.101 (0.184)	0.243*** (0.0597)	0.692*** (0.0826)	0.389*** (0.0552)	0.620*** (0.0161)
Fre	-0.0817 (0.198)	0.231*** (0.0749)	0.682*** (0.0946)	0.321*** (0.0577)	0,545*** (0.0180)
Constant	6.789*** (0.717)	7.862*** (0.368)	7.445*** (0.409)	8.402*** (0.205)	7.0859*** (0.0787)
Number of observations	3389	10495	10850	26875	277208
R squared	0.0133	0.0115	0.0327	0.0209	0.0239
F-Statistic	4.55	12.23	36.61	57.35	678.39

Notes: * indicates significance level of 0.10, ** for 0.05, and *** for 0.01. The values in brackets are the standard errors of the corresponding estimated coefficients.

Table 8: OLS Regression Results of the Wage Equation Across Occupations

	Part 1: First five occupations				
	(1)	(2)	(3)	(4)	(5)
NoEdu	-0.535*** (0.0631)	-0.260*** (0.0451)	-0.412*** (0.110)	-0.146 (0.128)	-0.808*** (0.133)
college	0.142*** (0.0373)	0.138*** (0.0244)	0.183*** (0.0428)	0.374*** (0.0538)	0.660*** (0.0586)
university	0.522*** (0.0331)	0.377*** (0.0251)	0.332*** (0.0409)	0.447*** (0.0540)	1.239*** (0.0512)
master	0.785*** (0.0484)	0.504*** (0.0513)	0.423*** (0.0535)	0.521*** (0.0916)	1.314*** (0.0576)
PhD	0.994*** (0.149)	0.125 (0.236)	0.443*** (0.0997)	-1.211*** (0.178)	1.244*** (0.0743)
age	0.154*** (0.0106)	0.0907*** (0.00741)	0.117*** (0.0107)	0.0841*** (0.0139)	0.124*** (0.0100)
age2	-0.00162*** (0.0001181)	-0.000978*** (0.0000836)	-0.00123*** (0.000123)	-0.000875* (0.000159)	-0.00123*** (0.000114)
sex	-0.219*** (0.0267)	-0.0825*** (0.0213)	-0.108*** (0.0323)	-0.0888*** (0.0476)	-0.215*** (0.0289)
Eng	0.750*** (0.0534)	0.430*** (0.0355)	0.282*** (0.0394)	0.466*** (0.0642)	0.737*** (0.0547)
Fre	0.665*** (0.0589)	0.381*** (0.0388)	0.240*** (0.0460)	0.221*** (0.0711)	0.508*** (0.0586)
Constant	6.274*** (0.236)	7.704*** (0.162)	7.552*** (0.230)	7.76*** (0.307)	5.927*** (0.224)
Number of observations	33520	56816	26130	17593	29634
R squared	0.0326	0.0107	0.0124	0.0173	0.0519
F-Statistic	112.8	61.15	32.9	31	162.25

Table 8: OLS Regression Results of the Wage Equation Across Occupations (continued)

	Part 2: Second five occupations				
	(6)	(7)	(8)	(9)	(10)
NoEdu	-0.734*** (0.245)	-0.276*** (0.0381)	-0.371*** (0.0371)	-0.143 (0.119)	-0.224*** (0.0492)
college	0.273*** (0.106)	0.143*** (0.0318)	0.0810** (0.0367)	0.186 (0.137)	0.221*** (0.0585)
university	0.458*** (0.101)	0.174*** (0.0358)	-0.0619 (0.0626)	-0.0647 (0.188)	0.148** (0.0719)
master	0.695*** (0.139)	0.115 (0.100)	0.0764 (0.187)	-0.105 (0.588)	0.151 (0.182)
PhD	-1.037** (0.466)	0.105 (0.406)	1.167* (0.616)	-2.982 (2.092)	-0.543 (0.512)
age	0.105*** (0.0269)	0.0979*** (0.00910)	0.0656*** (0.0101)	0.122*** (0.0339)	0.0711*** (0.0164)
age2	-0.00112*** (0.000312)	-0.00115*** (0.000103)	-0.000762*** (0.000114)	-0.00172*** (0.000381)	-0.000756*** (0.000184)
sex	-0.0929 (0.0709)	-0.443*** (0.0248)	-0.313*** (0.0625)	-0.921*** (0.132)	-0.448*** (0.0443)
Eng	0.861*** (0.148)	0.530*** (0.0377)	0.930*** (0.0492)	0.202 (0.204)	0.321*** (0.0529)
Fre	0.863*** (0.158)	0.497*** (0.0436)	0.939*** (0.0541)	0.0169 (0.220)	0.233*** (0.0598)
Constant	6.602*** (0.574)	7.465*** (0.197)	7.865*** (0.220)	7.514*** (0.748)	8.288*** (0.357)
Number of observations	5871	46994	41206	4746	14698
R squared	0.0189	0.0173	0.0146	0.0295	0.0174
F-Statistic	5871	82.75	61.21	14.4	25.93

Notes: * indicates significance level of 0.10, ** for 0.05, and *** for 0.01. The values in brackets are the standard errors of the corresponding estimated coefficients.

Table 9: Estimated Thresholds and Peaks for Earnings with Respect to Age Across Industrial Sectors

Sector	Estimated coefficient of age	Estimated coefficient of age2	Estimated threshold	Estimated peak
(1)	0.227	-0.00289	78.5	39.3
(2)	0.0433	-0.00047	92.1	46.1
(3)	0.108	-0.00123	87.8	43.9
(4)	0.0646	-0.00075	86.7	43.4
(5)	0.0859	-0.00089	96.6	48.3
(6)	0.0713	-0.00076	93.9	47.0
(7)	0.0952	-0.00104	91.5	45.8
(8)	0.107	-0.00126	84.9	42.5
(9)	0.184	-0.00199	92.5	46.2
(10)	0.158	-0.00178	88.8	44.4
(11)	0.00464	-0.00048	9.6	4.8
(12)	0.127	-0.00142	89.8	44.9
(13)	0.00604	-0.0000733	82.4	41.2
(14)	0.148	-0.00145	102.1	51.0
(15)	0.0849	-0.00085	99.6	49.8
(16)	0.136	-0.00147	92.5	46.3
(17)	0.0726	-0.00079	91.8	45.9
(18)	0.0741	-0.00073	101.0	50.5
(19)	0.0842	-0.00092	91.4	45.7
Estimated mean			87.0	43.5
Adjusted estimated mean			91.8	45.9

Notes: Adjusted estimated mean is the mean value of the 16 estimated thresholds, where the remaining 3 estimated thresholds of sector (2), (11) and (13) are omitted due to insignificance.

Table 10: Estimated Thresholds and Peaks for Earnings with Respect to Age Across Occupations

Sector	Estimated coefficient of age	Estimated coefficient of age2	Estimated threshold	Estimated peak
(1)	0.154	-0.00162	95.1	47.5
(2)	0.0907	-0.000978	92.7	46.4
(3)	0.117	-0.00123	95.1	47.6
(4)	0.0841	-0.000875	96.1	48.1
(5)	0.124	-0.00123	100.8	50.4
(6)	0.105	-0.00112	93.8	46.9
(7)	0.0979	-0.00115	85.1	42.6
(8)	0.0656	-0.000762	86.1	43.0
(9)	0.122	-0.00172	70.9	35.5
(10)	0.0711	-0.000756	94.0	47.0
	Estimated mean		91.0	45.5