Returns to Skills in Canadian Provinces and U.S. States

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Major paper presented to the Department of Economics of the University of Ottawa

In partial fulfillment of the requirements of the M.A. Degree

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December 2014

Abstract

This paper examines the expected mean wages and the parameters of returns to skills in 10 Canadian provinces and 48 American states. I replicate the Hunt and Mueller (2002) paper using updated data sets: the 2006 American Community Survey and the 2006 Canadian Census of Population. Like Hunt and Mueller, I find that the average values of the standardized mean weekly wages and of the standardized index of returns to skills in the U.S. are higher than those in Canada for males and females. The Canadian provinces with the top three rankings in the mean weekly wages remain the same, and the gender gap in mean weekly wage persists. By contrast, the average values of the mean weekly wages in the U.S. are higher than in Canada for males, while the values are similar for females in the two countries. If one focuses on the average value of returns to skills index, it is higher for females than it is for males.

1. Introduction

The relationship between wage disparities and skill differences across regions has long been recognized as an important issue in many industrially developed and developing countries. Idu (2012), for example, examines the skill selection and educational attainment of migrants over the course of economic development and shows that both follow an inverted-U path. Specifically, the returns to human capital and skills are relatively high in the destination county at the beginning of the development phase, which attracts a relatively higher share of high-skill migrants. As the origin country develops and catches-up to the destination country, the relative returns to human capital and skills bengin to decline, thus the relative share of high-skill migrants decreases in the latter part of the development phase. Ingram and Neumann (2006) study the returns to various categories of skill in the U.S. labour market, such as years of education, mathematical ability and other physical measurements of skill, and show that such skill factors play an important role in an increasing variation in the wage rates. Using 1990 American and Canadian Census data, Hunt and Mueller (2002) find important disparities in returns to skills in 10 Canadian provinces and 48 states in the U.S., even after controlling for interregional skill differences.

The world economy has experienced two recessions since the early 1990s. Recent years have witnessed important political, economic and social development in the U.S. and Canada. As such, I believe that it is important to update the evidence of wage and skill disparities. I therefore replicate the Hunt and Mueller (2002) methodology, but using more recent (i.e., 2006) data. More precisely, I estimate the wage returns to skills in 10 Canadian provinces and 48 American states by using the Hunt and Mueller methodology that control for the interregional effects. I also compute the regional mean wages as well as the index of returns to skills.

As with Hunt and Mueller (2002), I find that the average values of the standardized mean weekly wages and standardized index of returns to skills in the U.S. are higher than in Canada for males and females. The Canadian provinces with the top three rankings in the mean weekly wages remain the same, and the gender gap in mean weekly wage persists. By contract, the average values of the mean weekly wage in the U.S. are higher than Canada for males, while the values are similar for females in the two countries. If one focuses on the average value of returns to skills index, it is higher for females than for males.

This paper is organized as follows. Section 2 provides an overview of the literature on returns to skills in Canada, the U.S. and at interregional levels. Section 3 presents the datasets used in this study, discusses the sample restrictions and provides the summary statistics of all variables. Section 4 introduces the theoretical and empirical models of individuals' wages with skill compositions. Section 5 provides the estimation results and section 6 summarizes the conclusions.

2. Previous Literature

A growing body of research has demonstrated that the skill-biased technological change contributed to the income disparities across countries. The causes and implications of the skills differences account for income disparities have attracted the attention of economists. This paper touches many aspects of the literature regarding human capital, migration, skill supply and mismatch and discriminatory wages, which in light of the relationship between skills and income. The neoclassical theory of human capital explains that the differences in pay to individuals attributes to human capital, which is the stock of skills that an individual has (e.g., Becker, 1965; Mincer, 1974). They focus on the role of education, and how it affects a worker's productivity, and thus the wage rate. Schooling and job training are expected to have a positive impact on the wage rate, reflecting time spent on attaining education and job skills. Mincer (1974) indicates that the future income gains must be sufficient enough to compensate for the postponed earnings required in order to spend time on education and training. Such job training can be taken as investment in work experience which improves productivity. Becker and Tomes (1979) argue that the human capital endowment of a worker, referring to individual characteristics, such as socialization type, gender and race, could improve individual productivity.

Economists have argued that the education and experience of individuals are acquired in the latter stage of life, but human capital development starts from one's earlier stage of life and is influenced by social origin and family background (e.g., Becker and Tomes, 1979 and Solon, 1999). Becker and

Tomes (1979) point out that education and work experience help with the job skills attained by workers in their later life, while family background contributes to an individual's socioeconomic characteristics which form the basis of his or her human capital. In addition, Becker and Tomes further explain that complex social characteristics of families, for instance, the race, parents or grandparents' education, also affect work ability later in life. To be more specific, family culture plays a role in cultivating a child's ability to learn and to acquire skills, thus affecting education levels and careers in later life. Solon (1999) studies the influence of family background on the economic success of children, and concludes that children living in professional families tend to have better communication skills, social networks and career goals. Furthermore, these advantages contribute eventually to higher wages for these offspring. Results from Solon's U.S. study demonstrate that family background factors explain 40 per cent of long time earnings and family background contains factors more than education and work experience of the individuals.

Education is designated as one of the principal elements of human capital. Jencks (1972) shows that the number of years of schooling is strongly correlated with occupational attainment, however no strong relationship between cognitive skills and occupational attainment is found in his study. Martins and Pereira (2004) estimate the returns to education for male workers from 16 countries in the mid-1990s, and show that returns to education are higher for high-skill workers. They also find that education is positively correlated with within-education-levels wage inequality.

Economists have focused on the relationship between language skills and wage differences. Carliner (1981) uses the 1971 Canadian Census and finds that economic rewards to learning English or French for males who speak neither is substantial and the rewards to speaking English for those native French speakers is also substantial in Quebec. In addition, his results reveal that native French speakers in Quebec who are men earn less than monolingual English men even if the native French speakers learn English. In other provinces, monolingual English men have a significant wage premium over those whose native language is neither French nor English. However, these have changed since 1971(see Vaillancourt et al. (2013) for more details).

There are also links between human capital and the decision to migrate. Sjaastad (1962) suggests that migration is an investment in human capital. Individuals will make a migration decision if the additional returns to migrating exceed the relocation costs. In addition, age is considered as a significant factor which affects migration decision and interregional income differences. Hunt and Mueller (2004) focus on North American migration. They examine the influence of returns to skills, amenities, distance, and language on migration between the U.S. and Canada. Their results show that high-skilled individuals will migrate to regions with higher returns to skills. In addition, small decreases in relocation costs lead to increases net migration to the U.S., while large reductions in the relocation costs contribute to the increases net migration to Canada. As for internal migration, inter-provincial wage differentials and how these affect internal migration in Canada have been empirically analyzed by Dickie and Gerking (1998). Their results show that these wage differentials are influenced by migration costs and inter-provincial transfer payments. They also find that inter-provincial wages differences tend to be smaller for workers who are young, educated and English speaking because these workers can more easily access information and have relatively low relocation costs. Chiswick (1978) examines the earning differences between foreign-born white men and the native born using the 1970 American Census of Population. After controlling for the birth place, years entry the U.S., and citizenship, his results show that immigrants' earnings increase more rapidly with the U.S. labour market experience given that their initial earnings are less than the native born. The immigrants' earnings are equal to the native born after 10 to 15 years, and then exceed those of the native born. Specifically, there is no correlation between earnings and the U.S. citizenship of the foreign born men.

Migration is also found to be an implication of interregional differences in returns to skills (Borjas et al., 1992). As for the methodology of measuring the differences in the returns to skills, some estimate regional dummy intercepts or parameters on returns to skills (usually proxies for skills, like education) in the wage equation (Beeson, 1991). Hunt and Mueller (2002) provide an inspiring method to calculate returns to skills by controlling for interregional skills characteristics. They use two individual level datasets: the 1991 Canadian and the 1990 U.S. population data to estimate the parameters of regional returns to skills in the logarithm wage equations. Area-specific returns to skills indicators, such as years of schooling, potential work experience, marital status, householder, English ability, immigrant status and cohorts of entering the country are considered by Hunt and

Mueller. In addition, the “skill mix” variables, such as minority status, urban versus rural location, work status, and occupation and industry categories are usually included in these types of models. The key contribution of the Hunt and Mueller (2002) study is that they use a standardized skills distribution methodology to control for inter-area variations of skill mix and the differences in returns to skills that result from the interregional wage disparities (as detailed below in section 4). This methodology specializes in the estimates of regional parameters and has not been employed in the previous regional science studies. Therefore, it is worthwhile to replicate their method by using updated data as more recent social and economic developments might contribute to distinct changes in the returns to skills in the U.S. and Canada since 1990.

Some literature focuses on skill mismatches and earnings. Vahey (2000) uses Canadian data from the National Survey of Class Structure and Labour Process to examine the wage returns to over and under education. Results indicate that the wage returns for males are positively correlated with over education in jobs that require a bachelor’s degree. However, wage returns are negatively associated with under-educated males in jobs that required lower education. On the contrary, no significant relationship between over or under education and educational requirements is found for females. Slonimczyk (2009) investigates the wage distributions of the over- and under-educated workers in the United States. The “mismatch” of skills is defined as workers’ possessing skills above or below that which is required for their job. This study finds decreasing returns to over-educated workers and increasing returns to the under-qualified workers. Furthermore, Slomimczyk investigates the influence of minimum wages on high-skilled and low-skilled workers, and shows that a decreasing minimum wage will reduce employment. Specifically, it finds that decreases in the minimum wage have negative effects on the employment and relative wages of low-skilled workers when compared to those with higher skills. Thus, a decreasing minimum wage results in increased inequality across these two skill groups.

The imbalance between the demand and supply of skills, which is related to skill mismatch and the wage returns to skills, has been the focus of a number of papers. Several studies find that a greater supply of skills results in depressing wages (e.g., Freeman, 1976; Easterlin, 1987 and Akhmetsin, 2004). Freeman (1976) documents that increasing the supply of individuals with college education results in a decrease in wages. Easterlin (1987) demonstrates that the wage returns to work experience is negatively correlated with workers who were born in larger birth cohorts. Akhmetsin (2004) analyzes the differences in returns to skills in terms of skill supply in the United States and shows that the correlation between the supply of college graduates and the returns to a college education is negative. This effect is found for both black and white men, and for black women. By contrast, the influence of the supply of college graduates on the returns to white women graduates is positive: although more women have the college degree, they still enjoy higher wages returns to education.

Discriminatory wages based on the biases of employers have been examined by some economists. Bergmann (1986) discusses a situation in which women earn less than men in occupations that are dominated by men. Since employers will not hire women in those predominantly male occupations, the supply of women for female dominated occupations will increase, leading to lower wages for females in those occupations. Corcoran and Duncan (1979) and England (1992) find that social skills influence on the gender wage gap. England (1992) divides social skills into two types: nurturant and authority. Results show that women tend to concentrate in nurturant skills required occupations while men in authority-required occupations, and that this explained six per cent of the wage gap in gender in 1980. Kilbourne et al. (1994) focus on occupational characteristics and wages differences between white females and males. The skills demanded for individuals' occupations are measured by cognitive, physical and social skills. Their results show that the correlation between the net returns to education, work experience, occupation-relative cognitive and physical skills is positive regardless of gender, which is consistent with the neoclassical theory of human capital. Moreover, they find that gender differences in work experience play an important role in the gender wage gap. Further findings show that female wages are positively associated with the occupations that are the female dominated and nurturance-skills demanded.

Overall, it is clear that the question of the wage returns to skills is still ongoing. I plan on contributing to this literature by using the methodology proposed by Hunt and Mueller (2002), but with more recent data sets, in order to see whether their conclusion that the returns to skills in the U.S. are higher than those in Canada, persists. This seems like a particularly interesting question given the ever-increasing ties between our two countries.

3. Data

I use two datasets in this study: the 2006 (long-form) Census of Population Canada and the 2006 American Community Survey (ACS). I start by providing some general information on each dataset, a short description of my sample restrictions and some summary statistics.

The key reasons why the 2006 Census is appropriate for my study include: 1) its size; every fifth Canadian household receives a long form questionnaire from Statistics Canada; 2) the long-form has earnings/income related questions and detailed socio-demographic characteristics; and 3) the 2006 long-form Census was mandatory, thus the coverage is almost universal.[1] For this major paper I rely on the public use microdata files (PUMF), which are available through ODESI.[2] It is a random sub-sample of all long-form respondents. It contains 844,476 individual records, representing 2.7 per cent of the population in Canada.

The ACS, which is conducted by the U.S. Census bureau, is the American equivalent of the Canadian long-form Census. It has large sample sizes (the 1-year PUMF file contains approximately 3.5 million records per year and about 290,000 records per month),[3] it has detailed socio-economic characteristics and most importantly, it is also mandatory.[4] Given that I am updating a paper that uses earlier Census data with almost universal coverage,[5] it is important that I also rely on similar data as it makes my findings more comparable. As with the Canadian case, I rely on the public use microdata sample (PUMS) population file of the ACS which is available through the United States Census Bureau.

[1] It should be noted that the long-form Census was replaced by the National Household Survey (NHS) in 2011. Unlike its predecessor, the NHS is not mandatory. Although, the overall response rate is around 68.6 to 77.2 percent (Statistics Canada, National Household Survey 2011), the non-response rate for certain subgroups, and the non-response bias resulting from it, may be substantial. This is the main reasons why many economists (e.g. Veall, 2010) were so critical of this new survey. Their belief was that the data would not be easily comparable to earlier long-form censuses. It is for this very reason that I do not use this data in my major paper.
[2] ODESI stands for Ontario Data Documentation, Extraction Service and Infrastructure.
[3] Source: U.S. Census Bureau, An Overview of the American Community Survey (2013).
[4] The ACS replaced the American long-form Census in 2000. Unlike previous censuses it is held every year, and a smaller representative sub-group of the population is enumerated.
[5] 1991Census of Population Canada Public Use Microdata Files; 1990 Census of Population and Housing United States: Public Use Microdata Sample: 5-Percent Sample.

3.1 Sample Restrictions

Since I am replicating the Hunt and Mueller (2002) paper using more recent data, it is important that I impose the same restrictions. I impose the following eight restrictions. First, only Canadian-born or American-born individuals are retained in the sample. Second, I keep individuals who are between the ages of 25 and 64. Third, I select individuals who worked at least one week in the previous year (i.e., 2005). Fourth, the self-employed are excluded from the sample; the self-employed individuals are not working for an employer, and as such, the return to education is not as clearly defined. Fifth, I exclude individuals whose main activity is attending school either part-time or full-time. This is again a natural restriction as working may not be their main activity. Sixth, I impose a lower bound on wages and salaries. More precisely, I drop individuals with a yearly wage below $1,000 in 1990 dollars (in local currency).[6] Seventh, I focus on individuals from the 10 Canadian provinces, and the 48 contiguous U.S. states. That means that I drop individuals from the Canadian territories, Alaska, Hawaii and the District of Columbia. Finally, I drop individuals with missing observations. Those restrictions result in a total sample size of 217,785 observations for the Canadian data, which includes 111,268 males and 106,517 females. The American final sample size has 870,634 observations containing 442,377 males and 428,257 females.

3.2 Comparisons between Canada and the U.S.

Tables 1 and 2 provide summary statistics of males and females, respectively. Although most variables are self-explanatory, a few of the variables require some clarification. The dependent variable weekly wage in Canadian dollar is converted into U.S. dollar.[7] Unlike previous data, the 2006 Canadian Census and the 2006 ACS focus on highest educational attainment. To be compatible with Hunt and Mueller (2002), I therefore convert educational attainment into years of schooling. I code the people who reported “no” diploma or degree in the PUMF to 10 years because students are not allowed to drop out of school before reaching the age of 16.[8] In the ACS, the education

[6] Hunt and Mueller (2002) imposed a $1,000 bottom threshold. Taking into account the inflation rates from 1990 to 2005, the 1990 and 2005 CPI are 78.4 and 107.0 for Canada, and 130.7 and 195.3 for the U.S.. Therefore the thresholds are $1,364.8 for the Canadian sample and $1,494.3 for the U.S. sample. Source: Statistics Canada: Consumer Price Index, historical summary; the U.S. Bureau of Labor Statistics: CPI Detailed Report 2014.

[7] I use the year average of exchange rate in 2005, which is 1.211. Source: Bank of Canada, Annual Average Exchange Rates.

[8] Because of the data limitation, individuals who have 0 to 10 years of education are all measured by 10 years, since the data only

attainment variable provides more detailed information than is found in the Canadian Census: for instance, the ACS reports an explicit education level from “no school completed” to “grade 10”. However, in order to be consistent with the education variable in the Canadian Census, I code the people who have no education attainment or have fewer or equal to 10 years education to 10 years. A high school diploma is coded to 12 years in the PUMF. In the U.S. Census, education levels from grade 11 to grade 12 with or without high school diploma are coded to 12 years. Post-secondary levels of education are coded to 14 years, and Bachelor’s degrees, university certificates above the bachelor level and those medical relative degrees are assigned 16 years of education. Finally, a master’s degree and professional school degree are assigned 18 years, and doctorate degrees are given 20 years of education.

As with the data used by Hunt and Mueller (2002), the 2006 Canadian Census and the 2006 ACS do not have any variables on actual labour market experience. I therefore, use the Mincerian proxy (Mincer, 1974) to calculate the potential work experience which is the individual’s age (in years) minus schooling (in years) minus 5. It should be noted that Hunt and Mueller (2002) also had to follow this approach. I face an additional difficulty in the Canadian data: the ages of the respondents are presented in 5-year age groups in the public-use files of the 2006 Census. I therefore use the midpoints of the age groups as an approximation. For example, 25 to 29 years is considered as 27 years. Because the variable years of schooling is obtained from non-continuous intervals, the potential work experience is coded to 0 if the derived value is negative. As for the weeks individuals worked in 2005, the variable indicating part-time or full-time work exists in the Canadian Census, while no such variable in the U.S. Census. In order to be consistent with the Canadian Census, which defines part-time jobs as less than 30 hours or more per week, I therefore use the variable hours of work to generate the variable part-time work in the U.S. Census (as in Hunt and Mueller (2002)).

Given that I only focus on Canadian and American-born individuals, all individuals born elsewhere are excluded from the data. However, I include an “immigrant” variable which needs to be clarified. In the Canadian data, it is a dummy variable that equals one if the individual was born in the U.S.,

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report people who at least hold a high school degree or diplomat, people who have less than high school degree are reported as “none” in the Canadian Census, which account for 23 per cent of the total observations in the 2006 Census.

and zero if born in Canada. For the U.S. data, it is the opposite. The immigrant dummy equals one if the person is born in Canada, and zero if born in the U.S.. For both countries datasets, marital status equals one if the person is married or in a common-law relationship. The English dummy is a variable that equals to one if individuals reported they can speak English well enough to conduct a conversation and zero otherwise.[9]

Finally, the occupational and industrial classifications also require some discussion. The Canadian dataset relies on the 2006 National Occupational Classification for Statistics (NOCS). In the U.S. Census, occupational classification is based on the Standard Occupational Classification (SOC) 2000. Given that I am focusing only on broad categories, the matching across these two occupational classifications is relatively straightforward. More precisely, I define nine categorical variables: management occupations; business, finance and administration; natural and applied sciences; health related occupations; social sciences, education, government service and religion; art, culture, recreation and sport; sales and service; trades, transport and equipment operators; primary industry, manufacturing and utilities.[10] For the industrial classification, both datasets are based on the 2002 North American Industry Classification System. Eight categories of industry variables are generated and they are classified according to the industry codes which describe the main business activity: agriculture, construction, manufacturing, natural resource industries, sales, services and lastly, wholesalers or distributors.[11]

From Table 1 one can observe that for men there are several noteworthy differences across the U.S. and Canadian data. The weekly earnings of American men are higher than those of Canadian men after adjusting for the exchange rate between the two currencies.[12] Canadian men have more work experience on average than the American men, even though they have similar average education

[9] In the Canadian Census, the universe of the question about ability to speak English or French to conduct a conversation is the total population. However, in the U.S. Census, only those who report other language than English speak at home will answer the question about “how well does this person speak English”.

[10] The reference category is management occupation.

[11] In the Canadian Census, there is no information indicates military in occupation or industry categories. According to the definition in National Occupational Classification-Statistics 2006, armed forces are belonged to protective services, which are under the category of sales and service occupations. Same case applies to the industry category. On the other, military relative occupations and industries are classified separately from the service category in the U.S. Census. In order to be consistent with the classification of the Canadian data, I classify military relative occupations and industries into service category in the U.S. data. In addition, the reference category is agricultural, forestry, fishing and hunting industry.

[12] I recognize that this approach does not deal with purchasing power.

attainment (i.e., 13 years of schooling). Men who have the ability to conduct a conversation well enough in English make up 86.4 per cent of the Canadian sample, but 99.6 per cent of American men claim that they speak English well or very well. This can mainly be explained by the fact that Canada has two official languages, and that there is a significant minority of Canadians that only speak French (the dummy variable for the province of Quebec will be picking up much of this effect). The difference in the questions between the two Census surveys can also explain some language differences.

With regard to immigrants, although they make up a relatively small portion on average of the Canadian and U.S. samples (0.79 per cent and 0.43 per cent respectively), American born individuals are more likely to migrate to Canada than the Canadian born individuals to the U.S.. Those who are minorities account for 16.1 per cent of the U.S. sample,[13] but only 2.0 per cent of the Canadian sample. This is due to the fact that belonging to a minority in the U.S. is defined more broadly than in Canada, including, for instance, aboriginal individuals. In Canada, a visible minority is identified as non-white (in colour) or non-Caucasian in race, excluding the aboriginals in the Census.[14] The immigrants in either country are classified into seven cohorts of entry into the country. Taking into account the periods after year 1975, a relatively large number of males who are American born came to Canada over the 1975 to 1979 period. More Canadian born males entered the U.S. in the 1995 to 2000 cohort than other periods. Shocks to the business cycle could explain the immigration from the United States to Canada in the years from 1975 to 1979. The oil crisis began in 1973, since the U.S. economy was particularly dependent on imported oil, the Oil Embargo imposed significant pressure on the U.S. economy (Balassa, 1981). In addition, the Vietnam War which ended in the mid-1970s had profound effects on U.S. society, and encouraged individuals to leave the U.S. (Henry and Oliver, 1987). In the period from 1995 to 2000, the post-1995 technological acceleration boosted the U.S. economy. The “New Economy” emerged from 1995 and ended in 2000 which resulted in a period of economic prosperity (Black and Lynch, 2004). The robust economic growth, steady job creation, low inflation rate and increasing productivity could attract people to remit to the United States. These

[13] It should be noted that African Americans are considered part of the minority group. The definition of the minority variable will be discussed later in this section.
[14] I recognize that aboriginals could have been included in the visible minority group. However, I try to stay true to Hunt and Mueller (2002) paper and rely only on the visible minority question in the Canadian Census to identify this variable.

empirical facts are consistent with migration theories: economic incentives influence international migrations (Borjas, 1994; Chiswick 1978, 1999); and migration is a human capital investment decision that the migrants expect a premium in the labour market income in compare with the present value of migration costs (Sjaastad, 1962).

As for occupational differences, Canadian men are less likely to in the area of health, while American men are less likely to hold jobs in art, culture, recreation and sport. Males are more likely to perform work in trades, transport and equipment operation in either Canada or the United States. Moreover, males in both countries prefer to work in the services related industry rather than in the agricultural, forestry, fishing and hunting industry. Such findings follow from the fact that both the U.S. and Canada are post-industrialized economies with an increasingly important service sector.

Additionally, Table 2 reveals some differences across the mean values of several factors for the female samples. As found for the male sample, American females enjoy higher weekly wages than Canadian females. Given that the potential work experience is roughly 24 years for both Canadian and American women, the years of schooling of U.S. women on average are slightly higher than Canadian women (14.1 and 13.7 respectively). Women who have part-time jobs account for 19.7 per cent in Canada, while 12.5 per cent in the United States. Moreover, women are more likely to perform work in business, finance and administration, which represent approximately 32 per cent of the samples in these two countries. Nevertheless, Canadian females are less likely to perform work in the trades and transportation or equipment operation; American females barely hold jobs in art, culture, recreation and sport. Further, a distinct difference emerges in the industry. The proportion of females who engage in nature resource industry is only 0.56 per cent in Canada. In addition, those who engage in agriculture, forestry, fishing and hunting industry make up merely 0.31 per cent in the United States.

Comparisons of males and females within each country also illustrate typical differentials. Overall, the gender gap in the mean of weekly wage exists in the two countries. The income inequality in the U.S. is slightly larger than that in Canada. In Canada, more women were born in the U.S. than men, which account for roughly one per cent and 0.8 per cent respectively. As for class of worker, about

20 per cent of Canadian females perform part-time jobs, while that proportion for Canadian males is lower: only 4.6 per cent of the total observations. This could be explained by the family role of women who undertake the responsibly of taking care of children or housekeeping. The data also reveal that nearly 60 per cent of women are married, which is slightly higher than men, meaning that those married women are more likely to spend time on childcare and housework, and thus have more probability to hold part-time jobs than their male counterparts. Furthermore, it is noticeable that men tend to perform works in trades, transportation and equipment operation. On the contrary, a large number of women have business, finance and administration occupations and only a few of them perform works in the trades, transport or operation, which are men dominated occupations. Women do not prefer to engage in the nature resource industry, such as coal mining, electric power generation and natural gas distribution, while men are less likely to engage in the agriculture or hunting industry in Canada.

With reference to the U.S., one of the noticeable differences is that women tend to have slightly higher education attainment and more work experience than men on average. As for occupations choices, both men and women are less likely to perform work in the art, culture recreation and sport relative occupations. However, American women prefer to have jobs in business, finance and administration, men tend to choose trades, transport and equipment operation.

4. Measuring Returns to Skills

In this section, I discuss the theoretical and empirical methodology used by Mueller and Hunt (2002) to measure returns to skills. I first provide some intuitive background, and then present the necessary steps required to get the expected mean wages and the parameters of returns to skills. Although I am relying on an existing method, that of Hunt and Mueller (2002), I believe that presenting the main steps is necessary for the understanding of the approach. I do not present all the equations of the original paper, but only focus on the main ones.[15]

The underpinning of this methodology goes back to Borjas et al. (1992) who utilize a self-selection

[15] It should also be noted that I rely on the same notation as Hunt and Mueller (2002). See Hunt and Mueller (2002) for more detail on the methodology.

model to predict the equilibrium sorting across regions. Earnings are assumed to be perfectly correlated across areas, meaning that if individuals are high ranking in the income distribution in one area, then these individuals would also in high ranking of any other areas. Therefore, high-skill workers would prefer to migrate to areas with higher returns to skills. In addition, Borjas et al. (1992) indicate that an area's ranking in the returns to the mean skill level is determined by the ranking of skill prices of that area. The parameters of the income distributions for the area, or the "rate of return" to skills, play an important role in the decision of migration and the skill composition of that area. The empirical model of Hunt and Mueller (2002) estimates the mean wages and the returns to skills parameters across 58 regions.

Following the theoretical framework of Borjas et al. (1992), Hunt and Mueller (2002) denote the logarithm wage of individual i in region j by

$$\ln(wage_{i,j}) = \mu_j + \phi_j(v_i - v) \tag{1}$$

where μ_j is the mean logarithm wages in area j, ϕ_j indexes the returns to skills parameter in area j, v_i denotes the individual i's skill level, and v represents the mean skill level for all regions combined. Equation (1) implies that the wage distribution is determined by the mean wage in a region (μ_j) and the deviation from the mean skill level of all the population in all regions (i.e., v_i-v). Thus, the interregional variation in individual wage distribution can be obtained by taking the expectation and variance of equation (1)

$$\mathrm{E}[\ln(wage_{i,j})] = \mathrm{E}(\mu_j) + \phi_j E[(v_i) - v] \tag{2}$$

$$\mathrm{Var}[\ln(wage_{i,j})] = \phi_j^2 \mathrm{Var}(v_i) \tag{3}$$

Equation (2) indicates that if individuals in area j have skills ranking above or below the mean skill level, then the expectation of the individuals' skill $E(v_i)$ is greater or smaller than the skill level of the population v. Equation (3) demonstrates that the interregional variance in the wage distribution is attributed to the area specific returns to skills and individual variance skill level $\mathrm{Var}(v_i)$.

In order to estimate the regional differences in returns to skills, the variations in the inter-area logarithm wage distribution (i.e., $E(v_i)$ and $\mathrm{Var}(v_i)$) need to be isolated from the skill parameter

ϕ_j. Because such variations result from the differences in skills rather than differences in returns to skills. This can be done by focusing on the standardized skills distribution. The mean and variance of the standardized skills distribution take the following form:

$$\begin{aligned} \mathrm{E}[\ln(wage_{i,j})^*] &= \mu_j + \phi_j[E(v_i) - v] \\ &= \mu_j + \phi_j(v - v) \\ &= \mu_j \end{aligned} \tag{4}$$

$$\begin{aligned} \mathrm{Var}[\ln(wage_{i,j})^*] &= \phi_j^2 \mathrm{Var}(v_i) \\ &= \phi_j^2 \sigma^2 \end{aligned} \tag{5}$$

where $E(v_i) = v$ and $\mathrm{Var}(v_i) = \sigma^2$. From equations (4) and (5), one can see that the value of the area specific mean logarithm wage μ_j and the returns to skills parameter ϕ_j are equal to the expectation of logarithm weekly wages and

$$\phi_j = \{\mathrm{Var}[\ln(wage_{i,j})^*] \,/\, \sigma^2\}^{1/2} \tag{6}$$

Substituting these values into equation (1) indicating that the distribution of logarithm wage of individual in specific areas is determined by the mean and the variance of the standardized distribution of the logarithm wage ($\mathrm{E}[\ln(wage_{i,j})^*]$ and $\mathrm{Var}[\ln\left(wage_{i,j}\right)^*]$), the variance of individual skill distribution (σ^2), and the individual's skill deviation from the population skill level in the regions ($v_i - v$). The deviation from the population skill level is denoted as individual's skill differential, meaning that a person with a positive skill differential will rank higher than the average skill level in a region, thus that person will have a relatively higher parameter of returns to skills and have a higher ranking of wage in an area, which is consistent with Borjas, Bronars and Trejo (1992) theoretical framework of spatial equilibrium model.

Following equation (4), the μ_j is identified by the expected value of the standardized distribution of the logarithm wage in area *j*. I employ the econometric model of Hunt and Mueller (2002) to estimate μ_j for individual *i* in each of the 58 regions

$$\ln(\mathrm{wage_i}) = \alpha_0 + \beta_1 \mathrm{YSC_i} + \beta_2 \mathrm{PX_i} + \beta_3 (\mathrm{PX})_i^2 + \beta_4 \mathrm{MS_i} + \beta_5 \mathrm{ENG_i} + \beta_6 \mathrm{IMMI_i} +$$

$$\textstyle\sum_k \beta_k \mathrm{COE_i} + \gamma_1 \mathrm{MIN_i} + \gamma_2 \mathrm{PT_i} + \sum_m \gamma_m \mathrm{OCC_{mi}} + \sum_n \gamma_n \mathrm{IND_{ni}} + \varepsilon_i \tag{7}$$

where $\ln(wage_i)$ is individual i's natural logarithm of weekly wage (in 2005 U.S. dollars), $\mathrm{YSC_i}$ denotes years of schooling, and $\mathrm{PX_i}$ represents potential work experience. $\mathrm{MS_i}$ and $\mathrm{ENG_i}$ are binary variables representing marital status and English ability as defined in the data section. For the immigration related variable, $\mathrm{IMMI_i}$, is the immigrant dummy,[16] and $\mathrm{COE_i}$ indexes cohorts of immigrants entry (seven time periods, with before 1975 being the reference group). $\mathrm{MIN_i}$ is the minority dummy, and $\mathrm{PT_i}$ is the dummy variable indicating part-time work status. Finally, $\mathrm{OCC_{mi}}$ and $\mathrm{IND_{ni}}$ are the occupational and industrial categorical variables, respectively.[17]

The framework of the empirical methodology of estimating the mean logarithm wage in each region is carried out in three steps. First, I estimate equation (7) (using the ordinary least-squares method) for each of the 58 regions and for males and females respectively.[18] Second, I compute the mean of the independent variables for the male and female sample separately. Third, employing the sample means and the estimated coefficients, I calculate the predicted logarithm wages. Because both the differences in skills and returns to skills would affect the wage distribution, the expectation of the standardized skills distribution is introduced in the calculation to isolate the effect of skill differences. Then the expectation of logarithm wage is identified by the mean logarithm wage.

The estimated variance of the logarithm wage distribution in each of the regions (i.e., $\mathrm{Var}[\ln(wage_{i,j})^*]$) can be obtained using a three-step procedure. Firstly, I compute the mean values of the non-skilled variables (i.e., the variables with γ parameters) for males and females separately. Secondly, using the estimated parameters in each region and the means of non-skill variables, I generate a predicted logarithm weekly wage for each individual. Finally, I compute the estimated variance of logarithm wage distribution in each area.

For the variance of the skills distribution (σ^2), I first need to estimate the following equation for all individuals

$$\ln(\mathrm{wage_{ij}}) = \alpha_0 + \beta_1 \mathrm{YSC_{ij}} + \beta_2 \mathrm{PX_{ij}} + \beta_3 (\mathrm{PX})^2_{\mathrm{ij}} + \beta_4 \mathrm{MS_{ij}} + \beta_5 \mathrm{ENG_{ij}} + \beta_6 \mathrm{IMMI_{ij}} +$$

[16] $\mathrm{IMMI_i}$ indicates the immigrant status: the individual was born in the U.S. (or Canada) and inhabiting in Canada (or the U.S.).
[17] There are 9 categories in the occupation variables, with management occupation being the reference group. Industry variables are classified into 8 categories with agricultural, forestry, fishing and hunting industry being the reference group.
[18] Given that there are 58 regressions results, I do not provide the estimated coefficients. I do, however, provide the estimated results for equation (8) in the Appendix.

$$\sum_m \beta_m \mathrm{COE}_{ij} + \gamma_1 \mathrm{MIN}_{ij} + \gamma_2 \mathrm{PT}_{ij} + \sum_m \gamma_m \mathrm{OCC}_{mij} + \sum_n \gamma_n \mathrm{IND}_{nij} + \sum_j \gamma_j \mathrm{AREA}_{ij} + \varphi_{ij} \qquad (8)$$

where AREA_{ij} is a set of categorical variables for each of the regions.[19] Secondly, I use the mean values of the non-skilled variables in equation (8) and use the values of entire male or female sample for the skill related variables. Finally, I compute the variance of the standardized skills distribution for males and females.[20]

Consequently, the estimate of the returns to skills parameter ϕ_j in each of the 58 areas can be calculated by using equation (6). This parameter is an index number which indicates the returns to skills variance to the standardized skills distribution.

An example is given to illustrate the individual's logarithm wage difference between two areas. The logarithm wage of individual *i* who is at one standard deviation above the mean skill level of individuals in area *j* and *k* are as followed

$$\ln(wage_{ij}) = \mu_j + \phi_j(\sigma)$$

$$\ln(wage_{ik}) = \mu_k + \phi_k(\sigma)$$

Therefore, the logarithm wages difference between two areas takes the following form

$$\ln(\mathrm{wage}_{ij}) - \ln(wage_{ik}) = (\mu_j - \mu_k) + \sigma(\phi_j - \phi_k) \qquad (9)$$

The logarithm wages difference between two areas is attributed to the differences in the mean logarithm wages $(\mu_j - \mu_k)$ and the difference for individual who are at one standard deviation above the mean of skills distribution i.e., $\sigma(\phi_j - \phi_k)$.

5. Estimation Results

As discussed in Section 4, the estimation was carried out for males and females separately. As such, I present the results sequentially, starting with the male results. Table 3 presents the male estimates focusing only on U.S. regions. It shows estimates of the standardized mean weekly wages (μ_j), the standardized index of returns to skills (ϕ_j), and area-specific log wage differentials for individuals at

[19] Recall that there are 58 regions across two countries. As such, there are 57 region dummies with Prince Edward Island being the reference group.

[20] Tables A in the Appendix shows the estimated parameters for equation (8) by gender.

different points of skill distribution. Finally, Table 3 also provides rankings of each region within the U.S. Table 4 repeats the same exercise, but for Canada, and it also presents the average values for two countries.

Three broad patterns emerge in the male sample. First, the average estimated mean logarithm weekly wage is slightly higher in the U.S. (6.680) than in Canada (6.585). Using older (1990) data, however, Hunt and Mueller (2002) found mean weekly wages that were essentially the same across the two countries. The average value of the mean weekly wage for two countries is 6.633 in 2005, whereas it was 6.262 in 1990.[21] This could be explained by the economic development during these 15 years period in two countries.

Second, there are notable inter-regional differences within each country. In the U.S., the states in the top 5 rankings of the mean weekly wages in 1990 remain the same in 2005; these are New Jersey, Connecticut, Massachusetts, Maryland and California. On the other hand, the five states with the lowest mean weekly wages are different from Hunt and Mueller (2002). More specifically, only one state, South Dakota is still in the lower rankings of the mean weekly wages as in 1990. The other four states which are now parts of the bottom five in terms of mean weekly wages are Vermont, Oklahoma, West Virginia, and Montana. In Canada, the three provinces with higher rankings in the mean weekly wages in 1990 (i.e., Alberta, Ontario and British Columbia) maintain the top three places with the more recent data. Nova Scotia and New Brunswick are at the lower rankings of the mean weekly wage, and Prince Edward Island maintains at the bottom across time.

The average value of the returns to skills index in two countries is 0.833, which is lower than that in 1990 (0.999). According to Hunt and Mueller (2002), a ϕ_j greater (or smaller) than 1 means the area specific returns to skills are greater (or lower) than the returns to skills variance for the standardized skill distribution across all areas. It also implies that the area has a more (or less) dispersed returns to skills distribution than the average for all areas. In addition, the value of the standardized index of returns to skills in the U.S. is higher than that in Canada: 0.932 compared to 0.733 on average, which is consistent with the results of Hunt and Mueller (2002). It means that the

[21] Hunt and Mueller (2002) convert wages to U.S. dollar (as I do).

returns to skills is less dispersed in Canada than in the U.S.. These findings are also in line with other studies that focus on comparative earnings differences and income distributions in the two countries. I do observe some differences, when one focuses on specific states. Unlike Hunt and Mueller (2002) who find that all states have higher index of returns to skills than any of the Canadian provinces, I find ten states that now have lower values of the returns to skills index as compared to the highest provincial value in Canada. In addition, five states in the top ten rankings of the returns to skills index in 2005 are different from those in 1990. The remaining five states: Texas, New York, Maryland, New Jersey and Georgia, remain in the top lists as 1990. Furthermore, 13 states have returns to skills index with values greater than 1, while no Canadian province has such high value of the index. This indicates that those states have returns to skills distribution more dispersed than the average of 58 regions.

The standard deviations above the mean standardized skills distribution are derived from the index of returns to skills, thus these three standard deviations have the same rankings as the index in each region. Males in Connecticut at three standard deviations above the mean would earn weekly wages 0.468 logarithm points higher than males in Wyoming (1.051 – 0.583).

I now turn to the female results. In Table 5, I show the estimates of the standardized mean weekly wages in each region in the U.S. (μ_j), and the standardized index of returns to skills (ϕ_j). This same table also shows the area-specific log wage differentials for individuals at different points of skills distribution; more specifically, 1, 2 or 3 standard deviations from the mean. Table 6 repeats this exercise for Canada and shows average results for both countries.

An interesting finding for women is that the mean weekly wages are very similar across the two countries (6.263 in the U.S. versus 6.246 in Canada). This is not consistent with the results of Hunt and Mueller (2002) who find that Canadian women earn higher weekly mean wages than American women. However, as was the case for the male sample, the average value of the returns to skills index for females is greater in the U.S. than in Canada (0.966 compared to 0.738). In addition, the average value of the returns to skills index in the U.S. is smaller in 2005 (0.966), than it was in 1990 (1.254). For Canada, the changes across time are more modest. I find an average returns to skills index of 0.852, which is greater as compared to the 0.755 found by Hunt and Mueller (2002) for 1990. Finally, 7 states now have returns to skills index values below the highest value of Canadian province.

Comparisons between males and females also reveal several noteworthy points. The gender gap in the mean weekly wage is present in the two countries. However, the values of returns to skills index are similar for both men and women in Canada, while women have a slightly higher value of returns to skills index on average than men in the United States. In Canada, the provinces with the top three rankings in the mean weekly wages are the same for both male and female samples. Two of three provinces with the lower mean weekly wages are identical to the male sample, except for Newfoundland in the female sample. The provinces with the top three rankings in the returns to skills index are completely different with the male sample, which are Prince Edward Island, Nova Scotia and Quebec in the female sample. In the U.S., the states with the top five rankings in the mean weekly wages are the same for males and females. Six of the states in the top ten rankings of returns to skills index are similar in both male and female samples, which are Texas, Virginia, Georgia, California, New York and Maryland.

6. Conclusions

In this paper, I estimate the wage returns to skills in 10 Canadian provinces and 48 American states, using the Hunt and Mueller (2002) methodology – a methodology that controls for interregional effects. A few findings are consistent with the results of Hunt and Mueller (2002): the average values of the standardized mean weekly wages and the standardized index of returns to skills in the U.S. are higher than Canada for male and females; The Canadian provinces with the top three rankings in the mean weekly wages remain the same, and the gender gap in mean weekly wage persists. By contrast, the average values of the mean weekly wage in the U.S. are higher than in Canada for males, while the values are similar for females in the two countries. The average value of the returns to skills index for females is higher than for males. In the U.S., the states in the top five rankings of mean weekly wages are the same for males and females.

The fact that the returns to skills differential persists in the 2006 data suggest that policies aimed at reducing gender wage gaps still have merit today. It also suggests that, although the movement of workers across national boundaries has increased as a result of free-trade policies, this movement has not been enough to eliminate inter-country differentials. In many ways this is not surprising, as there are a number of differences between Canada and the U.S. that are simply not captured in my model.

For future work, it would be worthwhile to analyze further the reasons for and influences of these inter-area differences in returns to skills. My paper (like Hunt and Mueller) is constrained by the fact that I am only using data from one year. It would be fruitful to examine the question of return to skills using data across several years, and this would allow one to look more carefully at why these returns may differ by regions or by gender, for instance.

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Table 1
Summary Statistics: Weighted Means and Standard Deviations in Brackets, Male Sample

Variables	American Community Survey 2006	Canadian Census of Population 2006
A. Independent Variable		
Weekly Wage	1116.602 (2042.908)	996.1434 (1422.780)
B. Explanatory Variables		
Years of Schooling	13.952 (2.202)	13.437 (2.164)
Potential Work Experience	23.911 (10.594)	24.500 (10.550)
Married	0.654 (0.476)	0.576 (0.494)
English Ability	0.996 (0.060)	0.864 (0.343)
Immigrant	0.004 (0.066)	0.008 (0.089)
Minority	0.161 (0.367)	0.020 (0.141)
Part-Time Work	0.034 (0.182)	0.046 (0.208)
Cohorts of Entry the Country		
Before 1975	0.0015 (0.0388)	0.0037 (0.0614)
1975-1979	0.0003 (0.0182)	0.0011 (0.0345)
1980-1984	0.0003 (0.0179)	0.0006 (0.0252)
1985-1988	0.0002 (0.0157)	0.0002 (0.0143)
1989-1994	0.0005 (0.0229)	0.0007 (0.0274)
1995-2000	0.0008 (0.0293)	0.0005 (0.0241)
2001-2006	0.0005 (0.0227)	0.0007 (0.0274)
Occupational Categories		
Management	0.115 (0.319)	0.127 (0.334)
Business, Finance and Administration	0.112 (0.316)	0.103 (0.304)
Natural and Applied Sciences	0.069 (0.253)	0.103 (0.304)
Health	0.025 (0.157)	0.016 (0.124)
Social Science, Education, Government Service and Religion	0.063 (0.244)	0.057 (0.232)
Art, Culture, Recreation and Sport	0.016 (0.124)	0.018 (0.132)
Sales and Service	0.209 (0.407)	0.160 (0.367)
Trades, Transport and Equipment	0.281 (0.450)	0.293 (0.455)
Primary Industry or Processing, Manufacturing and Utilities	0.107 (0.311)	0.122 (0.327)
Industrial Categories		
Agriculture, Forestry, Fishing and Hunting	0.010 (0.096)	0.026 (0.160)
Natural Resource	0.027 (0.162)	0.030 (0.172)
Construction	0.112 (0.315)	0.113 (0.316)
Manufacturing	0.187 (0.390)	0.193 (0.394)
Wholesalers-Distributors	0.051 (0.220)	0.065 (0.247)
Sales	0.098 (0.298)	0.081 (0.273)
Services	0.448 (0.497)	0.403 (0.490)
Public Administration	0.067 (0.250)	0.089 (0.285)
Observations	442,377	111,268

Table 2

Summary Statistics: Weighted Means and Standard Deviations in Brackets, Female Sample

Variables	American Community Survey 2006	Canadian Census of Population 2006
A. Independent Variable		
Weekly Wage	749.102 (1070.702)	662.811 (787.679)
B. Explanatory Variables		
Years of Schooling	14.135 (2.135)	13.676 (2.086)
Potential Work Experience	24.308 (10.820)	24.368 (10.535)
Married	0.613 (0.487)	0.585 (0.493)
English Ability	0.997 (0.053)	0.851 (0.356)
Immigrant	0.004 (0.066)	0.010 (0.098)
Minority	0.183 (0.387)	0.020 (0.141)
Part-Time Work	0.125 (0.331)	0.197 (0.398)
Cohorts of Entry the Country		
Before 1975	0.0018 (0.0426)	0.0043 (0.0652)
1975-1979	0.0003 (0.0198)	0.0017 (0.0418)
1980-1984	0.0003 (0.0176)	0.0007 (0.0282)
1985-1988	0.0002 (0.0162)	0.0006 (0.0252)
1989-1994	0.0004 (0.0214)	0.0007 (0.0268)
1995-2000	0.0006 (0.0248)	0.0006 (0.0261)
2001-2006	0.0004 (0.0223)	0.0008 (0.0298)
Occupational Categories		
Management	0.086 (0.280)	0.085 (0.278)
Business, Finance and Administration	0.316 (0.465)	0.321 (0.467)
Natural and Applied Sciences	0.021 (0.142)	0.030 (0.171)
Health	0.130 (0.336)	0.112 (0.315)
Social Science, Education, Government Service and Religion	0.148 (0.355)	0.139 (0.346)
Art, Culture, Recreation and Sport	0.015 (0.121)	0.024 (0.153)
Sales and Service	0.210 (0.407)	0.225 (0.417)
Trades, Transport and Equipment	0.030 (0.170)	0.021 (0.142)
Primary Industry or Processing, Manufacturing and Utilities	0.045 (0.208)	0.044 (0.204)
Industrial Categories		
Agriculture, Forestry, Fishing and Hunting	0.003 (0.056)	0.010 (0.100)
Natural Resource	0.007 (0.082)	0.006 (0.074)
Construction	0.016 (0.125)	0.022 (0.147)
Manufacturing	0.083 (0.275)	0.075 (0.263)
Wholesalers-Distributors	0.024 (0.152)	0.034 (0.181)
Sales	0.107 (0.309)	0.115 (0.319)
Services	0.704 (0.456)	0.659 (0.474)
Public Administration	0.057 (0.231)	0.080 (0.271)
Observations	428,257	106,517

Table 3

μ_j, ϕ_j and standard deviations above the means in the U.S. (2005), Males

Regions	Number of observations	μ_j Value	μ_j Rank	ϕ_j	$+1\sigma$	$+2\sigma$	$+3\sigma$	Rank
				Values				
Connecticut	5,375	6.874	2	1.204	0.350	0.700	1.051	1
Texas	31,839	6.699	19	1.166	0.339	0.678	1.018	2
Virginia	12,928	6.755	11	1.148	0.334	0.668	1.002	3
New Jersey	12,128	6.935	1	1.132	0.329	0.658	0.988	4
California	38,036	6.853	3	1.128	0.328	0.656	0.984	5
New York	25,025	6.803	7	1.128	0.328	0.656	0.984	6
Georgia	14,239	6.709	18	1.083	0.315	0.630	0.945	7
Tennessee	10,132	6.621	33	1.044	0.304	0.607	0.911	8
Illinois	19,854	6.792	8	1.042	0.303	0.606	0.909	9
Maryland	8,880	6.844	5	1.029	0.299	0.599	0.898	10
New Hampshire	2,343	6.736	13	1.009	0.293	0.587	0.880	11
Pennsylvania	21,487	6.687	21	1.004	0.292	0.584	0.876	12
Massachusetts	9,928	6.850	4	1.001	0.291	0.582	0.873	13
Missouri	10,033	6.626	32	0.991	0.288	0.576	0.865	14
North Carolina	14,075	6.640	29	0.983	0.286	0.572	0.858	15
Arizona	8,329	6.712	17	0.973	0.283	0.566	0.849	16
Ohio	20,627	6.677	23	0.969	0.282	0.564	0.845	17
Alabama	7,543	6.646	28	0.967	0.281	0.563	0.844	18
Utah	3,937	6.669	24	0.967	0.281	0.563	0.844	19
Florida	23,117	6.684	22	0.965	0.281	0.561	0.842	20
Kentucky	6,908	6.618	34	0.957	0.278	0.557	0.835	21
Arkansas	4,326	6.600	38	0.957	0.278	0.556	0.835	22
Washington	10,283	6.750	12	0.952	0.277	0.554	0.831	23
Colorado	8,057	6.715	16	0.945	0.275	0.550	0.825	24
Kansas	4,751	6.632	30	0.945	0.275	0.549	0.824	25
Michigan	16,823	6.718	15	0.937	0.273	0.545	0.818	26
Delaware	1,267	6.772	10	0.935	0.272	0.544	0.816	27
New Mexico	2,618	6.628	31	0.925	0.269	0.538	0.807	28
South Carolina	7,027	6.615	35	0.912	0.265	0.531	0.796	29
Oregon	5,873	6.662	25	0.898	0.261	0.522	0.784	30
Vermont	1,065	6.563	45	0.893	0.260	0.520	0.779	31
Idaho	2,332	6.582	41	0.891	0.259	0.518	0.778	32
Minnesota	9,111	6.718	14	0.889	0.259	0.517	0.776	33
Indiana	11,651	6.656	27	0.888	0.258	0.517	0.775	34
Oklahoma	5,481	6.575	44	0.878	0.255	0.511	0.766	35
West Virginia	3,073	6.539	46	0.870	0.253	0.506	0.759	36
Wisconsin	10,488	6.656	26	0.845	0.246	0.491	0.737	37
Louisiana	6,443	6.696	20	0.841	0.245	0.489	0.734	38
Maine	2,149	6.582	42	0.826	0.240	0.480	0.720	39

Iowa	5,365	6.590	40	0.806	0.235	0.469	0.704	40
Nevada	3,799	6.811	6	0.788	0.229	0.458	0.687	41
Rhode Island	1,573	6.776	9	0.778	0.226	0.452	0.678	42
Mississippi	4,355	6.602	37	0.757	0.220	0.440	0.660	43
Nebraska	2,927	6.582	43	0.735	0.214	0.428	0.641	44
South Dakota	1,290	6.490	47	0.720	0.210	0.419	0.629	45
Montana	1,403	6.474	48	0.695	0.202	0.404	0.606	46
North Dakota	1,089	6.594	39	0.681	0.198	0.396	0.594	47
Wyoming	995	6.613	36	0.669	0.194	0.389	0.583	48
U.S. Average	9,216	6.680		0.932	0.271	0.542	0.813	

NOTE: 1. σ= 0.291 and is the value of the standard deviation of the standardized skills distribution for the male sample.

2. +1σ= $\phi_j * \sigma$ and is the value of one standard deviation above the mean of the skills distribution.

Table 4

μ_j, ϕ_j, standard deviations above the means in Canada and average values in two countries (2005), Males

Regions	Number of observations	μ_j Value	μ_j Rank	ϕ_j	$+1\sigma$	$+2\sigma$	$+3\sigma$	Rank
				Values				
Ontario	37,482	6.739	2	0.827	0.240	0.481	0.721	1
Manitoba	4,072	6.550	7	0.810	0.236	0.471	0.707	2
Alberta	12,847	6.786	1	0.786	0.229	0.457	0.686	3
Nova Scotia	3,992	6.482	8	0.764	0.222	0.444	0.666	4
Newfoundland	2,293	6.553	6	0.716	0.208	0.416	0.625	5
New Brunswick	3,390	6.471	9	0.713	0.207	0.415	0.622	6
British Columbia	12,576	6.708	3	0.696	0.202	0.405	0.607	7
Quebec	30,449	6.623	4	0.685	0.199	0.399	0.598	8
Prince Edward Island	551	6.364	10	0.672	0.195	0.391	0.586	9
Saskatchewan	3,616	6.578	5	0.660	0.192	0.384	0.576	10
Canada Average	11,127	6.585		0.733	0.213	0.426	0.639	
Canada and U.S. Average	10,171	6.633		0.833	0.242	0.484	0.726	

Table 5

μ_j, ϕ_j and standard deviations above the means in the U.S. (2005), Females

Regions	Number of observations	μ_j Value	μ_j Rank	ϕ_j	$+1\sigma$	$+2\sigma$	$+3\sigma$	Rank
				Values				
New York	25,008	6.405	7	1.208	0.314	0.628	0.942	1
Virginia	12,285	6.337	12	1.156	0.300	0.601	0.901	2
Georgia	14,203	6.314	16	1.123	0.292	0.584	0.876	3
Texas	30,246	6.273	22	1.117	0.290	0.581	0.871	4
Louisiana	6,526	6.214	27	1.083	0.282	0.563	0.845	5
Alabama	7,358	6.176	38	1.076	0.280	0.559	0.839	6
Maryland	9,084	6.449	4	1.066	0.277	0.554	0.831	7
Kentucky	6,765	6.196	33	1.060	0.275	0.551	0.826	8
New Mexico	2,616	6.186	34	1.054	0.274	0.548	0.822	9
California	35,457	6.485	3	1.053	0.274	0.547	0.821	10
Illinois	19,255	6.331	14	1.048	0.272	0.545	0.817	11
West Virginia	2,742	6.102	46	1.029	0.267	0.535	0.802	12
Wyoming	871	6.121	45	1.028	0.267	0.534	0.801	13
Michigan	15,786	6.285	18	1.027	0.267	0.534	0.801	14
New Jersey	12,113	6.511	1	1.022	0.266	0.531	0.797	15
Tennessee	9,810	6.212	28	1.020	0.265	0.530	0.795	16
Pennsylvania	20,571	6.275	20	1.012	0.263	0.526	0.789	17
Kansas	4,523	6.186	35	1.010	0.263	0.525	0.788	18
North Carolina	14,256	6.253	25	1.009	0.262	0.524	0.786	19
Arkansas	4,299	6.135	43	1.006	0.261	0.523	0.784	20
Oklahoma	5,215	6.145	42	0.995	0.259	0.517	0.776	21
Nebraska	2,976	6.179	37	0.979	0.254	0.509	0.763	22
Delaware	1,293	6.392	8	0.977	0.254	0.508	0.762	23
Ohio	19,687	6.274	21	0.974	0.253	0.506	0.760	24
Massachusetts	10,091	6.441	5	0.970	0.252	0.504	0.756	25
Connecticut	5,502	6.488	2	0.961	0.250	0.500	0.749	26
Indiana	10,865	6.226	26	0.960	0.249	0.499	0.748	27
Missouri	9,823	6.209	30	0.954	0.248	0.496	0.744	28
Idaho	2,096	6.170	40	0.954	0.248	0.496	0.744	29
Minnesota	9,177	6.330	15	0.954	0.248	0.496	0.744	30
Florida	23,205	6.308	17	0.931	0.242	0.484	0.726	31
Arizona	7,739	6.348	10	0.924	0.240	0.480	0.720	32
Utah	3,138	6.181	36	0.909	0.236	0.473	0.709	33
Oregon	5,374	6.259	24	0.908	0.236	0.472	0.708	34
Washington	9,356	6.343	11	0.906	0.235	0.471	0.706	35
Wisconsin	10,228	6.271	23	0.894	0.232	0.464	0.697	36
New Hampshire	2,322	6.285	19	0.888	0.231	0.461	0.692	37
Colorado	7,538	6.333	13	0.873	0.227	0.454	0.681	38
Rhode Island	1,628	6.350	9	0.871	0.226	0.453	0.679	39

South Carolina	7,057	6.210	29	0.869	0.226	0.451	0.677	40
Maine	2,124	6.202	32	0.865	0.225	0.449	0.674	41
Iowa	5,362	6.173	39	0.860	0.224	0.447	0.671	42
Mississippi	4,385	6.165	41	0.856	0.222	0.445	0.667	43
Vermont	1,123	6.203	31	0.848	0.220	0.441	0.661	44
North Dakota	1,128	6.073	48	0.842	0.219	0.438	0.657	45
Nevada	3,235	6.407	6	0.812	0.211	0.422	0.633	46
Montana	1,451	6.087	47	0.789	0.205	0.410	0.615	47
South Dakota	1,365	6.131	44	0.639	0.166	0.332	0.498	48
U.S. Average	8,922	6.263		0.966	0.251	0.502	0.753	

Table 6
μ_j, ϕ_j, standard deviations above the means and average values in two countries (2005), Females

Regions	Number of observations	μ_j Value	μ_j Rank	ϕ_j	$+1\sigma$	$+2\sigma$	$+3\sigma$	Rank
				Values				
Prince Edward Island	587	6.146	9	0.856	0.223	0.445	0.668	1
Nova Scotia	3,955	6.148	7	0.811	0.211	0.421	0.632	2
Quebec	28,597	6.306	4	0.787	0.204	0.409	0.613	3
Manitoba	3,992	6.258	5	0.783	0.203	0.407	0.610	4
Ontario	36,643	6.396	1	0.768	0.200	0.399	0.599	5
Alberta	11,685	6.364	2	0.723	0.188	0.376	0.564	6
Saskatchewan	3,992	6.238	6	0.684	0.178	0.355	0.533	7
Newfoundland	2,179	6.148	8	0.673	0.175	0.350	0.524	8
New Brunswick	3,197	6.100	10	0.656	0.170	0.341	0.511	9
British Columbia	11,940	6.356	3	0.636	0.165	0.331	0.496	10
Canada Average	10,677	6.246		0.738	0.192	0.383	0.575	
Canada and U.S. Average	9,799	6.255		0.852	0.221	0.443	0.664	

Appendix

Table A

Estimates of equation (8): coefficients and standard deviations in brackets, males and females

Variables	Males	Females
Years of Schooling	0.112 (0.001)***	0.124 (0.001)***
Potential Work Experience	0.034 (0.0004)***	0.021 (0.0004)***
Potential Work Experience Squared	-0.0005 (0.000)***	-0.0003 (0.000)***
Married	0.206 (0.002)***	0.010 (0.002)***
English Ability	0.073 (0.008)***	0.064 (0.008)***
Immigrant	-0.021 (0.023)	0.040 (0.020)**
Minority	-0.162 (0.003)***	-0.052 (0.003)***
Part-Time Work	-0.927 (0.008)***	-0.835 (0.004)***
Cohorts of Entry the Country		
1975-1979	-0.022 (0.050)	0.086 (0.050)
1980-1984	0.079 (0.055)	-0.062(0.068)
1985-1988	0.106 (0.075)	0.040 (0.055)
1989-1994	0.139 (0.053)*	-0.013 (0.043)
1995-2000	0.302 (0.048)***	0.076 (0.041)
2001-2006	0.058 (0.047)	0.027 (0.052)
Occupational Categories		
Business, Finance and Administration	-0.33 (0.004)***	-0.311 (0.004)***
Natural and Applied Sciences	-0.119 (0.004)***	0.007 (0.006)
Health	-0.125 (0.008)***	-0.149 (0.004)***
Social Science, Education, Government Service and Religion	-0.396 (0.005)***	-0.354 (0.004)***
Art, Culture, Recreation and Sport	-0.302 (0.009)***	-0.283 (0.009)***
Sales and Service	-0.366 (0.004)***	-0.473 (0.004)***
Trades, Transport and Equipment	-0.349 (0.004)***	-0.359 (0.008)***
Primary Industry or Processing, Manufacturing and Utilities	-0.400 (0.005)***	-0.469 (0.007)***
Industrial Categories		
Natural Resource	0.422 (0.011)***	0.348 (0.019)***
Construction	0.205 (0.010)***	0.179 (0.017)***
Manufacturing	0.237 (0.009)***	0.271 (0.016)***
Wholesalers-Distributors	0.224 (0.010)***	0.247 (0.017)***
Sales	0.051 (0.010)***	0.020 (0.016)
Services	0.114 (0.010)***	0.086 (0.015)***
Public Administration	0.204 (0.010)***	0.239 (0.016)***
Constant	4.428 (0.029)	4.395 (0.032)
R Squared	0.345	0.394
Observations	553,645	534,774

NOTE: Estimates of area fixed-effects are not reported in this table. All estimations are weighted. *p<0.1, **p<0.05, ***p<0.01.