

Rapport de recherche – ECN 6008

**Human Capital Externalities in the Canadian Metropolitan Areas: How
Do We Measure Human Capital?**

Par

Varvara Rakova

Dirigé par

François Vaillancourt

Le 1^{er} décembre 2005

Département des sciences économiques

Université de Montréal

Introduction

In educational economics, the discussion about the necessity to subsidize different levels of education presents a fundamental question. From the economic efficiency point of view, there is an economic reason for such subsidy when the social returns to education are higher than the private returns, a situation that may occur if there are externalities associated with education. The purpose of this essay is to assess this type of human capital externalities. In particular, the externalities resulting from the local concentration of the human capital that raise labour productivity of all workers through different channels such as, for example, learning of less qualified workers from more qualified workers, are econometrically examined here.

Four measures of human capital at Canadian census metropolitan areas (CMA) are proposed here: average education and experience, the share of workers with a university degree, the share of workers with a postgraduate degree and the share of scientists and engineers, all with respect to the total employed labour force in a CMA.

The study is organized in three main parts. First, the problem setting is presented in part 1. Then, the existing literature on the subject is reviewed in part 2 and under the light of the conclusions drawn from this review the model that will be estimated is described. Next, the samples and the data used in estimations are described and summarized in part 3. Finally, part 4 reports the method and the results of the estimations and analyzes them. A conclusion follows.

Part 1. The problem setting.

In majority of the econometric studies on the subject the aggregate human capital is measured by an average years of schooling. Intuition tells us that a positive and significant sign on this variable would indicate the presence of human capital spillovers, since human capital has an effect on individual wages beyond the effect of individual human capital. In other words, human capital externality means that an overall level of education in a given city has an amenity value since the presence of better educated workers influences the productivity of other workers. However, a positive effect of the aggregate human capital on the individual wages might be driven by simple supply and demand factors and a phenomenon of complementarity between low education and high education groups. A very simple model that illustrates the connection between aggregate human capital level and wages for different education groups of workers is shown in figure 1. The hypothesis here is that there are two types of workers, with high (indexed by H) and low education (indexed by L), and these two types of workers are complements. Moreover, the analysis is undertaken in one point in time so that the total number of workers available in a city is fixed (\bar{L})¹. Finally, the underlying hypothesis is perfectly competitive job markets so that workers' wages correspond to their marginal productivity value (MPV).

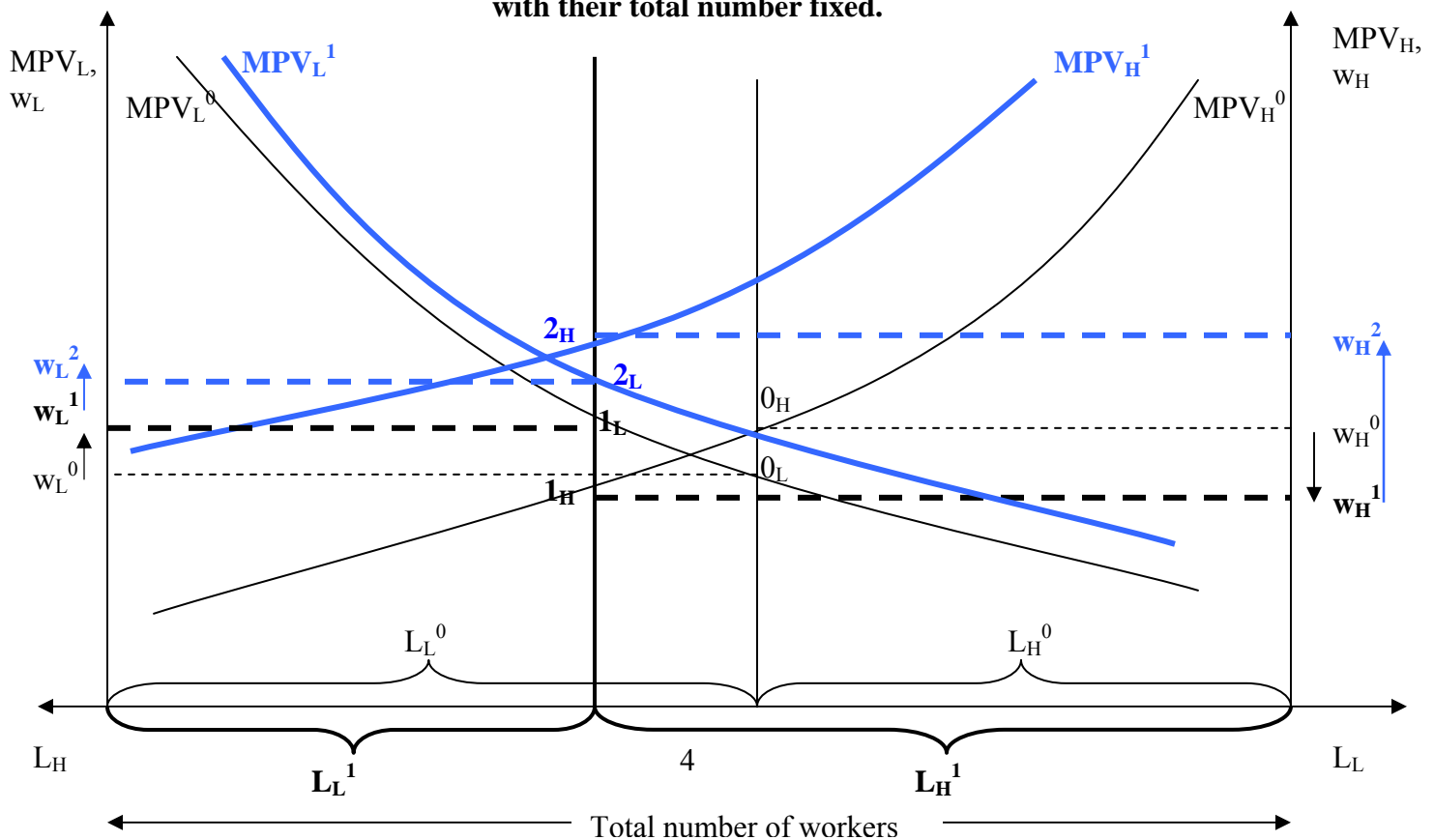
The initial equilibrium (0_L and 0_H) in a given CMA is given by intersection of MPV curves of each kind of workers (demand curve) with a supply curve of each type of labour, so that there are L_L^0 low education workers employed at w_L^0 wage and L_H^0 high education workers employed at w_H^0 wage. When the population becomes more educated in a city, it raises the number of educated workers to L_H^1 and decreases the number of less educated workers to L_L^1 , since a total number of workers is fixed. To reach a new equilibrium (1_L and 1_H) in the absence of human capital externalities, high education workers wages should fall to w_H^1 and low education workers wages should rise to w_L^1 .

¹ The hypothesis of the fixed number of workers in a city is necessary because the data used in this study are cross-sectional. A more elaborate model would allow for the demographic changes and migration among cities so that an increase of the share of educated workers in a city would not necessarily result in the decrease of the share of uneducated workers as this study supposes. On the contrary, as argued by some authors, there is certain number of uneducated workers for each educated worker, so that when their share increases the share of uneducated workers increases as well. However, the model described in this part and upon which an econometric specification of this study is based still produces the same results as the model that would allow for temporal dimension and therefore for demographic changes (see Moretti (2004), pp. 180-184).

However, if there were human capital externalities, the higher proportion of educated workers would also raise the productivity of both kinds of workers (these increases are not necessarily of the same magnitude). This would translate into the positive shifts of MPV curves to MPV_L^1 and MPV_H^1 for low education and high education workers respectively. So wages of both groups of workers would rise comparatively to the equilibrium without human capital externalities to attain a new equilibrium (2_L and 2_H). The final effect of the increase of the proportion of more educated labour on wages of the low education workers would be an increase combining two separate positive effects: the supply effect implying a movement along the demand (MPV_L^0) curve from w_L^0 to w_L^1 ; and the externality effect working through the shift of the MPV curve implying an increase of wages from w_L^1 to w_L^2 . The final effect of the increase of the proportion of more educated labour on their own wages would be ambiguous depending on the relative strength of two opposite sign effects: the supply effect implying a drop in wages from w_H^0 to w_H^1 ; and the externality effect implying a shift in the MVP curve and an increase in wages from w_H^1 to w_H^2 . If the externality effect were strong enough, as it is shown in the figure 1, then the overall effect of the increase in the proportion of educated workers in a given city on wages of the less educated ones would be positive.

Figure 1

The labour demand-supply model with two complementary types of workers and with their total number fixed.



This simple model² illustrates the basic problem associated with empirical attempts to assess human capital externalities. It shows that an observed effect is a combination of two separate effects, one being a simple supply-demand effect and the other representing a human capital externality effect working through an increased labour productivity of workers. This reasoning shows the weakness of using the average schooling as a measure of the aggregate human capital when the aim of a study is to identify human capital externalities, because the positive sign on the average schooling variable regressed on all workers individual wages might simply represent a positive supply effect on wages of less educated workers if their proportion in a labour force is higher than the proportion of more educated workers. So, it is important to keep in mind the problem of interpretation associated with an average education measure. The way to deal with it will be seen further in the text.

² For a richer general equilibrium model that explains the locational choice of individuals and the reasons behind the different levels of human capital level in two different metropolitan areas, but reaches the same conclusions as in figure 1, see Moretti(2004), pp. 180-184.

Part 2. Literature review and the adopted model.

There is a large literature that studies aggregate human capital externalities at the macroeconomic level by evaluating its effect on economic growth. However, there is less literature about human capital spillovers at the microeconomic level, in other words at the level of labour productivity. Only in last decade have papers on this subject been produced. This study will also explore the question of human capital externalities from the microeconomic perspective. Four papers are reviewed in this part, the first two estimating human capital externalities at metropolitan areas level and the two others at the state level.

2.1 Rauch (1993)

The earliest econometric study on this subject is Rauch (1993). This study assesses the effect of the average level of human capital measured at the level of Standard Metropolitan Statistical Areas (SMSA) on the individual hourly wage in United States. The study uses cross-sectional micro-data for the year 1980 from the United States Census of Population for that year. Rauch measures aggregate human capital as an average of the years of schooling and experience of workers in 237 SMSAs. He regresses individual wage on a large number of individual characteristics: sex, race, marital status, interaction terms of these variables, individual years of education and experience, occupational sector dummies, the unionization rate, the enrolment in school and the state of the health dummies. Then, as noted previously, the measures of the SMSA level human capital expressed by an average education and experience are added. It is the coefficients on these aggregate human capital variables that indicate a presence or an absence of human capital spillovers³. Finally, the author controls for some other aggregate level variables in some of his equations such as the geographical region or position of SMSAs (West, North Central, Northeast dummies and Coast dummy respectively), their climate, population and culture per capita index (based on SMSA possessions of symphony orchestras, opera companies, dance companies, theatres, public television, fine arts radio, museums and public libraries). He argues that these variables also affect individual labour productivity so that their omission could induce bias in all estimated coefficients and particularly in aggregate human capital coefficients.

³ Here and there after terms “spillovers” and “externalities” are used in the same sense and are interchangeable.

Rauch uses the Generalized Least Squares (GLS) method that corrects the standard errors for a possible bias resulting from cluster structure of SMSAs level variables. He finds significant effect resulting of a year increase in average education and experience ranging from 2,8% to 5,1% and from 0,2% to 0,7% respectively. In this paper the author also estimates a rent equation regressing housing rents on a set of individual variables as well as average education and experience variables. This regression is another equation in a model of location choice of individuals so that estimating both equations allows the author to estimate an effect of local concentration of human capital on total factor productivity, but this is of a less interest in the present study. The main conclusion of the author concerning labour productivity is that it gains from a local concentration of human capital.

2.2 Moretti (2004)

The next important study used as a reference here is Moretti (2004). This is probably the most extensive study on the subject of human capital externalities in terms of the econometric methods and data used. As reflected by the study title, the author estimates spillovers from the human capital at cities level on individual wages. The innovative approach of this study lies in a way the author measures the aggregate human capital. In fact, the author uses a share of college graduates in the labour force to measure the aggregate human capital and concentrates his analysis on its effect on the labour productivity of some specific education groups.

The interest of this method is that it distinguishes between groups and allows the author to go beyond the simple conclusions of the aggregate human capital effect on the overall labour productivity. In fact, examining the effect of an increase of educated workers separately for each of education groups would help to identify the presence of human capital externalities separately from demand-supply effect. As has been seen in the reasoning illustrated by figure 1, it is possible, on one hand, to examine an effect of the increase of the educated group of workers on wages of uneducated ones. However, it wouldn't prove the presence of externalities. Alternatively, the effect of the increase of the educated group of workers on their own wages can be explored. If there are no

externalities, then the effect should be negative as predicted by model in figure 1. Conversely, if a positive effect were to be observed, it would prove a presence of the positive externality that is at least as high in the absolute value as the negative supply effect, the former offsetting the latter.

In his study, the author explores a variety of data sets and combinations as well as methods of estimation. The main focus of this paper is the presence of unobservable characteristics of individuals and cities that could be correlated with a share of college graduates and could raise individual wages biasing by that a coefficient on the aggregate human capital measure. The instrumental variables method is proposed to deal with this problem.

First, Moretti estimates a general regression with longitudinal data from the United States National Longitudinal Survey of Youths (NSLY) from 1979 to 1994. The dependent variable being a log of the hourly wage, the author controls for some individual characteristics such as sex, race and individual education and experience as well as college share at level of 201 Metropolitan Statistical Area (MSA). He estimates that equation by Ordinary Least Square (OLS) method with various fixed effects from individual fixed effects to city x individual fixed effects. With these fixed effects, the author controls for a possible unobserved ability as well as heterogeneity of cities and he also corrects standard errors for “cluster” structure of MSA level data. He finds an effect ranging from 1,08% to 1,31% increase in a labour productivity following a 1% increase in the share of college graduates.

Then, he uses first-differentiated data and cross-sectional data from 1980 and 1990 Censuses of Population to estimate the effect of an increase of the college share in 282 MSAs on different education groups of workers. He uses an instrumental variable approach using lagged age structure for the differentiated equation and a presence of a land grant college for a cross – sectional regressions as instrumental variables. He finds an effect ranging from 0,58% to 2,22% on the less than high-school educational group of workers, an effect of 0,74% to 2,08% for the high-school education group, an effect of 0,63% to 1,66% on the educational group with some college and finally an effect of 0,45% to 0,86% on the educational group with college education or more. These results

lead to the main conclusion of the study that there is a presence of a human capital externality at a city level because the increase of a share of educated workers has a positive effect not only on a low education groups, but also on their own wages. The only weakness of this approach it is the inability to estimate the importance of these externalities since the observed positive effect is not a pure externality effect, but a combination of a negative supply or demand effect and a positive externality.

2.3 Acemoglu and Angrist (2000)

Another recent study on the human capital externalities on the labour productivity is Acemoglu and Angrist (2000). In this study, authors measure an aggregate human capital by an average schooling. However, the difference from previously cited studies is that aggregate human capital is measured at state level instead of the metropolitan area level.

The interest of this study is a strong econometric approach. The authors use panel data from 1960, 1970 and 1980 United States Censuses of Population adding in some of regressions 1950 and 1990 Census data. Their sample over which they estimate individual wages includes only white males aged from 40 to 49 years, but the human capital at state level is measured over a larger sample of workers aged from 16 to 64.

The main focus of this paper is in the problem of the potential bias of omitted variables resulting from correlation between average education and other state-year effects captured by the error term, as well as unobserved ability correlated with both individual and state-level education variables. In this case OLS estimates would be biased. To solve this problem, the authors adopt an instrumental variables approach and use quarter-of-birth dummy variables to instrument the individual schooling in their regressions. They also construct a series of dummies based on Compulsory attendance laws and child labour laws that are used as an alternative mean to instrument individual as well average schooling variables. In their econometric model, authors control for individual education, state of birth and year of birth effects as well as state of residence and census year effects, the dependent variable being a log of hourly wage. The standard errors in all regression were corrected for a cluster structure of average schooling variable.

The main finding of authors was the absence of large human capital externalities because an effect of the aggregate human capital at state level was found statistically insignificant in many specifications. In specifications where the effect was found significant, its numerical value was low according to authors, from only 1 to 3% increase in wages after one year increase in a average schooling and that, when instrumental variables approach was used. This contrasts their OLS estimates that provided evidence for approximately 7% externalities. Comparing OLS and IV results provides a warning about an important bias that one could obtain if the endogeneity problem is not considered.

2.4 Rudd (2000)

Another recent paper exploring a question of human capital externalities from the microeconomic point of view is Rudd (2000). This paper estimates an effect of human capital at the state level on an individual log weekly wages using panel structured data for 1978-1991 taken from United States March Current Population Survey (CPS). Author controls in his regression for a series of individual characteristics: sex, race, marital status, their interaction terms, individual's own schooling and experience and industries dummies.

It is interesting to note that in contrast to all other studies, the author measures individual education not only by years of schooling, a measure which implies a strictly linear relationship between individual wages and education, but he includes instead dummies corresponding to different levels of education achieved by individuals. This is important to note because allowing for a non-linear relationship between wages and education changes considerably the results on the state-level education effect on an individual labour productivity.

The method to estimate human capital externalities proposed by the author is a two-step procedure. First, he estimates the individual earnings equation including state dummies for each year so he obtains a state-specific effect for each year. Then he constructs a pooled state-year data set and regresses state effect on specific state characteristics and state average education level. The regression method used by author is weighted least square method.

One of the specific problems addressed by the author is this study and already mentioned in previous studies is a possibility that the causality between labour income and average education runs in the opposite direction than proposed by the model to be estimated. In other terms, if education is a normal good and its demand increases with income, then average education might simply be a proxy of a wealth level of a state according to the author. However, Rudd emphasizes the fact that it is not a question of a contemporaneous relationship between state wealth and average education that would require an instrumental variables approach, but it is rather the question of omitted variables. That is the coefficient of average education would capture an omitted variable such as state's wealth effect. To deal with this problem, the author includes a measure of state non-wage income per capita in the second stage regression.

Another variable at the state level whose effect on wages might be captured by an average education variable are population density index reflecting agglomeration economies and region's unemployment rate. Rudd also controls for state fixed effects and possibility of a region specific private returns to education. Finally, the author also controls for the fact that a coefficient on average education doesn't represent a pure spillover effect of an education since, but its combination with a negative supply effect of highly educated workers on their own wages. So Rudd estimates an effect of an increase of a proportion of workers with certain level of education, for example, postcollege education, on wages of less educated workers, for example with 12 years of schooling or less. This method is similar to one used by Moretti.

Author finds an average state education statistically insignificant in majority of his regressions, including those examining an effect of a share of educated workers on the wages of less educated groups. The only specifications seeming to provide significant results are those where the individual education is measured by a series of dummies, but where it is not allowed to vary by region. In these specifications, the effect of the one year increase in average education ranges from 1,8% to 2,9% increase in wages. There are also significant results in the regressions where state-wide human capital is measured as a proportion of workers with 16 years of education or more and a sample over which these are estimated includes workers with 12 years of education or less. But again, the significant results lying between 0,5% and 0,7% are obtained only when the return to

personal education is not allowed to vary by region. However, all these significant results might be simply due to the misspecification of individual education, because when the return to the latter is allowed to vary by region, all results become statistically insignificant. So the main conclusion of the author is the absence of statistically significant spillovers of an aggregate human capital at the state level.

Table 1
The summary of a literature review on a subject of human capital externalities at a microeconomic level

Author and year	Subject	Variables	Data	Estimation Method	Results
E. Moretti (2004)	Social returns to education and in particular, spillover effects from a college education at on different education groups.	<p>Dependant variable: Log(hourly wage)</p> <p>Individual control variables: Sex, race, experience, square experience; years of schooling</p> <p>MSA level control variables: Unemployment rate, log(monthly rent), Katz and Murphy index. MSA human capital measure: College share of workers</p>	<p>1) Longitudinal individual data from 1979 to 1994 (panel structure) United</p> <p>2) Cross-Sectional data from 1980 and 1990 Censuses of Population. Also used for a constructional of first-differentiated data. The college share effect on wages was estimated for different education groups: less the high school, high school graduates, workers with some college, workers with education superior to college.</p>	<p>1) Estimation with city and city*individuals fixed effects with correction for a cluster structure of MSA level variables</p> <p>2) Instrumental Variables method (age structure used as instrument for first differentiated model and a presence of a land grant college used as an instrument for cross-sectional estimations)</p>	<p>1,08% to 1,31% increase in a labour productivity following a one 1% increase in a college share; From 0,58% to 2,22% on a less then high-school educational group of workers, an effect of 0,74% to 2,08% for high-school education group, an effect of 0,63% to 1,66% on an educational group with some college and finally an effect of 0,45% to 0,86% on an educational group with college education or more. The positive effect of a college share on even most educated group provides evidence for a human capital externalities at MSA level</p>
D.Acemoglu et J. Angrist (2000)	Estimation of Human Capital Externalities	<p>Dependent variable: Log(hourly wage)</p> <p>Individual control variables : Age, individual years of education</p> <p>State level human capital measure: Average education</p>	<p>Individual panel data from 1960 to 1980 United States Censuses of Population (adding 1950 and 1990 Cenuses data in some regresions) Sampel of white males aged between 40 and 49 years old with an additional estimation for white males aged from 30 to 39 years.</p>	<p>Estimation with fixed state effects and with instrumental variables method at the same time (quarter of birth instrument for a potential heterogeneous individual education variable and constructed dummies from Compulsory Attendance and child labour laws to instrument the aggregate state human capital)</p>	<p>Human capital externality effect not always significant and when significant, ranging from 1 % to 3% increase in wages following one year increase in average state education. OLS estimates provide much higher estimates of around 7% increase in wages.</p>

J. Rudd (2000)	Human Capital Spillovers at state level	<p>Independent variable: Log(hourly wage)</p> <p>Individual control variables: Sex, race, marital status, experience, square experience, education (measured alternatively by years of schooling and by a set of dummies for different levels of education completed), industries dummies</p> <p>State level control variables: Non labour income per capita, unemployment rate, agglomeration index, education quality</p> <p>State level human capital measure : Average education and educated workers share (with 16 years or more of education)</p>	Individual data on a period from 1978 to 1991, United States (panel structure data)	Two-stage estimation : 1) Individual wage estimation with individual control variables and state dummies for each year. 2) Construction of panel data for state-year where a dependent variable is a re coefficients of state dummies from first stage regression. Independent variables are state level variables and state level human capital measure	Most of the results found insignificant, especially when individual returns to education from a first stage regression are allowed to vary by region and be non linearity From 1,8% to 2,9% increase in wages following a year increase in average education; From 0,5% to 0,7% increase in wages of workers with 12 or less years of education following a 1% increase in a share of workers with 16 years of education or more.
J. E. Rauch (1993)	Productivity gains from geographic concentration of human capital.	<p>Dependent variable: Log(hourly wage)</p> <p>Individual control variables: Sex, race, marital status, interaction terms, experience, square experience, profession dummies, education,</p> <p>SMSA level control variables: Population, climate, culture per capita</p> <p>SMSA level human capital measures: Average education; Average experience</p>	Cross-sectional individual data from 1980 United States Census of Population	GLS with correction of standard errors for a cluster data structure of the SMSA level variables	Significant external effect ranging from 2.8% to 5.1% and from 0.2% to 0.7% increase in wages after one year increase in average education and average experience respectively.

2.7 Implications for the Canadian data analysis and the model adopted.

In light of these studies, summarized in table 1 below, it is possible to make a choice of model and method to use in this study. First of all, it appears from all previous studies that the problem of the aggregate level omitted variables other than the aggregate human capital also increasing the individual labour productivity should be considered. These omitted variables embodied in the error term are a potential source of bias. So ideally, all of these variables should be included in the estimated model.

Second, an endogeneity issue of the aggregate human capital should be considered when human capital externalities are estimated. The unobserved ability that is correlated with the aggregate human capital as well as with the individual education and that might also increase the labour productivity is one of the potential causes of the endogeneity. Moreover, the simultaneity between the labour income and the aggregate human capital is another reason for a potential endogeneity of the latter. In fact, it is likely that the relationship runs in both directions. On one hand, the higher aggregate human capital increases individual labour income. On the other hand, if education is a normal good, the individuals with higher income acquire more education that raises in turn the aggregate human capital level. However there is a simultaneity problem only if there is a contemporaneous relationship between the aggregate human capital and labour income, but according to Rudd (2000) it is not the case. It is rather the individual's parents' income or the individual's general wealth that positively affects the education level of the individual. So the wealth of individual's parents or the aggregate wealth level should be treated as an omitted variable after all. Nevertheless, the aggregate human capital is still potentially endogenous because of the unobserved ability, so an instrumental variables method should be ideally used to avoid bias in estimated coefficients or panel structure data with various fixed effects could be exploited.

Third, it seems that in order to identify human capital externalities and distinguish them from demand and supply effect, it is important to measure an effect of a an increase in a share of individuals with certain human capital level on wages of groups with different education level separately.

Also, there are contradictory results on the existence of human capital externalities depending on the geographical area for which aggregate human capital is measured. Significant results are obtained when the aggregate human capital is measured at metropolitan areas level. In studies where the level of analysis is extended to a state level, the human capital externalities weren't significant. This is consistent with an intuition that human capital externalities should be more easily identified at local level since the channels of transmission of externalities such as, for example, learning from more educated workers, are also local and might not function as well for a larger geographical area.

Another conclusion that should be retained from previous revue is the impact that a bad measure of individual schooling might have on an aggregate schooling coefficients as it was the case in the study by Rudd (2000). So, it is better to allow for a non-linear return to private schooling including a set of dummy variables for different levels of education completed by an individual in opposition to the variable measured by years of schooling that would imply strictly linear private returns to schooling. It might be even interesting to allow this return to vary by region by including a set of interaction terms between individual schooling dummies and region dummies.

Finally, it is also important to consider different points in time, because in several studies reviewed above the simple cross-sectional estimations for different years generated a significantly different results indicating an important time specific effects captured by coefficients in the cross-sectional regressions.

So to summarize, the ideal econometric model to retain would be a model similar to the one used in Moretti's with longitudinal or first differentiated data or one used by Rudd with panel structured data, but using metropolitan areas instead of states geographical units for aggregate human capital. These models and this kind of data structure open a field for a large set of estimation techniques that solve in turn some econometric issues discussed above such as endogeneity for example. However, the available Canadian data and its particular geographical situation make the adoption of similar models very difficult or impossible. In fact, longitudinal micro data with all variables needed for

human capital externalities analysis are not easily available for Canada considering time and resource constraint so a relevant panel data with a sufficient number of years couldn't be constructed. As for the instrumental variables approach, the small number of the census metropolitan areas (CMA) available in Canadian Census (19 at most depending on the year) does not provide enough degrees of freedom to employ this approach even if an age structure change could be used as an instrument for the aggregated human capital in the first differentiated model. So, that the best model that we can use given data available for Canada is a model similar to that of Rauch (1993), combining it with some techniques proposed by Moretti (2004), that is a separate study of different educational groups of workers.

As for the omitted variables issue, one variable in particular examined in this study is the university R&D expenditures at the CMA level. The reason for the consideration of this variable is that higher level of university R&D expenditures in a CMA is likely to raise the labour productivity and therefore wages. However, this impact is not direct since the university R&D expenditures are mainly directed to the fundamental research, particularly in natural sciences that constitutes more than 80% of the total university sponsored R&D in 2004 in Canada ⁴. This fundamental R&D doesn't increase labour productivity and wages in a given CMA directly, but it fosters the private sector R&D that uses these first stage results to conduct further research⁵ aimed at commercialization and that rises the labour productivity and therefore wages. Therefore the university R&D expenditures have a public good aspect in a sense that it has a partial non-exclusion characteristic. In other words, a fixed amount of the university R&D increases labour productivity and attracts more high technology firms providing a general higher paying environment, so that an additional worker in this environment will still benefit from it in the same measure all other similar workers do without decreasing these benefits for others. It follows then that a more convenient measure of the university R&D expenditures is a total amount of the university R&D expenditures in a CMA rather than the amount of the R&D expenditures per capita that was used by Rauch (1993).

There is also a good side to be working with Canadian data. In fact, richer measures of human capital proposed in this study are made possible by the availability of the field of

⁴ Statistique Canada (2004)

⁵ Guellec, D. and B. van Pottelsberghe de la Potterie(2001), p. 114, p.125 and p. 127.

studies in the Canadian Census of Population. It is used to define more specific measure of human capital, such as a share of scientists and engineers with respect to the total employed labour force and that will be defined in detail below. This is an innovation comparing to all previous studies on human capital externalities that used more general measures.

However, a share of scientist and engineers is not the only measure proposed, commonly used aggregate human capital variables also being tested here. All together, four measures of aggregate human capital are proposed. First, it is measured by the average education at CMA level, the most general definition and the most commonly used in the reviewed literature on the subject of human capital spillovers. Second, there are two more specific measures of human capital that are the percentage of workers with university degree(s) and the percentage of workers with postgraduate degree(s). These two variables identify more educated labour and provide a room for an analysis similar to the one conducted in Moretti's study, that is studying the effect of these measures of aggregate human capital on the wages of less educated workers. Finally, as noted earlier, an original measure of a human capital, previously used in none of studies on the human capital externalities and made possible thanks to the use of Canadian Census of Population microdata, is a share of scientists and engineers among workers in each CMA.

So, the model adopted here is a mincerian wage equation with an aggregate human capital measure added, set of variables being very similar to those used by Rauch (1993), except for a more diversified measures of human capital at CMA level and different educational groups samples over which this model is estimated as it is done in Moretti's study. The equation (1) below represents a general form of a model estimated in this study:

$$\text{Log(LabourIncome}_{ij}) = \beta_0 + \beta X_{ij} + \gamma H_j + \alpha R\&D_j + u_{ij} + v_j \quad (1)$$

where

- i = individuals and j = CMA ;

- $LabourIncome_{ij}$ is a sum of the wage income and of the self-employment income for an individual i in a CMA j ;
- X_{ij} is the vector of the following individual characteristics: number of weeks worked during the year, dummy for a part time work, sex, marital status, their interaction term, visible minority or native status indicator, 8 dummies for a combination of mother tongue and spoken languages, experience, square of the experience, individual schooling measured by a set of 9 dummies for different levels of completed education and 5 profession and 14 industry dummies;
- H_j is a measure of a CMA level of human capital measured in one of the following measures: average schooling and average experience, share of workers with university degree(s), share of workers with postgraduate degree(s), share of scientists and engineers among workers⁶;
- $R\&D_j$ is the total amount of university R&D expenditures in a given CMA (x 1 000 \$ of 2000);
- u_{ij} and v_j are the terms of error.

The details on the construction of the variables are provided in the appendix 1.

⁶ Average schooling and average experience are measured as an average number of years for these individual variables for all individuals of a given CMA;
 The share of workers with university degree(s) is a percentage of workers with at least one of the following degrees: bachelor degree, the university degree superior to the bachelor, degree in medicine, master degree or doctorate degree;
 The share of workers with postgraduate degree(s) is a percentage of workers with at least one of the following degrees: degree in medicine, master degree or doctorate degree;
 The share of scientists and engineers is the percentage of workers with university degree(s) in the following fields from the classification of 2001 Census of Population (variable DGMFSP): agricultural, biological, nutritional and food sciences; engineering and applied sciences; data processing and computer technologies; electronic and electrical technologies; other engineering technologies n.e.c.; mathematics, computer and physical sciences.

Part 3. Data description and analysis.

In this part the data and variables used to estimate the equation (1) above are described and analyzed. All data used for variables construction are taken from 1991 and 2001 Canadian Census of Population microdata providing data for earnings for 1990 and 2000 respectively. Since the interest of this study is to assess the presence of human capital externalities, only a sample of individual with 15 years or more that had a job in a reference year and that weren't full time students was considered. Moreover, only workers from 19 Canadian Census Metropolitan Areas (CMAs) that can be identified in the microdata are considered in the study⁷. Table 2 below shows some of their characteristics.

Table 2
Some characteristics of 19 Canadian CMAs, 2000-2001

CMA	2001 population	Average labour income (2000 \$)	University R&D expenditures (x 1000 \$ of 2000)
Halifax	359 183	32 003	81 165
Québec	682 757	32 929	197 019
Montréal	3 426 350	33 637	493 101
Sherbrooke – Trois-Rivières	291 318	30 355	53 655
Ottawa – Hull	1 063 664	40 728	144 289
Oshawa	296 298	38 579	0
Toronto	4 682 897	39 062	409 509
Hamilton	662 401	37 147	106 766
St-Catharines – Niagara	377 009	32 388	4 342
Kitchener	414 284	35 570	0
London	432 451	34 868	108 795
Windsor	307 877	40 592	10 866
Sudbury – Thunder Bay	277 587	34 109	12 469
Winnipeg	671 274	31 451	78 906
Regina – Saskatoon	418 727	31 626	81 012
Calgary	951 395	37 924	124 442
Edmonton	937 845	33 817	186 580
Vancouver	1 986 965	35 034	191 465
Victoria	311 902	32 485	30 647

Source: author's computations using the 2001 Canadian Census of Population microdata and the CAUBO 2000-2001 database.

It appears from these data that there are only four CMAs in Canada with population over one million of individuals, Toronto being the biggest one among them followed by Montreal, Vancouver and National Capital. The smallest CMAs are Sudbury – Thunder-

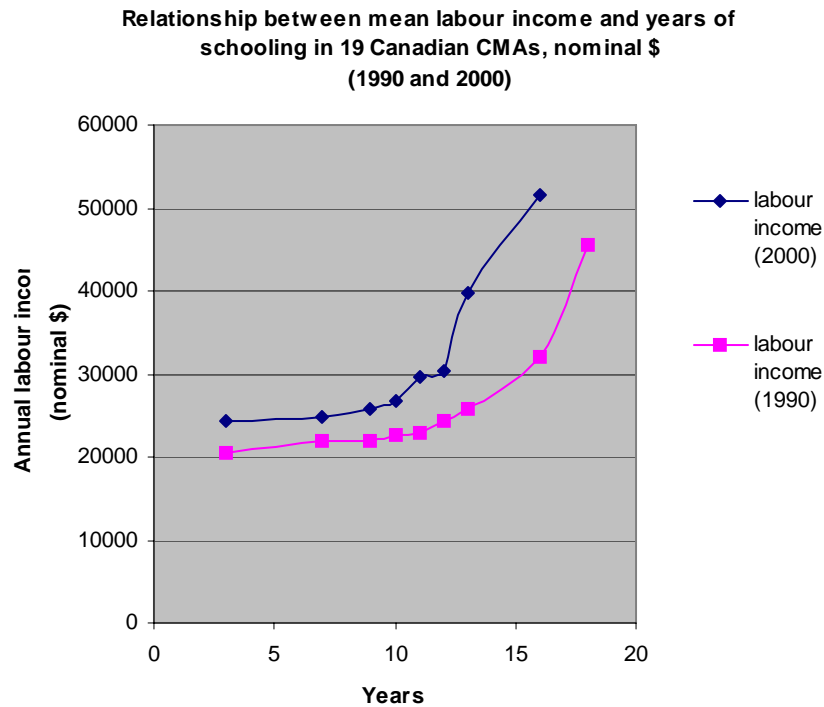
⁷ Halifax, Quebec, Montreal, Sherbrooke - Trois-Rivières, Ottawa – Hull, Oshawa, Toronto, Hamilton, St-Catharines – Niagara, Kitchener, London, Windsor, Sudbury – Thunder Bay, Winnipeg, Regina – Saskatoon, Calgary, Edmonton, Vancouver and Victoria.

Bay, Sherbrooke- Trois-Rivières, Oshawa and Windsor. The metropolitan areas with highest average labour income are Ottawa, Windsor, Toronto, Oshawa and Calgary. It is interesting to notice that four of these five CMAS and seven of nine CMAs with higher average labour income are in Ontario, also a province with the highest cost of living. Four CMAs with lowest average labour income are Sherbrooke-Trois-Rivières, Winnipeg, Regina-Saskatoon and Halifax. Comparing the biggest and the smallest CMAs with the richest and the poorest ones shows that the correlation between the labour income and the CMAs size is not very strong, only of 0,26 for 19 CMAs. Finally, table 2 also shows the total sponsored R&D executed by universities in each CMA. Four CMAs with higher university R&D are Montreal, where four universities are located, followed by Toronto, Quebec and Vancouver. The four CMAs with the lowest university R&D expenditures, beside Kitchener and Oshawa where is no university is located, are St-Catharines – Niagara, Sudbury – Thunder Bay, Windsor and Victoria. It shows that the correlation between the size of the CMAs and their university R&D expenditures is much stronger surpassing 0,90 for 19 CMAs.

Next, figure 2 below illustrates the relationship between individual mean labour income measured in nominal dollars and individual years of education for the years 1990 and 2000, the relationship that provides a first glance at the way the individual education should be measured and at the way it influences the labour income. It can be seen that there is a relatively flat labour income-education profile for first 11 years of education (normal number of years to get the high-school certificate) and that there are steeper increases in labour income for some subsequent years of education that correspond to certain levels of education, like undergraduate university degree (16 years), masters degree (18 years), etc. In other words, figure 2 clearly illustrates that the return to education is not linear and to capture this fact, it is better to measure the individual education by dummy variables corresponding to the highest level of education achieved by the individuals instead of measuring it by years of education. This conclusion is reinforced by the fact that in the used microdata the years of education variable is not perfectly continuous variable, the lowest level of education represented by less than 5 years of schooling category and the highest category stopping at 18 years of schooling or more. So that the use of the years of education constructed with these data would often underestimate the number of years of education for individual with PhD because to receive a PhD normally requires more than 18 years of education.

Another observation emerging from analysis of figure 2 is a strong similarity of the labour income-education profiles for 1990 and 2000. In fact, the only difference between two years is a positive shift of the income-education curve for the year 2000 due mainly to the inflation and also some changes in labour market laws and unions pressure.

Figure 2

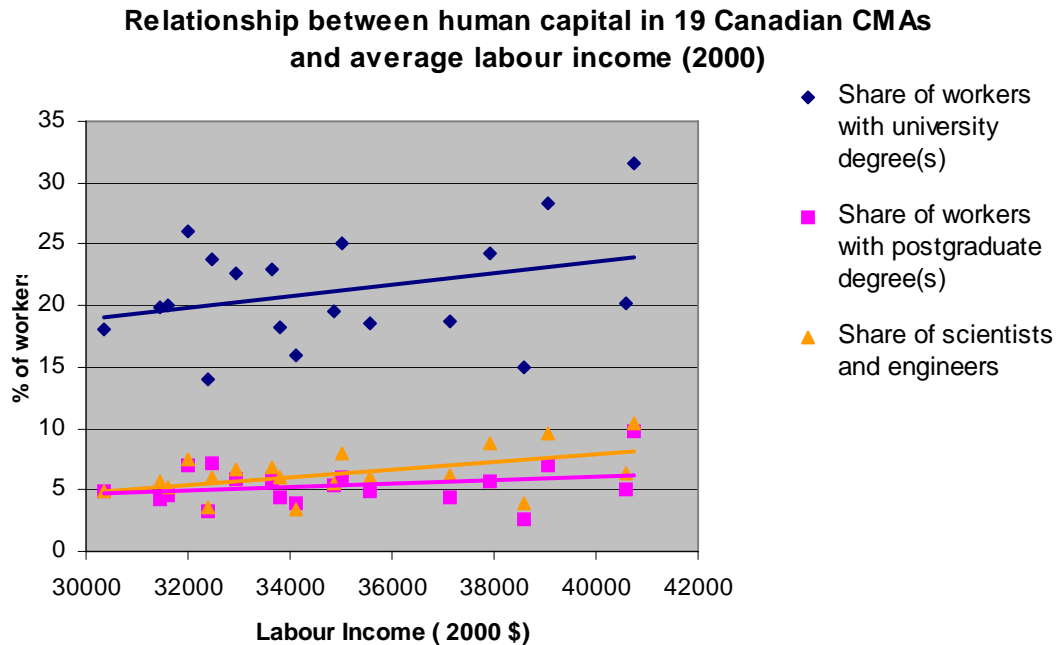


Source: Computation of the author using 2001 and 1991 Canadian Censuses of Population microdata.

The relationship between annual labour income and different measures of the aggregate human capital in 19 CMAs can be also established. Figure 3 below represents this relationship for three more specific measures of the aggregate human capital used in this study: shares of workers with university degree, with postgraduate degrees and of scientists and engineers measured in percentage points. It can be seen, that there is a clearly positive relationship between average labour income and shares of workers with university degree, with postgraduate degree and scientists and engineers. However, the relationships of labour income with the first and the third measures have superior slopes than the relationship with the second measure. Moreover, the relative strength of the correlations between average annual labour income and shares of workers with the different levels of education can be found by comparing R^2 of these linear relationships.

The strongest correlation is observed when the aggregate CMA human capital is measured by the share of scientists and engineers with R^2 of 0.26, followed by the correlation with the share of workers with university degree with R^2 of 0.11 and with R^2 of 0.08 for the correlation when the human capital is measured by the share of workers with postgraduate degree. It indicates that the most significant results in the estimation of equation (1) should be anticipated when the share of scientists and engineers variable is used to measure the aggregate CMA human capital.

Figure 3



Source: Computation of the author using 2001 Canadian Census of Population microdata.

Then, the summary statistics of the five main measures of the aggregate CMA human capital proposed here are presented in the table 2 below. It is important to note that these statistics are the means and standard deviations of the mean value of each variable for 19 CMAs. These measures are estimated for two different sample of workers: the large sample including workers of all industries and narrower sample including workers only of private sector, so that federal administration services, other government services, education & related services and health and welfare services as defined by Statistics Canada guide to census microdata are excluded. The motive for studying this particular subset of industries resides in the political role of certain cities, especially federal or provincial capitals, that tend to have a remarkably higher ratio of workers in public administration industries comparing to other CMAs as it will be further seen from table 4. Also, public sector industries tend to have higher ratio of workers with university

diplomas then in all other economy sector. So that it is possible that the major part of the variance in the metropolitan human capital measure might be explained by the public administration role of some cities in the sample of 19, when the human capital level in all other industries might be similar. Furthermore, the connections between different industries or workers inside the same industry should be stronger in the private sector than in the public one. Indeed, the latter is often characterized by bureaucratic relationships between workers, so that channels through which the aggregate human capital influences productivity of other workers should be less effective in the public sector.

Table 3
Summary statistics for five human capital measures in 19 Canadian CMAs, 1990 and 2000

Variable	1990			2000		
	Mean	Standard Deviation	n (19 CMAs)	Mean	Standard Deviation	n (19 CMAs)
All industries						
Share of workers with university degree (%)	16,64	3,42	43 612	21,20	4,57	59 825
Share of workers with postgraduate degree (%)	3,99	1,21	10 623	5,35	1,64	15 032
Share of Scientists and Engineers (%)	4,83	1,27	13 216	6,34	1,89	18 924
Average Schooling (years)	13,20	0,29	238 795	13,87	0,27	250 002
Average Experience (years)	19,51	0,79	238 795	28,02	0,58	250 002
Private Sector						
Share of workers with university degree (%)	10,97	3,28	23 998	15,13	4,95	35 790
Share of workers with postgraduate degree (%)	1,76	0,81	4 612	2,81	1,31	7 082
Share of Scientists and Engineers (%)	3,67	1,39	8 074	5,25	2,14	12 747
Average Schooling (years)	12,71	0,31	180 911	13,46	0,29	188 786
Average Experience (years)	19,49	0,89	180 911	27,34	0,64	188 786

Source: Computation of the author using 2001 and 1991 Canadian Censuses of Population microdata.

So, comparing summary statistics of human capital measures for all industries and for private sector shows that the share of workers with different levels of education falls significantly when it is measured for private sector comparing to all industries, and that for both years, 1990 and 2000. This is especially the case for the share of workers with

university degree and with postgraduate degree that fall respectively by more than one third and one half for the year 1990 and by a little less than one third and one half for the year 2000. However, the share of scientists and engineers is a less sensitive to the set of industries over which it is measured falling only by one fourth in 1990 and by one sixth in 2000 when the sample of industries is restricted only to a private sector. Finally, the most stable measure of human capital is represented by the average education and the average experience that remain almost constant whether those are measured for all industries or only private sector industries as it can be seen from the table 2. However, these measures are also very stable over different individuals, standard deviations being very low comparing to the mean value, oscillating between 1.9% and 4.5% of the mean value.

Another observation that can be made from the table 3 above, is that between 1990 and 2000 the shares of educated workers grew in CMAs, while the average education remained relatively stable as has been already noticed above. One of the reasons might be the measuring problem of the average education measure that is censored for more than 18 years of education as already described previously. Another reason may lay in the important share of less educated workers among all workers so that an important change in the share of the educated workers has a weak effect on the average education.

The human capital measures could be also compared for 19 CMAs. Table 4 below illustrates previously made conclusions about relative importance of the educated shares of workers and their evolution between 1990 and 2000. In addition, it also shows their distribution in different CMAs. The second column is added for 2000 measures to indicate the relative importance of the CMAs in terms of the human capital measure. The city that has the highest share of human capital is the national capital. However, as for the other CMAs, their relative importance in terms of human capital depends on the measure of the latter. When it is measured as the share of workers with university degree(s) Toronto, Halifax, Vancouver, Calgary and Victoria are the CMAs that follow Ottawa-Hull in terms of the importance of this variable. When the aggregate human capital is expressed as the share of workers with postgraduate degree(s), it is Victoria, Halifax, Toronto and Vancouver that have the highest shares after Ottawa-Hull. Finally, when the aggregate human capital is measured as the share of scientists and engineers, the Toronto, Calgary, Vancouver and Halifax are in first place after Ottawa-Hull. Montreal and Quebec City follow these CMAs for all the three measures of the aggregate human

capital. These observations seem to confirm the previously made statement that in CMAs that play a role of provincial or national capitals the shares of educated workers are higher than in other CMAs. The few exceptions are Vancouver that has for some measures of human capital higher values than Victoria, Calgary that has higher human capital shares than Edmonton and Montreal that has the human capital shares very similar to Quebec City.

Table 4
Three human capital measures in 19 Canadian CMAs, 1990 and 2000

CMA	Share of workers with university degree(s), %			Share of workers with postgraduate degree(s), %		Share of Scientist and Engineers, %			
	1990	2000		1990	2000	1990	2000		
Halifax	20.3	26.0	3	5.1	7.0	3	5.7	7.5	5
Québec	18.5	22.7	8	4.7	5.8	7	5.6	6.6	7
Montréal	17.5	22.9	7	4.3	5.9	6	5.0	6.8	6
Sherbrooke – Trois-Rivières	15.0	18.0	16	4.0	4.8	12	3.8	4.8	16
Ottawa-Hull	25.0	31.6	1	7.3	9.8	1	7.6	10.4	1
Oshawa	10.6	14.9	18	1.5	2.7	19	3.2	4.0	17
Toronto	21.1	28.4	2	4.9	7.0	4	6.5	9.6	2
Hamilton	14.1	18.8	13	3.1	4.5	14	4.1	6.1	9
St-Catharines – Niagara	11.3	14.0	19	2.6	3.2	18	3.5	3.5	18
Kitchener	14.9	18.6	14	3.7	4.9	11	4.4	6.1	11
London	16.6	19.5	12	4.2	5.3	9	4.4	5.5	14
Windsor	14.6	20.2	9	3.4	5.1	10	3.3	6.4	8
Sudbury –Thunder Bay	13.4	16.0	17	2.8	3.8	17	3.7	3.5	19
Winnipeg	16.5	19.8	11	3.6	4.2	16	4.3	5.6	13
Regina – Saskatoon	16.9	20.0	10	3.7	4.5	13	4.2	5.2	15
Calgary	19.5	24.3	15	4.1	5.6	8	7.4	8.8	3
Edmonton	15.6	18.3	5	3.4	4.4	15	4.8	5.9	12
Vancouver	17.2	25.0	4	4.1	6.1	5	5.2	8.0	4
Victoria	17.7	23.7	6	5.0	7.2	2	5.1	6.1	10

Source: Computation of the author using 2001 and 1991 Canadian Censuses of Population microdata.

Further, table 5 below shows the relative importance of three measures of the aggregate human capital comparing all industries and private sector for the year 2000. It appears clear from this table that if only the private sector is considered, the relative importance of some CMAs in terms of the shares of the aggregate human capital change. In fact, one of the few noticeable differences is observed for Toronto that passes to the first place leaving behind Ottawa-Hull terms of the share of workers with university diploma. Another important difference comparing to the case of all industries is the relatively less important role of the Quebec City comparing to Montreal in contrast with the similarity of these CMAs in terms of the educated human capital shares. These changes confirm the importance of the role of public administration sectors in some provincial capitals such as Quebec, Victoria or Halifax that become relatively less important when only private sector is considered.

However, CMAs of Ottawa-Hull, Toronto, Calgary and Vancouver still remain in first ranges in terms of the importance of the shares of the aggregate human capital there. One of the explanations of this fact could be simply that in these metropolitan areas, the presence of highly educated workers in public sector presents a potential pool of educated workers for private sector so that high-tech private industries are attracted to these cities and increase therefore their shares of the educated human capital in the private sector also.

Table 5
Three human capital measures in 19 Canadian CMAs in 2000: all industries and private sector comparison

CMA	Share of workers with university degree(s), all industries	Share of workers with university degree(s), private sector	Share of workers with postgraduate degree(s), all industries	Share of workers with postgraduate degree(s), private sector	Share of Scientist and Engineers, all industries	Share of Scientist and Engineers, private sector			
Halifax	26.0	20.2	5	7.0	3.3	7	7.5	6.1	5
Québec	22.7	15.1	8	5.8	2.5	10	6.6	4.7	10
Montréal	22.9	18.2	6	5.9	3.7	5	6.8	5.9	6
Sherbrooke - Trois-Rivières	18.0	10.0	16	4.8	1.8	16	4.8	3.0	17
Ottawa-Hull	31.6	23.9	2	9.8	6.0	1	10.4	9.9	1
Oshawa	14.9	9.8	17	2.7	1.3	18	4.0	3.6	16
Toronto	28.4	24.9	1	7.0	5.2	2	9.6	9.1	2
Hamilton	18.8	13.6	10	4.5	2.4	11	6.1	4.8	9
St-Catharines - Niagara	14.0	8.5	18	3.2	1.2	19	3.5	2.5	18
Kitchener	18.6	13.6	11	4.9	2.5	9	6.1	5.5	8
London	19.5	12.6	14	5.3	2.1	12	5.5	3.7	15
Windsor	20.2	14.5	9	5.1	3.2	8	6.4	5.9	7
Sudbury - Thunder Bay	16.0	8.3	19	3.8	1.6	17	3.5	2.3	19
Winnipeg	19.8	13.0	12	4.2	1.8	13	5.6	4.2	13
Regina - Saskatoon	20.0	12.7	13	4.5	1.8	15	5.2	3.8	14
Calgary	24.3	20.5	3	5.6	3.7	4	8.8	8.3	3
Edmonton	18.3	11.9	15	4.4	1.9	14	5.9	4.5	12
Vancouver	25.0	20.4	4	6.1	3.9	3	8.0	7.3	4
Victoria	23.7	15.8	7	7.2	3.5	6	6.1	4.7	11

Source: Computation of the author using 2001 Canadian Census of Population microdata.

Tables 4 and 5 also show that the share of workers with university degree is more variable than the share of workers with postgraduate degrees and share of scientists and engineers, two last measures having very similar values.

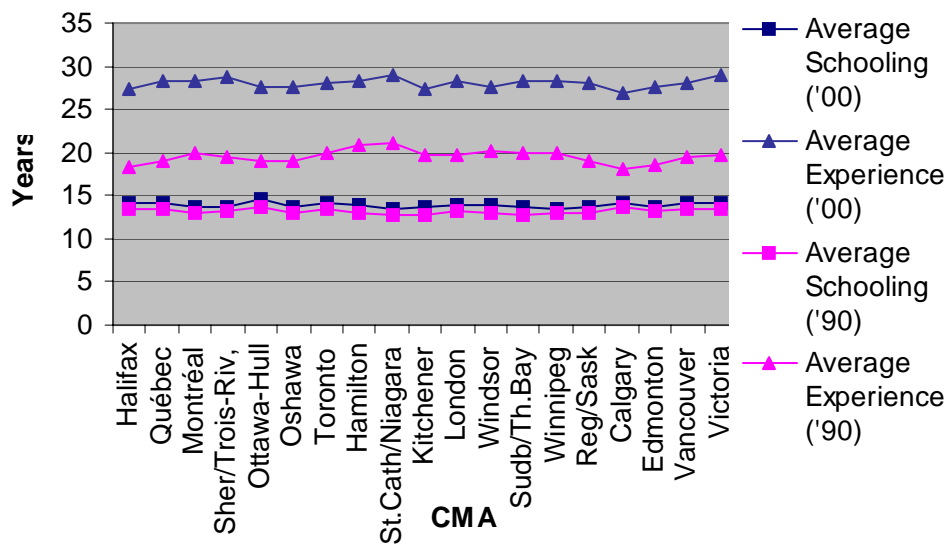
Finally, the distribution of the average education and experience in 19 CMAs can be analyzed from the figure 4. In particular, it confirms already emphasized fact that the

variance of these two measures of human capital is a lot smaller than the variance of the measures shown in tables 4 and 5. In fact, there is no city in which average education and average experience seem to be very different from the other cities. It also shows that there is a very slight increase in the average education between 1990 and 2000 as have been already seen in the table 3. However, there is almost 10 years increase in the average experience indicating that major part of individuals that were working in 1990 was still working in 2000, so that after 10 years period their experience increased by 10 years. The fact that this increase was slightly under 10 years is consistent with the fact that some part of workers with high experience retired and some young new workers with a small number of years of experience entered a labour force.

Also, figure 4 below illustrates the fact that there is negative relationship between average experience and average education. In fact, CMAs with higher average education have lower average experience because when individuals spend more years in school they logically have lower potential working experience and vice versa.

Figure 4

**Average Human Capital in 19 CMAs
Canada (1990 and 2000)**



Source: Computation of the author using 1991 and 2001 Canadian Censuses of Population microdata.

Part 4. Method and Results.

4.1 Samples and method.

As have been already seen in part 2, the equation (1) is estimated with several alternative samples and is based on cross-sectional data for two different years. The main sample is constituted of individuals of 15 years and more of 19 CMAs who had positive labour income in the reference year and weren't attending school full time. The main argument for focusing only on those effectively working is that the aim of the study is to assess the human capital externalities that result from an enhanced productivity of workers who interact with highly educated workers who transmit their knowledge and expertise by different means to the less educated ones. So, the interactions behind possible human capital externalities should mostly happen in a workplace. The model (1) is estimated for each of measure of human capital described in part 1, from the largest one - an average level of schooling, to the narrowest one - the ratio of scientists and engineers in a CMA. Then, this main sample is divided in several sub-samples.

First, the equation (1) with each measure of human capital in the metropolitan areas is estimated for the sub-samples of workers that are not included in this human capital measure. For example when the metropolitan human capital is measured as a ratio of scientists and engineers, then the equation (1) is estimated for the sub-sample of workers who are not defined as scientists and engineers.

Second, the effect of different shares of educated workers on their own labour income is estimated. As it have been already discussed in part 1 and show in figure 1, only the regressions of aggregate human capital on these workers' own labour income would allow to assess the presence of the human capital externalities beyond the supply effect if the total observed effect is positive. This is not done for the regressions with the average education and the average experience that are estimated over the whole sample of workers in 19 CMAs.

Then, the samples described in the paragraphs above are limited to the private sector only. The reasons for such a distinction were discussed in part 3 and the results are compared to those obtained when the estimations are done for all industries.

Finally, these estimations are carried out for two different points in time, 2000 and 1990. In this way, it can be seen if the results are robust through time.

All the specifications of the model (1) are estimated by Ordinary Least Squares (OLS) method with the correction for the bias in the standard errors caused by group structure of aggregate human capital method. The fact that aggregate human capital varies only among metropolitan areas and not individuals biases negatively all estimators' standard errors. So that without correction, standard errors tend to be much smaller, the t-statistic higher and some variables that might not be significant in reality are found significant⁸. Standard errors are therefore corrected for this problem and also for the potential heteroscedasticity problem.

It should be noted that problem of potential bias resulting from omitted variables correlated with the aggregate human capital measure and embedded in the error term is addressed here by an introduction of the variable measuring the university R&D expenditures per worker in a given CMA which is available only for the year 2000. As noted by Rauch (1993), the higher level of human capital in a given CMA might be associated with a higher concentration of the university R&D that potentially has a positive effect on the labour productivity as it was already explained above. So to specifications are estimated for the sample of all industries for the year 2000: with and without total university R&D expenditures. It is important to note that the question of the potential bias resulting from the size of the CMAs measured by their population was also explored. However these results are not shown in the study because this variable presents a potential problem. First, as mentioned by Rauch (1993), the CMA population does not seem to be an exogenous variable with respect to the individual labour income because it is likely that it is higher labour income that attracts individuals to a CMA raising therefore its population. And there are no easily available instrumental variable to deal with this simultaneity problem. Second, including the total R&D university expenditures and a CMA's population would cause a quasi perfect multicollinearity problem because of the strong correlation of these two variables that is more than 0,9. For these two reasons, the population is excluded from the preferred specifications that are presented in this part and in the appendix 2. Moreover, Rauch (1993) didn't find significant results for

⁸ For econometric theory behind this problem and the two-step correction method see pp.387-388 of Rauch (1993). However, the computer estimation tool such as Stata 8 program allows correcting directly standard errors by a simple command "cluster", the also mentioned by Rudd (2000) on the page 9.

population variable even when some instruments were used to correct its potential endogeneity, so the omission of this variable in this study doesn't seem to be a problem.

There could be also a productivity effect resulting from other omitted variables, like for example a shore location of some CMA. However, the small number of CMA identified in the Census microdata as well the poor availability of some other data at CMA level made the use of other omitted variables very difficult or impossible.

Another problem that was addressed by previously reviewed studies is a potential endogeneity of the individual and the average human capital variable indicating that it is not the higher human capital level that causes a higher productivity and labour income, but it is that richer individuals get more educated as education is a normal good. So that a higher labour income in CMAs may be a simple indicator of a higher proportion of rich individuals that in turn causes a higher level of the aggregate human capital because these individuals choose to get more education. This problem should be addressed by an instrumental variables technique impossible to implement due again to the data unavailability as already explained in part 1.8. Nevertheless, one of the measures of human capital proposed here is likely to suffer less from such endogeneity bias. It is the case for the share of scientists and engineers. In fact, retaining only workers educated in some specific fields of studies reduces the causal relationship between higher individual income and higher human capital in a given CMA, when it is measured by the share of scientists and engineers. In fact, even if it might be true that richer individuals acquire more education, there is no reason they would choose to acquire this education only in natural or pure sciences. So, the advantage of using a share of scientists and engineers as a measure of aggregate human capital is to reduce a potential bias of endogeneity of aggregate human capital.

4.2 Results for the year 2000.

4.2.1 Sample of workers of all industries.

Tables 6 and 7 below show the results for the estimation of the equation 1 for the year 2000 and that for four alternative measures of aggregate human capital described above for the sample of all industries. The similar regressions, but for the private sector and for the year 1990 are not completely reported in the main text here for space consideration.

Rather, only the results for the aggregate human capital variables are discussed in the main text, full results reported in the appendix 2.

Columns one, two, three and four report estimations where aggregate human capital is measured by average education and average experience, the share of workers with university degree(s), the share of workers with postgraduate degree(s) and the share of scientists and engineers, all four without the R&D variable and the columns with an “a” index correspond to the same regressions, but where the university R&D variable was included. The estimations in the table 6 were carried out for the labour income of individuals that are excluded from the aggregate human capital measure (except for the average education and experience regressions where all workers are considered as have been already mentioned before). Table 7 reports the results of the same regressions, but only for the labour income of workers for whom the aggregate human capital variable was measured.

Table 6

Regressions with alternative measures of aggregate human capital for the labour income
of workers that **are not included** in the human capital measures

All Industries

Individuals in 19 Canadian CMAs (2000)

Dependent variable	Log (annual labour income) of all workers	Log (annual labour income) of all workers	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers other than scientists and engineers	Log (annual labour income) of workers other than scientists and engineers
Specification	1	1a	2	2a	3	3a	4	4a
Individual independent variables :								
Intercept	4.1329 (3.60)	4.5621 (5.00)	6.2646 (52.35)	6.2857 (49.60)	6.259 (55.80)	6.2655 (56.99)	6.1701 (51.29)	6.1789 (49.62)
Personal characteristics:								
Number of weeks worked	0.0267 (57.83)	0.0267 (58.32)	0.0259 (59.86)	0.0259 (59.59)	0.0266 (61.90)	0.0266 (62.16)	0.0264 (63.02)	0.0264 (62.95)
Part time work (=1 if worked mostly at part time)	-0.729 (-48.60)	-0.7274 (-50.79)	-0.7118 (-49.44)	-0.7112 (-49.53)	-0.7226 (-47.27)	-0.7211 (-50.15)	-0.724 (-49.97)	-0.7236 (-51.86)
Sex (= 1 if Female)	-0.1313 (-11.89)	-0.1314 (-11.94)	-0.1591 (-11.83)	-0.1608 (-11.82)	-0.1348 (-11.69)	-0.1349 (-11.72)	-0.1307 (-10.86)	-0.1306 (-10.87)
Visible Minority (=1 if has visible minority status or native)	-0.1955 (-10.84)	-0.1983 (-10.59)	-0.2033 (-10.08)	-0.2043 (-9.98)	-0.1973 (-10.26)	-0.2004 (-9.94)	-0.2056 (-10.73)	-0.2064 (-10.67)
Marital Status (=1 if married)	0.1934 (16.07)	0.1947 (16.45)	0.1975 (15.70)	0.198 (15.82)	0.1962 (15.32)	0.1976 (15.89)	0.2015 (19.48)	0.2019 (19.70)
Sex * Married	-0.1676 (-12.20)	-0.1678 (-12.20)	-0.1736 (-10.87)	-0.1735 (-10.81)	-0.171 (-11.71)	-0.1709 (-11.63)	-0.1752 (-14.70)	-0.1751 (-14.63)
English bilingual ⁹ (=1 if English is a mother tongue and is bilingual)	-0.0082 (-0.44)	-0.0171 (-0.76)	-0.0282 (-1.14)	-0.0335 (-1.37)	-0.0189 (-0.75)	-0.0275 (-0.96)	-0.0133 (-0.62)	-0.0174 (-0.85)
French unilingual (=1 if French is a mother tongue and speaks only French)	-0.1777 (-4.29)	-0.1966 (-5.44)	-0.1781 (-6.66)	-0.1923 (-6.19)	-0.1834 (-5.89)	-0.2066 (-6.98)	-0.1666 (-6.74)	-0.1782 (-5.63)
French bilingual (=1 if French is a mother tongue and is bilingual)	-0.0513 (-2.39)	-0.0708 (-3.85)	-0.0777 (-5.19)	-0.0904 (-6.81)	-0.0704 (-3.35)	-0.0916 (-4.79)	-0.0583 (-4.22)	-0.0687 (-3.95)
Allophone English (=1 if mother tongue other than English and French and speaks English)	-0.0655 (-5.50)	-0.0684 (-5.75)	-0.0395 (-4.81)	-0.0408 (-5.16)	-0.0531 (-4.68)	-0.0564 (-4.91)	-0.0498 (-4.94)	-0.0508 (-5.06)
Allophone French (=1 if mother tongue other than English and French and speaks French)	-0.3573 (-14.99)	-0.3829 (-16.12)	-0.3618 (-14.92)	-0.3793 (-12.76)	-0.3689 (-18.51)	-0.3971 (-19.68)	-0.3447 (-12.19)	-0.3588 (-10.16)
Allophone bilingual (=1 if mother tongue other than English and French and speaks both)	-0.1051 (-4.43)	-0.1247 (-5.33)	-0.1618 (-6.86)	-0.1759 (-13.92)	-0.1379 (-4.61)	-0.1598 (-6.06)	-0.1271 (-4.70)	-0.1375 (-7.36)
Allophone (=1 if mother tongue other than English and French and doesn't speaks any of these languages)	-0.1979 (-6.73)	-0.2015 (-6.73)	-0.1974 (-7.70)	-0.1989 (-7.59)	-0.1902 (-6.44)	-0.1945 (-6.28)	-0.1809 (-6.46)	-0.1821 (-6.35)
English-French (=1 if English and French are both mother tongues)	-0.1347 (-3.90)	-0.1459 (-4.64)	-0.1306 (-3.32)	-0.1374 (-3.62)	-0.1407 (-4.04)	-0.1515 (-4.67)	-0.1246 (-4.10)	-0.1302 (-4.25)
Immigration Status (=1 if has a status of permanent resident or non permanent resident)	-0.0483 (-4.62)	-0.0534 (-5.64)	-0.0253 (-2.00)	-0.0279 (-2.76)	-0.0383 (-3.49)	-0.0443 (-5.10)	-0.0469 (-3.97)	-0.0486 (-4.74)
Experience	0.0487 (19.28)	0.0487 (19.39)	0.0491 (18.40)	0.0491 (18.35)	0.0481 (19.31)	0.0482 (19.38)	0.0486 (20.51)	0.0486 (20.46)
Square experience	-0.0007 (-15.78)	-0.0007 (-15.88)	-0.0007 (-15.16)	-0.0007 (-15.13)	-0.0007 (-15.75)	-0.0007 (-15.84)	-0.0007 (-16.98)	-0.0007 (-16.94)
Industry dummies¹⁰								
Primary industries other than agriculture	2.4041 (20.88)	2.4059 (20.59)	2.2864 (20.88)	2.2882 (20.73)	2.4017 (20.99)	2.4055 (20.44)	2.398 (20.84)	2.4003 (20.81)
Manufacturing	2.1216 (18.35)	2.1165 (18.44)	2.0079 (18.85)	2.0054 (18.77)	2.1164 (18.05)	2.1109 (18.10)	2.122 (18.70)	2.1202 (18.62)
Construction	2.0924 (16.17)	2.0884 (16.19)	1.993 (16.36)	1.9919 (16.30)	2.0931 (16.10)	2.0895 (16.06)	2.0983 (16.51)	2.0977 (16.47)

⁹ English unilingual (=1 if English is mother tongue and speaks only English) is a omitted category

¹⁰ Agriculture being an omitted category

Transportation/Storage	2.1163 (17.55)	2.1118 (17.55)	2.0159 (17.61)	2.0142 (17.53)	2.1159 (17.36)	2.1112 (17.29)	2.1266 (17.91)	2.1255 (17.83)
Communications	2.2211 (18.19)	2.2165 (18.21)	2.1044 (18.48)	2.1029 (18.38)	2.2171 (18.04)	2.2125 (18.00)	2.2249 (18.51)	2.2238 (18.43)
Wholesale and retail trade	1.9628 (15.99)	1.9584 (16.02)	1.8643 (16.69)	1.8625 (16.61)	1.9634 (15.99)	1.9588 (15.96)	1.97 (16.44)	1.9688 (16.36)
Finance/Insurance/Real estate	2.1867 (17.69)	2.1818 (17.74)	2.0782 (19.13)	2.0766 (19.04)	2.1846 (17.75)	2.1796 (17.76)	2.2 (18.46)	2.1987 (18.38)
Business Management Services	2.0603 (16.37)	2.0553 (16.41)	1.928 (16.28)	1.9263 (16.23)	2.0598 (16.21)	2.0549 (16.21)	2.0597 (16.66)	2.0586 (16.61)
Federal Administration Services	2.1738 (20.45)	2.1844 (20.08)	2.1257 (20.65)	2.135 (20.53)	2.192 (20.15)	2.2086 (19.96)	2.2059 (20.41)	2.2127 (20.46)
Other Government Services	2.1859 (17.71)	2.1856 (17.68)	2.1084 (18.08)	2.1082 (18.04)	2.192 (17.44)	2.191 (17.42)	2.2104 (18.06)	2.2102 (18.02)
Education & Related Services	2.0034 (17.80)	2.002 (17.84)	1.8561 (17.34)	1.8555 (17.31)	1.9877 (17.24)	1.9862 (17.25)	2.0245 (18.22)	2.0244 (18.20)
Accommodation/ Food services	1.7835 (14.86)	1.7824 (14.87)	1.703 (15.17)	1.7029 (15.16)	1.7849 (14.82)	1.7838 (14.82)	1.7998 (15.11)	1.7997 (15.10)
Health and Welfare Services	2.0177 (17.28)	2.0163 (17.29)	1.9054 (17.51)	1.9049 (17.48)	2.0066 (17.18)	2.0053 (17.17)	2.0232 (17.64)	2.0229 (17.61)
Other Services	1.8071 (14.14)	1.8037 (14.18)	1.7209 (14.68)	1.7198 (14.65)	1.8123 (14.13)	1.8089 (14.14)	1.8205 (14.61)	1.8198 (14.58)
Occupational Category dummies¹¹:								
Professional or technical staff	0.011 (0.51)	0.0116 (0.55)	0.0519 (2.24)	0.0521 (2.25)	0.0232 (1.01)	0.0238 (1.05)	0.0023 (0.10)	0.0025 (0.11)
Supervisor	0.0735 (1.66)	0.0739 (1.68)	0.1281 (3.17)	0.1279 (3.17)	0.0857 (1.97)	0.0861 (1.99)	0.0791 (1.75)	0.0791 (1.75)
Administration and Office staff	-0.1743 (-6.38)	-0.1744 (-6.40)	-0.0922 (-3.82)	-0.0925 (-3.82)	-0.1566 (-5.81)	-0.1568 (-5.83)	-0.165 (-6.05)	-0.1652 (-6.05)
Sale and Services staff	-0.2558 (-9.53)	-0.2544 (-9.69)	-0.2022 (-8.31)	-0.2019 (-8.40)	-0.2416 (-9.23)	-0.2402 (-9.49)	-0.2478 (-9.81)	-0.2474 (-9.88)
Manual or Artisan workers	-0.2033 (-5.88)	-0.2011 (-5.92)	-0.1439 (-4.51)	-0.1435 (-4.52)	-0.1913 (-5.56)	-0.1893 (-5.63)	-0.1884 (-5.53)	-0.1879 (-5.54)
Individual Education level dummies¹²:								
Less than high-school	-0.1146 (-17.89)	-0.1148 (-18.11)	-0.132 (-20.03)	-0.1319 (-20.29)	-0.12 (-19.40)	-0.1199 (-19.82)	-0.1207 (-19.77)	-0.1206 (-19.94)
Trades certificate/diploma	0.0525 (7.01)	0.054 (7.86)	0.0476 (6.82)	0.0483 (7.27)	0.0507 (6.83)	0.0524 (7.79)	0.0524 (7.97)	0.0529 (8.21)
College (cegep) certificate/diploma	0.1229 (11.92)	0.1235 (12.11)	0.1371 (13.27)	0.1375 (13.55)	0.1267 (12.23)	0.1273 (12.48)	0.1294 (12.89)	0.1296 (13.15)
University < bachelor level	0.1456 (6.88)	0.1449 (6.83)	0.1575 (6.88)	0.1573 (6.84)	0.1486 (6.98)	0.1478 (6.85)	0.1498 (7.11)	0.1495 (7.02)
Bachelor degree(s)	0.2954 (14.54)	0.2949 (14.37)	-----	-----	0.3026 (15.01)	0.3023 (14.74)	0.2846 (17.27)	0.2846 (17.17)
University > bachelor level	0.3173 (22.68)	0.3161 (22.49)	-----	-----	0.3277 (25.80)	0.3263 (25.53)	0.3449 (33.99)	0.3445 (34.81)
Medicine/Dentist/vet/Optomety	0.8355 (14.40)	0.8347 (14.21)	-----	-----	-----	-----	0.2569 (2.56)	0.2561 (2.58)
Master degree(s)	0.3634 (13.41)	0.3633 (13.41)	-----	-----	-----	-----	0.3598 (19.08)	0.3599 (19.17)
Earned Doctorate	0.4269 (8.53)	0.4301 (8.82)	-----	-----	-----	-----	0.4279 (11.10)	0.4294 (11.47)
CMA human capital measure:								
Average Education	0.1427 (2.60)	0.1249 (2.83)	-----	-----	-----	-----	-----	-----
Average Experience	0.0081 (0.34)	0.0009 (0.04)	-----	-----	-----	-----	-----	-----
Share of workers with university degree	-----	-----	0.0069 (2.16)	0.0054 (1.51)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	-----	-----	0.0152 (1.38)	0.0098 (1.24)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	-----	-----	0.0231 (3.08)	0.0205 (2.36)
CMA level control variable								
University R&D expenditures per worker	-----	1.18x10 ⁻⁷ (1.67)	-----	7.64x10 ⁻⁸ (0.72)	-----	1.37x10 ⁻⁷ (1.35)	-----	5.59x10 ⁻⁸ (0.59)
N	249207	249207	189551	189551	234226	234226	230340	230340
R ²	0.40	0.40	0.37	0.37	0.39	0.39	0.39	0.39

T-statistics in the brackets

Source: author's estimations using the 2001 Census of Population microdata and STATA program

¹¹ Higher administration staff is an omitted category

¹² High school diploma is an omitted category

Table 7

Regressions with alternative measures of aggregate human capital for the labour income
of workers that **are included** in the human capital measures

All Industries

Individuals in 19 Canadian CMAs (2000)

Dependent variable	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of scientists and engineers	Log (annual labour income) of scientists and engineers
Specification	2	2a	3	3a	4	4a
Individual independent variables :						
Intercept	6.1423 (32.65)	6.1572 (33.37)	6.0769 (41.41)	7.0767 (40.64)	6.652 (46.03)	6.6419 (46.38)
Personal characteristics:						
Number of weeks worked	0.0296 (28.39)	0.0296 (28.44)	0.0273 (15.48)	0.0273 (15.50)	0.0297 (19.91)	0.0297 (19.80)
Part time work (=1 if worked mostly at part time)	-0.7571 (-35.25)	-0.7565 (-36.04)	-0.8277 (-28.58)	-0.8277 (-28.62)	-0.7574 (-24.43)	-0.7069 (-46.77)
Sex (= 1 if Female)	-0.0636 (-6.56)	-0.0636 (-6.59)	-0.0835 (-3.09)	-0.0835 (-3.10)	-0.0948 (-2.86)	-0.0943 (-2.86)
Visible Minority (=1 if has visible minority status or native)	-0.1382 (-9.45)	-0.1389 (-9.52)	-0.1176 (-5.14)	-0.1176 (-5.09)	-0.0965 (-5.55)	-0.0954 (-5.37)
Marital Status (=1 if married)	0.1815 (14.19)	0.1821 (14.29)	0.1583 (8.16)	0.1583 (8.17)	0.1202 (5.12)	0.1197 (5.11)
Sex * Married	-0.1617 (-8.73)	-0.1619 (-8.71)	-0.1361 (-5.12)	-0.1361 (-5.10)	-0.1196 (-2.73)	-0.12 (-2.74)
English bilingual ¹³ (=1 if English is a mother tongue and is bilingual)	-0.0118 (-0.84)	-0.0149 (-1.03)	-0.0032 (-0.17)	-0.0033 (-0.17)	-0.0056 (-0.32)	-0.0008 (-0.04)
French unilingual (=1 if French is a mother tongue and speaks only French)	-0.1884 (-8.86)	-0.1985 (-8.67)	-0.3006 (-8.74)	-0.3007 (-7.88)	-0.175 (-3.61)	-0.1611 (-2.76)
French bilingual (=1 if French is a mother tongue and is bilingual)	-0.0343 (-1.50)	-0.0448 (-1.80)	-0.0317 (-1.00)	-0.0319 (-0.87)	-0.005 (-0.17)	0.0107 (0.29)
Allophone English (=1 if mother tongue other than English and French and speaks English)	-0.1524 (-6.84)	-0.1535 (-6.88)	-0.2076 (-7.69)	-0.2076 (-7.52)	-0.2342 (-8.19)	-0.2328 (-8.07)
Allophone French (=1 if mother tongue other than English and French and speaks French)	-0.4935 (-9.37)	-0.5071 (-11.02)	-0.8783 (-18.28)	-0.8786 (-18.03)	-0.6102 (-4.68)	-0.5907 (-4.68)
Allophone bilingual (=1 if mother tongue other than English and French and speaks both)	-0.0626 (-2.10)	-0.0707 (-2.58)	-0.0413 (-1.28)	-0.0415 (-1.31)	-0.0774 (-2.48)	-0.0655 (-2.09)
Allophone (=1 if mother tongue other than English and French and doesn't speak any of these languages)	-0.3927 (-3.54)	-0.3928 (-3.55)	-0.4371 (-2.26)	-0.4372 (-2.25)	-0.8125 (-4.13)	-0.8125 (-4.14)
English-French (=1 if English and French are both mother tongues)	-0.1976 (-2.89)	-0.2029 (-3.03)	-0.1607 (-1.73)	-0.1609 (-1.78)	-0.2897 (-1.35)	-0.2768 (-1.33)
Immigration Status (=1 if has a status of permanent resident or non permanent resident)	-0.109 (-7.70)	-0.1103 (-7.93)	-0.0943 (-4.21)	-0.0944 (-4.07)	-0.0986 (-4.86)	-0.0963 (-5.06)
Experience	0.0548 (29.78)	0.0548 (29.80)	0.0618 (11.50)	0.0618 (11.57)	0.0548 (7.72)	0.0549 (7.73)
Square experience	-0.0009 (-23.85)	-0.0009 (-23.85)	-0.0009 (-11.42)	-0.0009 (-11.48)	-0.0008 (-6.81)	-0.0008 (-6.82)
Industry dummies¹⁴						
Primary industries other than agriculture	2.8095 (18.18)	2.8129 (18.18)	2.3632 (13.84)	2.3633 (13.79)	2.1768 (11.12)	2.1703 (11.19)
Manufacturing	2.5433 (19.81)	2.5409 (19.65)	2.1014 (15.55)	2.1014 (15.61)	1.9324 (11.33)	1.9348 (11.32)
Construction	2.3345 (18.80)	2.3328 (18.69)	1.8801 (10.26)	1.8801 (10.32)	1.7361 (8.76)	1.7389 (8.77)
Transportation/Storage	2.4542 (18.71)	2.4529 (18.59)	2.0947 (14.24)	2.0947 (14.26)	1.7633 (8.24)	1.7651 (8.25)
Communications	2.6151	2.6128	2.2245	2.2244	2.0193	2.0223

¹³ English unilingual (=1 if English is mother tongue and speaks only English) is a omitted category

¹⁴ Agriculture being an omitted category

	(19.62)	(19.49)	(14.62)	(14.73)	(11.39)	(11.41)
Wholesale and retail trade	2.3335 (15.88)	2.3311 (15.78)	1.8666 (10.81)	1.8665 (10.89)	1.7591 (9.33)	1.762 (9.33)
Finance/Insurance/Real estate	2.5599 (17.60)	2.5574 (17.48)	2.1478 (13.13)	2.1477 (13.28)	1.8992 (9.31)	1.9029 (9.31)
Business Management Services	2.4708 (18.71)	2.4694 (18.62)	1.9927 (13.89)	1.9927 (13.95)	1.8438 (10.05)	1.8453 (10.05)
Federal Administration Services	2.4485 (20.25)	2.4572 (20.72)	1.9681 (15.10)	1.9682 (14.83)	1.7942 (10.50)	1.7845 (10.58)
Other Government Services	2.4839 (18.76)	2.4841 (18.74)	2.0125 (13.95)	2.0125 (13.93)	1.8051 (9.72)	1.8049 (9.67)
Education & Related Services	2.3766 (19.41)	2.3764 (19.39)	1.9534 (14.25)	1.9534 (14.23)	1.7018 (9.92)	1.7026 (9.90)
Accommodation/ Food services	2.0216 (15.47)	2.0208 (15.42)	1.5643 (8.41)	1.5643 (8.45)	1.3327 (8.20)	1.3349 (8.18)
Health and Welfare Services	2.4034 (18.79)	2.4029 (18.76)	2.0065 (14.14)	2.0064 (14.16)	1.8184 (9.99)	1.8199 (9.98)
Other Services	2.1179 (14.64)	2.1164 (14.59)	1.5948 (10.14)	1.5948 (10.16)	1.4952 (8.53)	1.4978 (8.53)
Occupational Category dummies¹⁵:						
Professional or technical staff	0.079 (-6.47)	-0.0787 (-6.42)	-0.0938 (-8.48)	-0.0938 (-8.47)	-0.0072 (-0.50)	-0.007 (-0.49)
Supervisor	0.0913 (-1.71)	-0.0913 (-1.71)	-0.1513 (-1.38)	-0.1513 (-1.38)	-0.0167 (0.41)	0.0171 (0.41)
Administration and Office staff	-0.3752 (-17.01)	-0.3751 (-16.96)	-0.4584 (-13.55)	-0.4584 (-13.55)	-0.3592 (-9.44)	-0.3585 (-9.52)
Sale and Services staff	-0.3641 (-11.51)	-0.3634 (-11.44)	-0.6183 (-11.19)	-0.6183 (-11.19)	-0.4157 (-9.67)	-0.4157 (-9.69)
Manual or Artisan workers	-0.5514 (-15.60)	-0.5508 (-15.59)	-0.6786 (-10.93)	-0.6786 (-10.95)	-0.5455 (-9.68)	-0.5449 (-9.77)
Individual Education level dummies¹⁶:						
Less than high-school	-----	-----	-----	-----	-----	-----
Trades certificate/diploma	-----	-----	-----	-----	-----	-----
College (cegep) certificate/diploma	-----	-----	-----	-----	-----	-----
University < bachelor level	-----	-----	-----	-----	-----	-----
Bachelor degree(s)	-0.1738 (-5.10)	-0.1749 (-5.26)	-----	-----	0.0592 (1.83)	0.0585 (1.80)
University > bachelor level	-0.1459 (-3.23)	-0.1477 (-3.38)	-----	-----	Omitted Category	Omitted Category
Medicine/Dentist/vet/Optometry	0.4038 (13.97)	0.4023 (13.80)	Omitted Category	Omitted Category	0.5411 (8.66)	0.5403 (8.63)
Master degree(s)	-0.1035 (-3.32)	-0.1046 (-3.45)	-0.14541 (-10.92)	-0.4541 (-10.92)	0.123 (3.51)	0.1219 (3.50)
Earned Doctorate	Omitted Category	Omitted Category	-0.3796 (-13.55)	-0.3795 (-13.71)	0.1813 (2.92)	0.1789 (2.91)
CMA human capital measure:						
Average Education	-----	-----	-----	-----	-----	-----
Average Experience	-----	-----	-----	-----	-----	-----
Share of workers with university degree	0.01 (3.49)	0.0089 (3.09)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	0.0241 (3.62)	0.0241 (3.85)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	0.0205 (3.45)	0.0238 (4.61)
CMA level control variable						
University R&D expenditures per worker	-----	6.27x10 ⁻⁸ (0.76)	-----	1.28x10 ⁻⁹ (0.02)	-----	-8.22x10 ⁻⁸ (-1.40)
N	59656	59656	14981	14981	18867	18867
R ²	0.42	0.42	0.38	0.38	0.40	0.40

T-statistics in the brackets

Source: author's estimations using the 2001 Census of Population microdata and STATA program

¹⁵ Higher administration staff is an omitted category

¹⁶ High school diploma is an omitted category

Since the dependent variable is the log of the annual labour income, the coefficients reported in the result tables are expressed in the log-points. However, for the interpretation purpose, they are converted into the percentage by the following formula:

$$\text{The percentage} = (e^{\beta} - 1) \times 100$$

where $e = 2,71828$ and β is the estimated coefficient.

The first control variable necessary to include in all regressions is the number of weeks worked since the log of the labour income is reported for the year. This variable is strongly significant at more than 99.9% of confidence. The coefficient of the variable remains almost unchanged in different specifications of the table 2, indicating that an additional week of work in a year increases individual labour income by 2.6% to 2.9%. These results are reasonable, because one week of work represents 2.2% of the average number of weeks worked that is 46 weeks in the year.

Another variable that is strongly correlated with annual labour income is the binary variable indicating that individual worked mostly at part time. As it should be anticipated, this variable is significant in all specifications and has a negative coefficient ranging from -0.71 to -0.83. This indicates that otherwise identical workers would have the annual labour income from 103% to 129% inferior to the income of full time workers.

Next set of variables consists in individual characteristics, from the attributed characteristics, such as sex or visible minority status, to characteristics that are acquired by individual with time, such as individual education, potential work experience, etc.

The dummy variable taking a value of 1 when the individual is a female is significant in all specifications and has the negative coefficient indicating that women have an annual labour income inferior to men by 6% to 14%. The visible minority dummy variable, that takes a unit value when the worker can be identified as belonging to a visible minority or to native people, is also significant over all specifications of the table 3 and shows that individuals belonging to visible minorities receive from 9,9% to 22,9% less of labour income than similar workers not belonging to visible minority. The largest differences are observed in the samples with the less educated workers (column 2, 3 and 4).

The next variable explaining annual individual labour income is a marital status dummy variable taking a unit value when the worker is married. This variable is significant and has positive coefficient ranging from 0,11 to 0,20, showing that married workers has higher labour income then other workers, the smaller effect found for more educated workers. The positive effect of being married might be explained by a fact that married people have more expenses to cover and tend to accept less easily jobs that pay less and chose more constant and more lucrative jobs. However, when the marital status variable is interacted with a sex variable, the coefficient becomes negative, showing that for women the fact of being married affects negatively their annual labour income that could be reduced by 13% to 19% comparing to unmarried women. One of the reasons may be a tendency by married women to have children so they have to interrupt their carrier and when they come back to the labour market, they often have to restart their carrier from the lower positions with lower pay-off. It is also possible that even if a woman effectively doesn't have plans to have children, the fact that she is married make provide a signal to employers that she does plan to have children, so that employers may be less likely to provide more long lasting and more constant jobs to marred women then to unmarried ones.

Next set of variables concerns mother tongue as well as official languages spoken by the workers. There are 9 possible combinations that correspond each to a dummy variable. The four possibilities for the mother tongue is English, French, French and English without difference and other language and four possible combinations for official languages spoken is only English, only French, bilingual and no official languages spoken. The omitted variable is the dummy variable that takes a unit value when individual's mother is English and individual doesn't speak French. All these variables are significant in all specifications except for the dummy for individuals whose mother tongue is English and who are bilingual, meaning that the labour income of English speaking workers that also speak French is not significantly different from the income of those who speak English only. All other language dummies are significant and their coefficients are negative, indicating that if workers don't speak English by birth, even if they learn it during their live and speak it however, their labour income will be still inferior to otherwise similar but English speaking by birth workers.

The differences in the labour income are very high for the allophone workers that don't speak any of the official languages ranging from the 20% to 125% difference with English speaking workers, the lowest difference observed for the workers other than scientists and engineers and the highest difference observed for scientist and engineers. This is very reasonable result since scientist and engineers by education, but who don't speak English neither French are very likely to occupy other than scientists and engineers jobs in Canada so that comparing to scientists and engineers that speak English they have much lower labour income.

The smallest difference with the income of only English speaking workers is found for workers who are French by birth, but who are bilingual the difference being from 1% to 9% only. The results seem reasonable because language is an important asset in the labour market and it is evident that workers that don't speak any of the official languages should have sensibly lower labour income because they probably occupy jobs demanding low skills and consequently paying lower wages.

It is also reasonable that bilingual, but French by birth workers have slightly inferior labour income than workers whose mother tongue is English, because when English is learned as second language its quality may be affected, so that individuals who speak English by birth are still more "valuable" on the job market.

Finally, for all dummy variables that indicate that French is a mother tongue of the worker, the negative effect of these variable on the annual labour of income comparing to the English speaking individuals could be explained in terms of the strong correlation between the fact to be French and the residence in Quebec. In other words, this variable may be a proxy for the fact that the worker lives in the Province of Quebec. In fact, 97% of the workers that speak French only resided in the CMAs of the province of Quebec and 75% of workers who mother tongue is French but who are bilingual resided in Quebec CMAs. And Quebec, is one of the provinces in which wages are relatively lower comparing to such provinces as Ontario and British Columbia.

Another explanatory variable is a dummy variable taking a unit value if the worker is not Canadian by birth, but by naturalization or if the worker is non-permanent resident in Canada. The effect of being an immigrant have a negative effect on the labour income

reducing it from 2% to 11% comparing to labour income to otherwise similar workers but Canadian by birth. This is the reasonable result because immigrants are less likely to have interpersonal relationships and networks with potential employers than Canadian by birth. They also have less knowledge of the Canadian methods and tools of work and also can't practice some highly paying professions as doctors or engineers without accessing to Canadian professional Corporations. All this is likely to have a negative effect on the labour productivity of immigrants comparing to workers born in Canada.

Another explanatory variable is potential worker's experience measured as worker's age minus his years of education minus six. It should be noted that since this variable is based on the worker's age, the age variable is not included in the regression to avoid an almost perfect multicollinearity problem among these two variables. The experience variable is, as was expected, strongly significant in all specifications of the table 2 and its coefficient is positive showing that an additional year of potential work experience increases labour income from 4,9% to 5,7%. A square of the experience is also included in the regressions to control for the expected fact that the positive return to experience should decrease with the level of experience, having a high marginal return for the low levels of experience and having very low marginal returns when the potential work experience is high. This expectation is confirmed by a negative sign of coefficient of this variable that is statistically significant in all specifications.

Then there is a set of industry and occupational dummies that are equal to unit for each industry and profession that correspond to the main worker's job in the reference year. In the case of industry dummies, an omitted category is an agricultural industry. As it should be expected, all the coefficients of the industry dummy variables, that are all significant, have a positive sign indicating that comparing to the agricultural industry, workers in all other industries have higher labour incomes. For almost all industries, labour income is at least twice as high as for workers in the agriculture. The only industries in which the annual labour income is less than twice as high as in farming are wholesale and retail trade, accommodation and food services industry and "other services" industry.

In the case of the occupational dummies, the omitted category is Senior, middle and other managers. The statistical significance of these dummies as well as the value and sign of their coefficients are however highly variable depending on the sample of workers

considered. The dummy for the occupational category of professionals and technical staff is statistically significant only for the sample of workers with the university degree, for the sample of workers without university degree and a sample of workers without postgraduate university degree. The effect for the first sample is positive, showing that workers with university degree that occupy professional or technical staff category have by 5 % higher labour income than otherwise similar workers working as managers. However, for workers without university degrees, the professional or technical occupation reduces income by 8 % and 9% comparing to manager position.

Supervisor position seem to have a statistically significant positive effect on a labour income comparing to managerial occupational category for the sample of all workers and for the samples of educated workers (with university degree, with postgraduate degree and for scientists and engineers) the respective results ranging from 7% to 14% increase in labour income. However, for the workers without university degree the labour income of supervisor position is by 9% lower than the labour income of managers without university degree. For all other samples, the results are not significant for this occupational dummy variable.

Finally, for the three other occupational dummies, administration and office staff, sale and service staff and well as manual or artisan workers, the results are statistically significant for all samples of the table 2 and are all with a negative sign. In general, workers with one of these occupations have from 9% to 97% lower labour income than manager. The smallest difference with managerial occupation of 9 % is observed for administration and office staff with university degree and the biggest difference of 97% is observed for manual and artisan workers without postgraduate degree.

The final individually measured set of variables concerns individual education. As it was already argued earlier and as it was seen from the figure 2, the returns to education are not linear in the years of education, so that better measure of the individual education is a set of dummy variables for each level of education completed. The omitted category for the general sample of workers is a dummy variable that takes a unit value for the individuals that have only a high school certificate. The coefficients of these variables have an expected sign for all of these dummy variables and all samples of the table 2, all results without exception being statistically significant. However, the returns to different

levels of education inferior to bachelor degree are relatively stable for the different samples of workers. Workers with less than high school certificate have from 12% to 13% inferior labour income than high-school graduates, labour income of the workers with trade certificate or diploma is approximately 5% higher than the labour income of the reference category, the income of college or cegep graduates is from 13% to 15% and the income of university graduates with certificates inferior to bachelor level have approximately 15% higher labour income.

However for the bachelor and higher degrees, the results are not directly comparable because the omitted category varies from one sample to the other depending. For example a bachelor degree procures by around 35% higher incomes comparing to the labour income of the high-school graduates. It also procures by 19 % lower income than income of the doctorate graduates for the sample of workers with any university degree and also by 6% higher incomes than incomes of workers with university certificate superior to bachelor degree for the sample of workers not considered as scientists and engineers.

The same analysis could be conducted for each level of studies and for each sample of workers, but for space reasons they are not detailed here. In general, it could be noted that higher returns are associated to Medicine or similar diplomas ranging from 30% to 129% higher labour income than for high school certificate, followed by the returns to the earned PhD that are in the range of 54% higher incomes than returns to high school certificate.

Finally, the variables measuring the aggregate human capital, that represent the main focus of this study, are analyzed. However, first it is important to remind that another variable at the aggregate CMA level that was added to the regressions to control for the omitted variables bias as already discussed above is the total university R&D expenditures. It can be seen although this variable is not statistically significant except for the estimation where aggregate human capital is measured as an average schooling and average experience (Table 6, column 1a), this variable has a positive sign almost in all specifications as it was anticipated. These findings are consistent with findings of Rauch(1993) who also found the positive, but statistically insignificant effect of this variable. Still, the consideration of this variable remains important because its inclusion reduces t-statistics and the coefficients of the aggregate human capital variables, so that it

is better to include it in the estimations to make sure that the aggregate human capital doesn't capture the R&D effect on the labour productivity, even if this effect is weak. So that the estimations for the private sector reported in the next section all include the university R&D variable.

Focusing on the aggregate human capital variables themselves, the results depend on the definition of the aggregate human capital and the sample considered. The most general specification of the human CMA level human capital measured by an average education (significant with and without inclusion of the R&D variable) and an average experience (statistically insignificant), indicates that an increase of the average education by a year would increase individual labour productivity from 13% to 15 % when all workers are considered. However, it is important to keep in mind that this increase does not necessary represent a human capital externality, but results from its combination with a supply effect that is negative for educated workers but positive for uneducated ones.

The more restricted measure of the aggregate human capital, measured by the share of workers with university degree(s) is significant in all specifications at 10% or more in "other workers" sample and at more than 1% in "workers with the university degree(s)" sample. The values of the coefficients on this variable indicate that an increase of the 1% of this share increases the labour productivity of other workers by approximately 0,6% and their own labour productivity by 1%. The fact, that the effect of the workers with the university degree on their own labour income is positive indicates that the externality effect is positive and higher in absolute value than the negative supply effect. Moreover, the lower coefficient for the sample of workers that are not included in the human capital measure shows that if there is an externality effect affecting them as well, this effect is weaker than the human capital externality effect for the sample of the workers with university degree.

The CMA human capital measured by a share of workers with postgraduate degrees has stronger effect on the labour productivity, but is less statistically significant for the sample of workers not included in this measure. In fact, for this sample, it is significant only at 10% and that, considering a one-tailed test. The coefficient indicates a result from 1% to 1,5% increase in the labour productivity of other workers, when the share of workers with postgraduate degrees increase by 1%. The effect of the 1% increase of this

aggregate human capital variable is stronger and more significant on these workers own labour income resulting in 2.4% increase with more the 1% significance level. The same reasoning as for the previous aggregate human capital variable permits to assess the presence of the human capital externality that is stronger for more educated workers than for less educated ones.

Finally, the aggregate human capital measured as a share of the scientists and engineers in a CMA produces statistically significant results at more than 1% level and point out that a 1% increase in the share of scientists and engineers increases the labour productivity of other workers and their own labour productivity by approximately 2%. Again, the positive sign of the coefficient in the sample of scientists and engineers themselves supports a presence of human capital externalities, but contrary to two previous aggregate human capital measures, the effect is similar for both samples of workers.

In summary, the choice of all variables in the regressions reported in the tables 6 and 7 seem reasonable, majority of the variables being statistically significant and having an expected sign. Moreover, the R^2 in the regressions are also relatively high, ranging from 0.37 to 0.42, considering the fact that data used in regressions are cross-sectional data.

Next sections report and analyze results similar to those in the tables 6 and 7 above, but for three other samples: private sector for 2000, all industries sample for 1990 and private sector for 1990. However, the full results are not reported in the main text for the space issues, only the results on the aggregate human capital variables being presented. The full results are also not reported for the reasons of the strong similarity of the results on the individual variables in the table 6 and 7 with these results in other samples. The complete results for the regressions may be found in the tables A2.1, A2.2 and A2.3 in the appendix 2.

4.2.2 Sample of workers from the private sector only.

The table 4 below illustrates the results for aggregate human capital variables from estimating the equation (1) for the sample of workers only from the private sector for the year 2000.

Table 8

Results for the four alternative measures of the aggregate human capital in the regressions
 explaining the labour income of workers
 Private sector
 Individuals in 19 Canadian CMAs (2000)

T-statistics in the brackets

Dependent variable	Log (annual labour income) of all workers	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of workers other than scientists and engineers	Log (annual labour income) of scientists and engineers
Specification	1	2	2a	3	3a	4	4a
CMA human capital measure:							
Average Education	0.1716 (4.00)	-----	-----	-----	-----	-----	-----
Average Experience	0.0292 (1.39)	-----	-----	-----	-----	-----	-----
Share of workers with university degree	-----	0.0074 (1.94)	0.014 (4.26)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	-----	0.0295 (1.99)	0.0694 (6.26)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	-----	0.021 (2.43)	0.0331 (5.78)
CMA level control variable							
University R&D expenditures	5.88×10^{-8} (0.86)	3.36×10^{-8} (0.28)	1.48×10^{-8} (0.15)	5.78×10^{-8} (0.48)	1.28×10^{-7} (-1.63)	7.35×10^{-8} (0.70)	7.14×10^{-8} (-0.90)

Source: author's estimations using the 2001 Census of Population microdata and STATA program. Full results are reported in table A.2.1 in the Appendix 2.

The results from the table 8 are very similar to the results obtained for all industries. One of the differences is the higher significance level for all aggregate human capital variables, all being now significant at more than 5% level except for the average experience that remains insignificant. Moreover, all coefficients are slightly higher when the analysis is restricted to only private sector. In fact, a year increase in the average education now has an effect of 18.7% increase in the labour productivity. As for more specific measures of the aggregate human capital, 1% in the share of workers with university degree increases other workers labour productivity by 0.7% and their own labour productivity by 1.4%. The increase of the 1% in the share of workers with postgraduate degrees increases other workers labour productivity by 2.9% and their own labour productivity by 7.1%. Finally, 1% increase in the share of scientists and engineers raises other workers labour productivity by 2.1% and their own labour productivity by 3.4%.

As for the sample of all industries, the strongest effect comes from the share of workers with postgraduate degrees followed by the effect on the labour productivity from the share of scientists and engineers in a given CMA. The results also give evidence to the existence of human capital externalities beyond the supply effect.

Finally, the R^2 in the regressions partially reported in the table 8 ranges from 0.41 to 0.44 that is higher comparing to the regressions based on the sample for all industries. This observation as well as the fact that results in the table 8 are more significant and higher than in the tables 6 and 7 support both the previous argument that human capital externalities should be more easily transmitted in the private sector rather the public sector.

4.3 Results for the year 1990.

To examine the robustness of the results, it is interesting to estimate equation (1) for a different point in time. It is important to note that for this year the data on the university R&D in 19 CMAs are not available so that there might be bias of omitted variables. However, as it was noticed in the section 4.2, these biases are not strong, so that the estimations for 1990 are still viable.

4.3.1 Sample of workers of all industries.

Table 9 below reports the estimated coefficients for the aggregate human capital measures for the workers in all industries in 1990.

The first observation that may be made comparing to the results for the year 2000 is the weaker statistical significance of the results for the variables measured as shares of different types of human capital among workers. However, the average experience variable becomes statistically significant contrary to the estimations for the year 2000.

The increase by a year of the average education variable has even stronger effect on the labour productivity comparing to the 2000 results being of 23% increase in the labour productivity. The effect of one-year increase in the average experience is 7,3% that is lower then the average productivity effect, but now highly significant comparing to 2000 results.

Table 9

Results for the four alternative measures of the aggregate human capital in the regressions explaining the labour income of workers

All industries

Individuals in 19 Canadian CMAs (1990)

Dependent variable	Log (annual labour income) of all workers	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of workers other than scientists and engineers	Log (annual labour income) of scientists and engineers
Specification	1	2	2a	3	3a	4	4a
CMA human capital measure:							
Average Education	0.2102 (3.80)	-----	-----	-----	-----	-----	-----
Average Experience	0.0705 (3.71)	-----	-----	-----	-----	-----	-----
Share of workers with university degree	-----	0.0091 (1.60)	0.0114 (1.84)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	-----	0.0202 (1.26)	0.0148 (1.40)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	-----	0.028 (1.74)	0.0225 (2.18)
N	238137	194647	43490	227552	10585	224971	13166
R ²	0.47	0.44	0.51	0.46	0.49	0.46	0.49

Source: author's estimations using the 1991 Census of Population microdata and STATA program. Full results are reported in table A.2.2 in the Appendix 2.

The share of university graduates among a CMA workers of all industries is significant only at slightly less than 5% level if a one-tailed test is to be considered and 1% increase of this variable has an effect of 0,9% increase of the labour productivity of other workers. As for the effect on their own labour productivity, this effect is approximately 1,1% and is significant at 10% level (for two-tailed test).

The most restricted measure of aggregate human capital expressed as a share of workers with postgraduate degrees is not significant for the sample of workers that do not constitute this measure. It has however a significant effect on these workers own labour productivity indicating that 1% increase in their share raises their labour income by 1,5%, and that with 10% significance level if a one-tailed test is conducted.

Finally, the aggregate human capital measured by a share of scientists and engineers has a significant effect on the labour productivity of other workers that is reflected in 2,8% in

their labour productivity if the scientists and engineers share among workers increases. The significance level for this coefficient is 5% for one-tailed test. The effect of the 1% increase of this measure of the aggregate human capital on their own wages is more significant and is close to 2,3% increase in the labour productivity of the scientists and engineers.

Overall results for the year 1990 are similar to the results for the year 2000: the results point out to the existence of the human capital externalities and the effect of the 1% increase in the shares of workers with different type of education ranges from 0,9% to 2,8% increase in the labour productivity. The one of the difference from the previous results is that the strongest effect comes now from the increase of the share of scientists and engineers and not from the increase of the share of workers with postgraduate degree. However, the share of workers with any university degree still has the weakest effect, as it was the case in the results for the year 2000. Finally, the R^2 is also higher for these regressions comparing to the year 2000 regressions for all industries, altering from 0,44 to 0,51.

4.3.2 Sample of workers from private sector.

Finally, the 1990 sample is also restricted to the private sector only to confirm or to infirm the conclusions made from the 2000 results that human capital externalities are stronger in private sector.

From table 10 below that reports the results for the year 1990 for the workers from the private sector, this conclusion still seem to hold. In fact, all results are again more significant then for all industries sample and coefficient values are also higher as well as R^2 . The coefficients values range from 1,3% increase in other workers labour productivity after 1% increase in the share of workers with university degree to 8,5% increase in labour productivity of other workers after 1% increase in the share of workers with postgraduate degrees. Also, the same trend as in the tables 6 and 7 for the year 2000 emerge as for the relative importance of these effects. Table 10 shows that the strongest effect on the labour productivity is produced by an increase in a share of workers with postgraduate degrees, followed by scientists and engineers and then by workers with university degree.

Finally, contrary to the results of the year 2000, the average experience variable is statistically significant and suggests almost 7% increase in the labour productivity of all workers in private sector when average experience increases by a year.

Table 10

Results for the four alternative measures of the aggregate human capital in the regressions explaining the labour income of workers
Private Sector
Individuals in 19 Canadian CMAs (1990)

Dependent variable	Log (annual labour income) of all workers	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of workers other than scientists and engineers	Log (annual labour income) of scientists and engineers
Specification	1	2	2a	3	3a	4	4a
CMA human capital measure:							
Average Education	0.2529 (6.60)	-----	-----	-----	-----	-----	-----
Average Experience	0.0683 (5.29)	-----	-----	-----	-----	-----	-----
Share of workers with university degree	-----	0.0132 (2.78)	0.0216 (3.81)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	-----	0.0561 (2.40)	0.0813 (2.78)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	-----	0.0307 (1.77)	0.0304 (2.67)
N	180304	156408	23896	176170	4134	172272	8032
R ²	0.46	0.44	0.5	0.45	0.49	0.45	0.49

Source: author's estimations using the 1991 Census of Population microdata and STATA program. Full results are reported in table A.2.3 in the Appendix 2.

Conclusion

The estimation of the impact of the aggregate human capital at the level of CMA on the individual labour productivity over different samples and in different points in time suggests consistent results that point out to the existence of human capital externalities. Four alternative measures of human capital were proposed: combination of an average education and average experience variables, share of workers with university degrees, share of workers with postgraduate degree and share of scientists and engineers. It was found that an increase of 1% in the three last measures of the aggregate human capital increases the labour productivity of other workers by 0.6 to 1.3%, by 1.5% to 5.8% and by 2.1% to 3.1% respectively. The effect on the labour productivity of workers that constitute the human capital measures range respectively from 0.5% to 2.2%, from 0.9% to 8.5% and from 2.1% to 3.1% if the shares of the workers with university degree, the share of workers with postgraduate degree and the share of scientists and engineers increases by 1%. As for the average education and average experience variables, a one year increase in these measures produces respective increase in the labour productivity of 12,7% to 28.9% and of 7%. Comparing to reviewed studies, the results for the average education are higher than in the other studies that found from 1 % to 5% increase in the labour productivity following one year increase of the average education. As for the effect of the share of workers with university degrees, the effect of 1% increase of this variable on the labour productivity is closer to the results of Rudd (2000) and Moretti (2004) whose results oscillate between 0,5% and 2,22% increase in the labour income. Finally, all other aggregate human capital variables used in this study are not comparable with previous studies since they haven't been previously used.

However, the found effects do not correspond to the human capital externalities but rather reflect a combination of a supply effect and the externality. Nevertheless, the positive significant effect found for the estimations of the aggregate human capital on those workers' own labour productivity indicates that there is a positive human capital externality effect that is at least as large as the negative supply effect in absolute value.

To conclude, this study is one of the first works about human capital externalities at microeconomic level for Canada and produces similar results to the studies using United States metropolitan-level data. This study innovates particularly by exploring various definitions of human capital and proposing a new measure, but it uses data with the

relatively simple structure allowing only for the cross-sectional dimension. For future studies it would be interesting to explore temporal data or panel-structured data to consider a possibility of the demographic changes and migration in the metropolitan areas. It would also be interesting to examine possible instrumental variables to control for a potential endogeneity of the individual and the aggregate human capital.

APPENDIX 1

Variables definitions and construction

	Regression for the year 1990	Regression for the year 2000
Data source	Canadian Census of Population 1991	Canadian Census of Population 2001
Selected sample	Observations were excluded: if CMAPUMFP (Census Metropolitan Areas) =999 (other than metropolitan areas) if CHATTP (school attendance) =2 (full time school attendance) if WAGESP (wages) =9999999 (if individual is under 15) if labour income (see definition below) is less or equal to 0	Idem to 1990
Variables		
Labour income	= WAGESP (wages) + SELFIP (self employment income)	Idem to 1990
Number of weeks worked	= WKSWKP variable of the Census microdata	Idem to 1990
Part time work (=1 if worked mostly at part time)	=1 if FPTWKP (Full time or part time weeks worked) = 2	Idem to 1990
Sex (= 1 if Female)	= 1 if SEXP ==1	Idem to 1990
Visible Minority (=1 if has visible minority status or native)	=1 if VISMINP (Visible minority indicator)=1 & if ABSRP (aboriginal identity) = 2 or 3 or 4 or 5 or 6	= 1 if VISMINP (Visible minority indicator)=1 or 2 or 3 or 4 & if ABSRP (aboriginal identity) = 2 or 3 or 4 or 5 or 6
Marital Status (=1 if married)	=1 if MARSTLP (legal marital status) = 2	Idem to 1990
English unilingual (=1 if English is a mother tongue and speaks only English)	=1 if MTNP (mother tongue) =1 & if OLNP (official languages spoken) = 1	Idem to 1990
English bilingual (=1 if English is a mother tongue and is bilingual)	=1 if MTNP (mother tongue) =1 & if OLNP (official languages spoken) = 3	Idem to 1990
French unilingual (=1 if French is a mother tongue and speaks only French)	=1 if MTNP (mother tongue) =2 & if OLNP (official languages spoken) = 2	Idem to 1990
French bilingual (=1 if French is a mother tongue and is bilingual)	=1 if MTNP (mother tongue) =2 & if OLNP (official languages spoken) = 3	Idem to 1990
Allophone English (=1 if mother tongue other than English and French and speaks English)	=1 if MTNP (mother tongue) =19 & if OLNP (official languages spoken) = 1	=1 if MTNP (mother tongue) =4 or 5 & if OLNP (official languages spoken) = 1
Allophone French (=1 if mother tongue other than English and French and speaks French)	=1 if MTNP (mother tongue) =19 & if OLNP (official languages spoken) = 2	=1 if MTNP (mother tongue) =4 or 5 & if OLNP (official languages spoken) = 2
Allophone bilingual (=1 if mother tongue other than English and French and speaks both)	=1 if MTNP (mother tongue) =19 & if OLNP (official languages spoken) = 3	=1 if MTNP (mother tongue) =4 or 5 & if OLNP (official languages spoken) = 3
Allophone (=1 if mother tongue other than English and French and doesn't speaks any of these languages)	=1 if MTNP (mother tongue) =19 & if OLNP (official languages spoken) = 4	=1 if MTNP (mother tongue) =4 or 5 & if OLNP (official languages spoken) = 4
English-French (=1 if English and French are both mother tongues)	=1 if MTNP (mother tongue) =3 & if OLNP (official languages spoken) = 3	Idem to 1990
Immigration Status (=1 if has a status of permanent resident or non permanent resident)	= 1 if IMMPOPP (indicator of the immigration status) = 2 or 3	Idem to 1990
Experience	= years of education – age – 6 where years of education = 0 if TOTSCHP (total years of schooling) =1 years of education = 3 if 0 if TOTSCHP (total years of schooling) =2 years of education = 7 if 0 if TOTSCHP (total years of schooling) =3 years of education = 9 if 0 if TOTSCHP (total years of schooling) =4 years of education = 13 if 0 if TOTSCHP (total years of schooling) =8 years of education = 15 if 0 if TOTSCHP (total years of schooling) =9 years of education = 18 if 0 if TOTSCHP (total years of schooling) =10 age = AGEP	= years of education – age – 6 where years of education = 0 if TOTSCHP (total years of schooling) =1 years of education = 7 if 0 if TOTSCHP (total years of schooling) =2 years of education = 9 if 0 if TOTSCHP (total years of schooling) =3 years of education = 13 if 0 if TOTSCHP (total years of schooling) =7 years of education = 15 if 0 if TOTSCHP (total years of schooling) =8 years of education = 18 if 0 if TOTSCHP (total years of schooling) =9 age = AGEP

Industry dummies		
Farming Industry	= 1 if IND80P (Industry from 1980 Classification of industries) =1	Idem to 1990
Primary industries other then agriculture	= 1 if IND80P (Industry from 1980 Classification of industries) =2	Idem to 1990
Manufacturing	= 1 if IND80P (Industry from 1980 Classification of industries) =3	Idem to 1990
Construction	= 1 if IND80P (Industry from 1980 Classification of industries) =4	Idem to 1990
Transportation/Storage	= 1 if IND80P (Industry from 1980 Classification of industries) =5	Idem to 1990
Communications	= 1 if IND80P (Industry from 1980 Classification of industries) =6	Idem to 1990
Wholesale and retail trade	= 1 if IND80P (Industry from 1980 Classification of industries) =7 or 8	Idem to 1990
Finance/Insurance/Real estate	= 1 if IND80P (Industry from 1980 Classification of industries) =9	Idem to 1990
Business Management Services	= 1 if IND80P (Industry from 1980 Classification of industries) =10	Idem to 1990
Federal Administration Services	= 1 if IND80P (Industry from 1980 Classification of industries) =11	Idem to 1990
Other Government Services	= 1 if IND80P (Industry from 1980 Classification of industries) =12	Idem to 1990
Education & Related Services	= 1 if IND80P (Industry from 1980 Classification of industries) =13	Idem to 1990
Health and Welfare Services	= 1 if IND80P (Industry from 1980 Classification of industries) =14	Idem to 1990
Accommodation/ Food services	= 1 if IND80P (Industry from 1980 Classification of industries) =15	Idem to 1990
Other Services	= 1 if IND80P (Industry from 1980 Classification of industries) =16	Idem to 1990
Occupation dummies		
Managers	= 1 if OCC91P (Occupation with 1991 Classification)=1 or 2	= 1 if NOCHRDP (Occupation from national classification of occupations)=1 or 2
Professional or technical staff	= 1 if OCC91P (Occupation with 1991 Classification)=3 or 4	= 1 if NOCHRDP (Occupation from national classification of occupations)=3 or 4
Contremaître	= 1 if OCC91P (Occupation with 1991 Classification)=6	N/A
Supervisor	= 1 if OCC91P (Occupation with 1991 Classification)=5	= 1 if NOCHRDP (Occupation from national classification of occupations)=5 or 6
Administration and Office staff	= 1 if OCC91P (Occupation with 1991 Classification)=7 or 10	= 1 if NOCHRDP (Occupation from national classification of occupations)=7 or 10
Sale and Services staff	= 1 if OCC91P (Occupation with 1991 Classification)=8 or 11 or 13	= 1 if NOCHRDP (Occupation from national classification of occupations)=8 or 11 or 13
Manual or Artisan workers	= 1 if OCC91P (Occupation with 1991 Classification)=9 or 12 or 14	= 1 if NOCHRDP (Occupation from national classification of occupations)=9 or 12 or 14
Individual Education level dummies¹⁷:		
Less than high-school	= 1 if DGREEP (the highest grade, certificate or diploma) = 1	Idem to 1990
High – school certificate	= 1 if DGREEP (the highest grade, certificate or diploma) = 2	Idem to 1990
Trades certificate/diploma	= 1 if DGREEP (the highest grade, certificate or diploma) = 3	Idem to 1990
College (cegep) certificate/diploma	= 1 if DGREEP (the highest grade, certificate or diploma) = 4	Idem to 1990
University < bachelor level	= 1 if DGREEP (the highest grade, certificate or diploma) = 5	Idem to 1990
Bachelor degree(s)	= 1 if DGREEP (the highest grade, certificate or diploma) = 6	Idem to 1990
University > bachelor level	= 1 if DGREEP (the highest grade, certificate or diploma) = 7	Idem to 1990
Medicine/Dentist/vet/Optometry	= 1 if DGREEP (the highest grade, certificate or diploma) = 8	Idem to 1990
Master degree(s)	= 1 if DGREEP (the highest grade, certificate or diploma) = 9	Idem to 1990
Earned Doctorate	= 1 if DGREEP (the highest grade, certificate or diploma) = 10	Idem to 1990
CMA human capital measure:		
Average Education	= mean (years of education)	Idem to 1990
Average Experience	= mean(experience)	Idem to 1990
Share of workers with university degree	= % of workers if DGREEP (the highest grade, certificate or diploma) = 6 or 7 or 8 or 9 or 10	Idem to 1990
Share of workers with postgraduate degree	= % of workers if DGREEP (the highest grade, certificate	Idem to 1990

¹⁷ High school diploma is an omitted category

	or diploma) = 8 or 9 or 10	
Share of scientists and engineers	=% of workers if DGREEP (the highest grade, certificate or diploma) = 6 or 7 or 8 or 9 or 10 & if DGMFSP (the main field of studies) = 7 or 8 or 9 or 11 or 12	=% of workers if DGREEP (the highest grade, certificate or diploma) = 6 or 7 or 8 or 9 or 10 & if DGMFSP (the main field of studies) = 10 or 11 or 13 or 14 or 15 or 17 or 18
University R&D expenditures	N/A	= Sum of university R&D expenditures for all universities in a given CMA (source: ACPAU 2000-2001) , 1 000 \$ de 2000

APPENDIX 2

Complete regression results for the tables 8, 9 and 10

Table A2.1

Regressions a with alternative measures of aggregate human capital

Private Sector, 2000

Dependent variable	Log (annual labour income) of all workers	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of workers other than scientists and engineers	Log (annual labour income) of scientists and engineers
Specification	1	2	2a	3	3a	4	4a
Individual independent variables :							
Intercept	4.9788 (4.91)	7.9576 (201.93)	8.1294 (75.40)	7.9812 (209.38)	8.6431 (66.70)	7.9662 (228.00)	8.2997 (84.77)
Personal characteristics:							
Number of weeks worked	0.0316 (101.21)	0.0311 (67.30)	0.0332 (56.80)	0.0315 (90.12)	0.0318 (18.81)	0.0313 (78.21)	0.0351 (32.85)
Part time work (=1 if worked mostly at part time)	-0.7263 (-48.65)	-0.7091 (-48.58)	-0.7842 (-32.38)	-0.7215 (-49.81)	-0.8426 (-15.70)	-0.7198 (-51.58)	-0.8141 (-15.23)
Sex (= 1 if Female)	-0.1412 (-11.32)	-0.1621 (-12.17)	-0.0728 (-7.31)	-0.1447 (-11.78)	-0.0646 (-1.04)	-0.1412 (-10.57)	-0.1008 (-3.20)
Visible Minority (=1 if has visible minority status or native)	-0.1917 (-11.89)	-0.1943 (-10.34)	-0.1389 (-10.39)	-0.1933 (-10.44)	-0.1233 (-4.36)	-0.2004 (-10.78)	-0.0874 (-6.10)
Marital Status (=1 if married)	0.1813 (17.33)	0.1758 (15.64)	0.2011 (11.25)	0.1807 (16.28)	0.199 (7.95)	0.1875 (19.75)	0.1097 (4.29)
Sex * Married	-0.1445 (-13.19)	-0.1419 (-12.86)	-0.1684 (-7.22)	-0.1457 (-12.33)	-0.1496 (-2.22)	-0.1532 (-15.81)	-0.0729 (-1.41)
English bilingual ¹⁸ (=1 if English is a mother tongue and is bilingual)	-0.0066 (-0.26)	-0.0247 (-1.05)	-0.0152 (-0.80)	-0.0216 (-0.77)	-0.0195 (-1.01)	-0.0117 (-0.45)	-0.0329 (-2.24)
French unilingual (=1 if French is a mother tongue and speaks only French)	-0.1893 (-4.65)	-0.1825 (-5.16)	-0.281 (-10.00)	-0.1983 (-6.34)	-0.3159 (-4.84)	-0.1839 (-5.54)	-0.2734 (-2.72)
French bilingual (=1 if French is a mother tongue and is bilingual)	-0.055 (-2.42)	-0.0747 (-4.55)	-0.0444 (-1.40)	-0.0782 (-4.57)	-0.0582 (-1.23)	-0.0689 (-3.30)	0.0077 (0.21)
Allophone English (=1 if mother tongue other than English and French and speaks English)	-0.0717 (-5.26)	-0.0468 (-5.28)	-0.1641 (-5.60)	-0.064 (-5.08)	-0.2086 (-6.04)	-0.0574 (-4.90)	-0.2169 (-5.97)
Allophone French (=1 if mother tongue other than English and French and speaks French)	-0.3528 (-13.67)	-0.3645 (-10.63)	-0.4756 (-7.52)	-0.3779 (-13.90)	-0.6619 (-6.79)	-0.3534 (-9.63)	-0.5688 (-4.06)
Allophone bilingual (=1 if mother tongue other than English and French and speaks both)	-0.1287 (-6.31)	-0.1737 (-11.87)	-0.0937 (-4.10)	-0.1633 (-9.33)	-0.0592 (-1.75)	-0.1587 (-9.76)	-0.0723 (-2.84)
Allophone (=1 if mother tongue other than English and French and doesn't speak any of these languages)	-0.2335 (-12.34)	-0.2291 (-12.46)	-0.3504 (-3.08)	-0.2279 (-11.70)	-0.391 (-1.73)	-0.218 (-11.67)	-0.6099 (-3.58)
English-French (=1 if English and French are both mother tongues)	-0.1424 (-4.15)	-0.1502 (-4.04)	-0.1349 (-3.14)	-0.1624 (-4.38)	-0.0206 (-0.15)	-0.1392 (-3.95)	-0.2531 (-1.17)
Immigration Status (=1 if has a status of permanent resident or non permanent resident)	-0.0612 (-8.37)	-0.0369 (-3.99)	-0.1289 (-14.00)	-0.0523 (-6.86)	-0.1368 (-5.83)	-0.0541 (-6.79)	-0.1055 (-3.18)
Experience	0.0405 (22.47)	0.0412 (19.89)	0.0461 (24.13)	0.0405 (22.82)	0.0423 (12.24)	0.0411 (22.45)	0.0388 (6.41)
Square experience	-0.0006 (-17.99)	-0.0005 (-15.96)	-0.0007 (-25.41)	-0.0005 (-18.13)	-0.0007 (-13.12)	-0.0006 (-18.21)	-0.0006 (-5.80)
Industry dummies¹⁹							
Primary industries other than agriculture	0.6539 (15.11)	0.6408 (12.19)	0.6694 (7.27)	0.6668 (14.40)	0.4246 (3.53)	0.6355 (12.43)	0.7349 (8.78)
Manufacturing	0.3479 (11.98)	0.3404 (11.03)	0.4171 (7.79)	0.362 (10.44)	0.1654 (1.24)	0.3437 (10.98)	0.4968 (8.02)
Construction	0.3379 (10.06)	0.3448 (10.07)	0.2189 (2.93)	0.3565 (9.02)	-0.0329 (-0.19)	0.3386 (10.01)	0.3033 (3.88)
Transportation/Storage	0.3444 (17.19)	0.349 (15.86)	0.3318 (4.45)	0.3623 (15.90)	0.1674 (1.05)	0.3483 (18.17)	0.3502 (3.24)
Communications	0.4334 (19.85)	0.4242 (18.82)	0.4733 (7.83)	0.4474 (16.65)	0.2662 (1.80)	0.4305 (19.43)	0.5778 (8.93)
Wholesale and retail trade	0.1683 (6.87)	0.172 (7.17)	0.2038 (3.71)	0.1884 (6.23)	-0.0833 (-0.68)	0.169 (6.74)	0.3181 (5.85)

¹⁸ English unilingual (=1 if English is mother tongue and speaks only English) is an omitted category

¹⁹ Farming is an omitted category

Finance/Insurance/Real estate	0.3823 (12.94)	0.3781 (13.83)	0.4169 (7.49)	0.3996 (11.74)	0.1752 (1.34)	0.39 (13.11)	0.4593 (6.52)
Business Management Services	0.2754 (9.10)	0.2483 (7.39)	0.3402 (6.30)	0.2901 (7.98)	0.0631 (0.50)	0.2674 (8.11)	0.4143 (6.54)
Accommodation/ Food services	-0.0058 (-0.32)	0.0143 (0.67)	-0.0944 (-1.87)	0.0165 (0.72)	-0.3559 (-2.81)	0.0036 (0.19)	-0.1092 (-1.25)
Other Services	0.0271 (0.99)	0.0446 (1.56)	0.0077 (0.15)	0.0514 (1.55)	-0.3055 (-2.65)	0.0346 (1.22)	0.0823 (1.09)
Occupational Category dummies²⁰:							
Professional or technical staff	-0.0771 (-9.00)	-0.0674 (-10.52)	-0.1147 (-8.23)	-0.0678 (-7.97)	-0.1917 (-9.05)	-0.0894 (-11.89)	-0.0969 (-6.50)
Supervisor	-0.2009 (-14.03)	-0.1659 (-12.50)	-0.3025 (-12.57)	-0.1894 (-14.27)	-0.3807 (-4.90)	-0.1952 (-13.99)	-0.2483 (-4.93)
Administration and Office staff	-0.2833 (-19.42)	-0.2304 (-28.81)	-0.424 (-19.89)	-0.2692 (-20.44)	-0.519 (-15.74)	-0.2716 (-19.92)	-0.4785 (-10.39)
Sale and Services staff	-0.3553 (-21.89)	-0.3303 (-24.48)	-0.3999 (-17.36)	-0.3451 (-22.15)	-0.6087 (-13.51)	-0.3489 (-23.49)	-0.4541 (-11.86)
Manual or Artisan workers	-0.3351 (-18.42)	-0.297 (-19.98)	-0.6081 (-20.11)	-0.3231 (-18.49)	-0.7621 (-9.59)	-0.3225 (-18.88)	-0.6235 (-10.17)
Individual Education level dummies²¹:							
Less than high-school	-0.1117 (-17.73)	-0.1286 (-20.25)	-----	-0.1174 (-19.71)	-----	-0.1198 (-20.28)	-----
Trades certificate/diploma	0.0538 (8.63)	0.0468 (8.03)	-----	0.0518 (8.72)	-----	0.0513 (9.10)	-----
College (cegep) certificate/diploma	0.0929 (8.17)	0.1048 (8.59)	-----	0.0956 (8.30)	-----	0.0988 (8.41)	-----
University < bachelor level	0.1082 (4.20)	0.1169 (4.12)	-----	0.1099 (4.20)	-----	0.1129 (4.21)	-----
Bachelor degree(s)	0.2697 (12.21)	-----	-0.0571 (-1.67)	0.2753 (12.40)	-----	0.2584 (14.54)	-0.1614 (-2.65)
University > bachelor level	0.269 (12.31)	-----	-0.0409 (-0.98)	0.2737 (12.35)	-----	0.3107 (25.17)	-0.2214 (-2.72)
Medicine/Dentist/vet/Optometry	0.3061 (6.95)	-----	0.0333 (0.69)	-----	Omitted category	0.0734 (0.54)	Omitted Category
Master degree(s)	0.3252 (8.12)	-----	0.0033 (0.11)	-----	0.006 (0.11)	0.3245 (9.49)	-0.1133 (-1.74)
Earned Doctorate	0.2828 (5.47)	-----	Omitted Category	-----	0.0064 (0.12)	0.2089 (3.83)	-0.1355 (-1.97)
CMA human capital measure:							
Average Education	0.1716 (4.00)	-----	-----	-----	-----	-----	-----
Average Experience	0.0292 (1.39)	-----	-----	-----	-----	-----	-----
Share of workers with university degree	-----	0.0074 (1.94)	0.014 (4.26)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	-----	0.0295 (1.99)	0.0694 (6.26)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	-----	0.021 (2.43)	0.0331 (5.78)
CMA level control variable							
University R&D expenditures	5.88x10 ⁻⁸ (0.86)	3.36x10 ⁻⁸ (0.28)	1.48x10 ⁻⁸ (0.15)	5.78x10 ⁻⁸ (0.48)	-1.28x10 ⁻⁷ (-1.63)	7.35x10 ⁻⁸ (0.70)	-7.14x10 ⁻⁸ (-0.90)
N	188153	152487	35666	181104	7049	175444	12709
R ²	0.43	0.41	0.44	0.43	0.41	0.42	0.44

²⁰ Higher administration staff is an omitted category

²¹ High school diploma is an omitted category

Table A2.2

Regressions with alternative measures of aggregate human capital

All Industries, 1990

Dependent variable	Log (annual labour income) of all workers	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of workers other than scientists and engineers	Log (annual labour income) of scientists and engineers
Specification	1	2	2a	3	3a	4	4a
Individual independent variables:							
Intercept	3.8356 (3.78)	7.8445 (79.99)	8.6134 (64.63)	7.9099 (104.17)	8.4152 (58.46)	7.8491 (93.87)	8.3619 (75.91)
Personal characteristics:							
Number of weeks worked	0.0323 (123.95)	0.0318 (100.51)	0.0352 (113.48)	0.0323 (126.52)	0.0347 (32.96)	0.0322 (125.81)	0.0357 (51.68)
Part time work (=1 if worked mostly at part time)	-0.6384 (-24.02)	-0.6249 (-22.49)	-0.6883 (-28.71)	-0.6359 (-23.37)	-0.6957 (-15.27)	-0.6354 (-23.12)	-0.6855 (-20.50)
Sex (= 1 if Female)	-0.1502 (-13.60)	-0.1675 (-13.60)	-0.0876 (-8.89)	-0.1509 (-13.65)	-0.1203 (-5.37)	-0.1487 (-13.70)	-0.1083 (-4.70)
Visible Minority (=1 if has visible minority status or native)	-0.1656 (-15.11)	-0.1638 (-10.91)	-0.1544 (-14.14)	-0.1644 (-12.54)	-0.1347 (-7.20)	-0.1685 (-12.01)	-0.1259 (-6.52)
Marital Status (=1 if married)	0.212 (38.75)	0.2192 (30.78)	0.1671 (17.59)	0.2128 (33.97)	0.1488 (8.71)	0.2153 (32.10)	0.1306 (11.19)
Sex * Married	-0.2066 (-19.61)	-0.2171 (-18.74)	-0.1556 (-11.38)	-0.2101 (-20.26)	-0.1189 (-4.15)	-0.2118 (-18.85)	-0.1557 (-5.94)
English bilingual ²² (=1 if English is a mother tongue and is bilingual)	0.0212 (1.64)	-0.0064 (-0.53)	0.0384 (3.49)	0.0089 (0.63)	0.0389 (1.74)	0.0131 (1.04)	0.0564 (3.22)
French unilingual (=1 if French is a mother tongue and speaks only French)	-0.0749 (-3.33)	-0.0939 (-4.16)	-0.0668 (-2.49)	-0.0989 (-3.50)	-0.0855 (-2.60)	-0.086 (-3.95)	-0.0495 (-1.59)
French bilingual (=1 if French is a mother tongue and is bilingual)	0.0179 (0.83)	-0.0048 (-0.24)	0.0091 (0.35)	-0.0101 (-0.38)	0.0353 (1.44)	0.0016 (0.08)	0.0459 (2.85)
Allophone English (=1 if mother tongue other than English and French and speaks English)	0.0092 (0.67)	-0.0005 (-0.03)	-0.054 (-1.93)	-0.0099 (-0.65)	-0.0055 (-0.14)	-0.0033 (-0.22)	-0.0796 (-1.69)
Allophone French (=1 if mother tongue other than English and French and speaks French)	-0.6875 (-2.15)	-0.5693 (-2.90)	-0.9374 (-1.53)	-0.7158 (-2.20)	-----	-0.7334 (-1.96)	-0.4632 (-14.56)
Allophone bilingual (=1 if mother tongue other than English and French and speaks both)	0.0221 (0.23)	0.0375 (0.22)	-0.1184 (-0.46)	-0.0495 (-0.53)	0.0855 (4.20)	0.056 (0.56)	-0.8144 (-28.96)
Allophone (=1 if mother tongue other than English and French and doesn't speak any of these languages)	-0.7443 (-30.54)	-0.9049 (-25.94)	-0.5037 (-10.89)	-0.8948 (-23.45)	-0.2105 (-2.78)	-0.8816 (-28.23)	-0.4092 (-5.24)
English-French (=1 if English and French are both mother tongues)	-0.1389 (-5.08)	-0.1752 (-5.56)	-0.0142 (-0.19)	-0.1611 (-5.41)	-0.0026 (-0.02)	-0.1378 (-4.92)	-0.3781 (-2.43)
Immigration Status (=1 if has a status of permanent resident or non permanent resident)	-0.0495 (-4.18)	-0.0282 (-1.56)	-0.0791 (-6.82)	-0.0309 (-1.76)	-0.0976 (-8.88)	-0.0351 (-2.06)	-0.0952 (-3.67)
Experience	0.0271 (59.35)	0.0265 (43.15)	0.0361 (25.86)	0.0267 (54.88)	0.0464 (14.30)	0.0269 (60.83)	0.0346 (9.59)
Square experience	-0.0005 (-42.10)	-0.0004 (-34.63)	-0.0007 (-21.92)	-0.0004 (-41.56)	-0.0009 (-12.82)	-0.0005 (-41.67)	-0.0006 (-7.91)
Industry dummies²³							
Primary industries other than agriculture	0.6386 (14.88)	0.609 (11.68)	0.601 (11.70)	0.6151 (13.28)	0.5188 (4.58)	0.5913 (11.30)	0.5503 (9.45)
Manufacturing	0.3813 (9.76)	0.3808 (8.44)	0.4207 (7.91)	0.3885 (8.64)	0.2749 (2.34)	0.3832 (8.87)	0.3753 (5.86)
Construction	0.4182 (10.70)	0.4238 (10.58)	0.2846 (4.50)	0.4267 (10.13)	0.1457 (1.76)	0.4226 (10.81)	0.1928 (2.07)
Transportation/Storage	0.4373 (13.25)	0.4362 (12.42)	0.3934 (6.71)	0.4406 (12.75)	0.2099 (1.66)	0.4336 (12.61)	0.3802 (5.69)
Communications	0.4862 (12.17)	0.4869 (11.29)	0.4525 (6.90)	0.4906 (11.51)	0.3215 (3.20)	0.4829 (11.68)	0.4535 (6.56)
Wholesale and retail trade	0.2368 (6.51)	0.2368 (6.09)	0.2495 (4.21)	0.2421 (5.89)	0.0843 (1.06)	0.2348 (6.17)	0.2516 (4.11)
Finance/Insurance/Real estate	0.4072 (10.85)	0.4073 (9.84)	0.4172 (7.36)	0.4128 (9.54)	0.3631 (4.13)	0.4099 (10.40)	0.3622 (6.23)

²² English unilingual (=1 if English is mother tongue and speaks only English) is an omitted category

²³ Farming is an omitted category

Business Management Services	0.3248 (7.56)	0.2997 (6.75)	0.3799 (6.45)	0.3315 (6.65)	0.2372 (2.87)	0.321 (6.91)	0.3234 (4.95)
Federal Administration Services	0.4581 (11.99)	0.4728 (10.00)	0.388 (7.10)	0.4666 (10.12)	0.2447 (2.08)	0.4648 (10.27)	0.3237 (5.66)
Other Government Services	0.4498 (13.08)	0.4663 (12.75)	0.3679 (6.67)	0.4571 (12.45)	0.2333 (2.73)	0.4542 (12.85)	0.3098 (4.61)
Education & Related Services	0.3437 (10.13)	0.3021 (8.78)	0.3421 (6.33)	0.3373 (9.23)	0.2329 (2.56)	0.3487 (10.09)	0.2628 (4.56)
Accommodation/ Food services	0.0503 (1.40)	0.0577 (1.45)	-0.0335 (-0.51)	0.0538 (1.37)	-0.2146 (-2.19)	0.0517 (1.37)	-0.0978 (-0.90)
Health and Welfare Services	0.3618 (10.62)	0.3629 (9.84)	0.3415 (6.26)	0.3543 (9.63)	0.3525 (3.89)	0.3524 (10.26)	0.4203 (7.48)
Other Services	0.0828 (2.08)	0.1013 (2.35)	-0.0221 (-0.34)	0.0927 (2.07)	-0.2066 (-2.21)	0.0855 (2.15)	-0.0746 (-0.65)
Occupational Category dummies²⁴:							
Professional or technical staff	-0.0672 (-6.33)	-0.05789 (-4.33)	-0.1083 (-13.40)	-0.0632 (-5.29)	-0.1086 (-7.48)	-0.0688 (-6.37)	-0.1004 (-9.09)
Supervisor	-0.1321 (-7.32)	-0.1025 (-5.54)	-0.2509 (-13.45)	-0.1275 (-6.82)	-0.2125 (-3.70)	-0.1272 (-7.26)	-0.2958 (-5.62)
Contremaîtres	-0.1761 (-9.81)	-0.1593 (-8.79)	-0.2842 (-6.58)	-0.174 (-9.82)	-0.377 (-2.20)	-0.1728 (-9.29)	-0.2406 (-5.23)
Administration and Office staff	-0.26 (-28.65)	-0.2221 (-22.44)	-0.3856 (-40.76)	-0.2529 (-27.55)	-0.3665 (-9.33)	-0.2534 (-29.79)	-0.4276 (-16.79)
Sale and Services staff	-0.3498 (-71.52)	-0.3324 (-56.21)	-0.3953 (-43.72)	-0.3459 (-64.59)	-0.5322 (-12.09)	-0.3467 (-69.07)	-0.397 (-14.02)
Manual or Artisan workers	-0.2742 (-13.97)	-0.2559 (-13.16)	-0.4797 (-15.35)	-0.2716 (-13.38)	-0.5512 (-15.01)	-0.2673 (-14.01)	-0.5167 (-16.03)
Individual Education level dummies²⁵:							
High-school certificate	0.1019 (11.43)	0.1119 (13.42)	-----	0.1071 (12.25)	-----	0.1073 (12.43)	-----
Trades certificate/diploma	0.1544 (19.86)	0.157 (20.12)	-----	0.1547 (19.29)	-----	0.1547 (19.17)	-----
College (cegep) certificate/diploma	0.2081 (13.70)	0.2244 (16.19)	-----	0.2153 (14.40)	-----	0.2157 (14.44)	-----
University < bachelor level	0.2701 (13.69)	0.2884 (14.98)	-----	0.2754 (14.07)	-----	0.2756 (14.06)	-----
Bachelor degree(s)	0.3556 (21.16)	-----	-0.5922 (-16.85)	0.3643 (21.75)	-----	0.3486 (20.59)	-0.1874 (-5.78)
University > bachelor level	0.3922 (16.98)	-----	-0.5628 (-13.94)	0.4049 (17.91)	-----	0.4095 (17.40)	-0.2032 (-5.12)
Medicine/Dentist/vet/Optomety	0.9168 (26.73)	-----	Omitted category	-----	0.2923 (12.23)	0.6155 (11.83)	0.2558 (10.03)
Master degree(s)	0.4762 (19.59)	-----	-0.4764 (-15.47)	-----	-0.0779 (-2.68)	0.4869 (21.40)	-0.1043 (-6.38)
Earned Doctorate	0.5576 (18.47)	-----	-0.3794 (-18.09)	-----	Omitted category	0.5433 (16.91)	Omitted Category
CMA human capital measure:							
Average Education	0.2102 (3.80)	-----	-----	-----	-----	-----	-----
Average Experience	0.0705 (3.71)	-----	-----	-----	-----	-----	-----
Share of workers with university degree	-----	0.0091 (1.60)	0.0114 (1.84)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	-----	0.0202 (1.26)	0.0148 (1.40)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	-----	0.028 (1.74)	0.0225 (2.18)
N	238137	194647	43490	227552	10585	224971	13166
R ²	0.47	0.44	0.51	0.46	0.49	0.46	0.49

²⁴ Higher administration staff is an omitted category

²⁵“ Less than high school certificate” is an omitted category

Table A2.3

Regressions with alternative measures of aggregate human capital

Private Sector, 1990

Dependent variable	Log (annual labour income) of all workers	Log (annual labour income) of workers with less than university degree	Log (annual labour income) of workers with university degrees	Log (annual labour income) of workers with less than postgraduate degrees	Log (annual labour income) of workers with postgraduate degrees	Log (annual labour income) of workers other than scientists and engineers	Log (annual labour income) of scientists and engineers
Specification	1	2	2a	3	3a	4	4a
Variables indépendantes individuelles :							
Intercept	3.4569 (5.17)	7.8538 (111.85)	8.3356 (74.69)	7.9003 (125.57)	8.3389 (44.08)	7.8863 (106.85)	8.5394 (75.07)
Personal characteristics:							
Number of weeks worked	0.032 (110.35)	0.0315 (97.81)	0.0354 (52.83)	0.0319 (109.19)	0.037 (19.01)	0.0319 (113.84)	0.0358 (32.58)
Part time work (=1 if worked mostly at part time)	-0.6344 (-26.31)	-0.6231 (-23.09)	-0.7033 (-31.01)	-0.6330 (-25.75)	-0.6625 (-9.99)	-0.6312 (-24.80)	-0.7648 (-18.26)
Sex (= 1 if Female)	-0.1722 (-12.20)	-0.1831 (-12.87)	-0.1072 (-8.28)	-0.1718 (-12.00)	-0.1297 (-4.36)	-0.1705 (-12.15)	-0.0977 (-2.71)
Visible Minority (=1 if has visible minority status or native)	-0.1871 (-14.52)	-0.1815 (-11.11)	-0.1952 (-15.68)	-0.1876 (-12.40)	-0.1719 (-5.15)	-0.1869 (-11.70)	-0.1545 (-5.79)
Marital Status (=1 if married)	0.2167 (32.05)	0.2161 (27.19)	0.1969 (22.09)	0.2148 (30.05)	0.218 (9.27)	0.2188 (27.92)	0.1215 (11.96)
Sex * Married	-0.2179 (-17.87)	-0.2229 (-16.59)	-0.1801 (-15.48)	-0.2189 (-18.27)	-0.1851 (-4.83)	-0.2238 (-17.49)	-0.1315 (-2.50)
English bilingual ²⁶ (=1 if English is a mother tongue and is bilingual)	0.0361 (2.21)	-0.0094 (-0.64)	0.0543 (3.10)	0.0061 (0.32)	0.0247 (0.70)	-0.0172 (1.01)	0.0513 (2.23)
French unilingual (=1 if French is a mother tongue and speaks only French)	-0.0705 (-4.39)	-0.1144 (-6.09)	-0.1124 (-4.30)	-0.1224 (-5.95)	-0.1817 (-3.88)	-0.1073 (-5.49)	-0.0844 (-3.58)
French bilingual (=1 if French is a mother tongue and is bilingual)	0.0393 (2.11)	-0.0082 (-0.57)	0.0106 (0.53)	-0.0175 (-1.02)	0.0508 (2.60)	-0.0015 (-0.08)	0.0608 (2.66)
Allophone English (=1 if mother tongue other than English and French and speaks English)	0.0237 (1.68)	0.0144 (0.67)	-0.0562 (-1.42)	0.009 (0.49)	-0.0232 (-0.26)	0.0067 (0.40)	-0.0719 (-1.24)
Allophone French (=1 if mother tongue other than English and French and speaks French)	-0.6956 (-4.80)	-0.747 (-5.45)	-----	-0.7473 (-5.19)	-----	-0.746 (-5.15)	-----
Allophone bilingual (=1 if mother tongue other than English and French and speaks both)	-0.0657 (-0.47)	0.0302 (0.15)	-0.6104 (-29.76)	-0.1192 (-0.92)	-----	-0.0109 (-0.07)	-1.6583 (-36.41)
Allophone (=1 if mother tongue other than English and French and doesn't speak any of these languages)	0.0298 (1.54)	0.1817 (5.48)	-0.5086 (-20.74)	0.2229 (6.84)	-0.2493 (-3.70)	0.2299 (6.66)	-0.4448 (-7.26)
English-French (=1 if English and French are both mother tongues)	-0.1322 (-4.00)	-0.1892 (-5.03)	0.0461 (0.47)	-0.1798 (-5.64)	0.2097 (1.35)	-0.1535 (-4.83)	-0.3566 (-3.23)
Immigration Status (=1 if has a status of permanent resident or non permanent resident)	-0.0572 (-4.82)	-0.0412 (-2.12)	-0.0908 (-5.35)	-0.0449 (-2.39)	-0.1178 (-5.67)	-0.0404 (-2.03)	-0.0764 (-2.12)
Experience	0.0278 (43.62)	0.028 (35.85)	0.0338 (23.06)	0.0278 (42.31)	0.0424 (20.68)	0.0278 (42.46)	0.0298 (10.87)
Square experience	-0.0005 (-30.60)	-0.0005 (-29.88)	-0.0007 (-17.71)	-0.0005 (-33.09)	-0.0009 (-16.75)	-0.0005 (-33.21)	-0.0005 (-7.63)
Industry dummies²⁷							
Primary industries other than agriculture	0.6181 (13.63)	0.6042 (11.20)	0.4702 (7.86)	0.6039 (12.53)	0.3429 (3.09)	0.5808 (10.94)	0.4195 (6.50)
Manufacturing	0.3661 (9.70)	0.3739 (8.36)	0.3033 (5.23)	0.3804 (8.52)	0.1062 (0.80)	0.3801 (8.82)	0.2571 (3.87)
Construction	0.3936 (10.14)	0.4099 (10.25)	0.1684 (2.60)	0.4079 (9.78)	-0.0154 (-0.15)	0.4103 (10.50)	0.0772 (0.83)
Transportation/Storage	0.4168 (12.54)	0.4248 (12.02)	0.2766 (4.36)	0.4252 (12.06)	0.0333 (0.24)	0.4247 (12.34)	0.2697 (3.87)
Communications	0.4732 (11.65)	0.4825 (10.96)	0.3357 (4.73)	0.4819 (11.08)	0.1449 (1.24)	0.4807 (11.40)	0.3403 (4.74)
Wholesale and retail trade	0.2246 (6.20)	0.2342 (5.98)	0.1369 (2.16)	0.2365 (5.78)	-0.0737 (-0.74)	0.2346 (6.05)	0.1346 (2.11)
Finance/Insurance/Real estate	0.3974 (10.53)	0.4074 (9.74)	0.2972 (4.98)	0.4091 (9.51)	0.1823 (1.77)	0.4138 (10.20)	0.2465 (4.32)

²⁶ English unilingual (=1 if English is mother tongue and speaks only English) is an omitted category²⁷ Agriculture being an omitted category

Business Management Services	0.3185 (7.38)	0.3019 (6.80)	0.2636 (4.19)	0.3278 (6.72)	0.0713 (0.72)	0.3287 (6.97)	0.2115 (3.04)
Accommodation/ Food services	0.0446 (1.23)	0.0621 (1.55)	-0.14 (-2.04)	0.0556 (1.40)	-0.3656 (-3.36)	0.0566 (1.49)	-0.2096 (-2.03)
Other Services	0.0769 (1.93)	0.1045 (2.41)	-0.1218 (-1.82)	0.0925 (2.08)	-0.3385 (-2.99)	0.0925 (2.30)	-0.1807 (-1.67)
Occupational Category dummies²⁸:							
Professional or technical staff	-0.08135 (-7.74)	-0.0816 (-7.41)	-0.1071 (-12.85)	-0.0795 (-7.04)	-0.1034 (-6.51)	-0.0871 (-9.31)	-0.1243 (-7.60)
Supervisor	-0.1243 (-5.61)	-0.0965 (-4.42)	-0.2741 (-13.97)	-0.1208 (-5.29)	-0.2021 (-2.47)	-0.1169 (-5.29)	-0.3829 (-4.99)
Contremaîtres	-0.179 (-10.39)	-0.1601 (-9.40)	-0.2993 (-6.96)	-0.1741 (-10.24)	-0.4095 (-2.23)	-0.1749 (-9.78)	-0.2801 (-5.79)
Administration and Office staff	-0.2443 (-18.43)	-0.2129 (-16.77)	-0.3738 (-53.82)	-0.2391 (-17.85)	-0.3325 (-10.17)	-0.2359 (-18.71)	-0.4599 (-18.97)
Sale and Services staff	-0.3439 (-48.57)	-0.3322 (-47.27)	-0.3752 (-26.86)	-0.3417 (-44.18)	-0.4636 (-11.09)	-0.3416 (-50.58)	-0.3961 (-12.99)
Manual or Artisan workers	-0.2686 (-13.69)	-0.2498 (-13.30)	-0.4729 (-16.38)	-0.2637 (-13.24)	-0.4908 (-10.13)	-0.2615 (-13.68)	-0.5358 (-18.53)
Individual Education level dummies²⁹:							
High-school certificate	0.0966 (9.57)	0.1082 (11.27)	-----	0.1024 (10.56)	-----	0.1034 (10.65)	-----
Trades certificate/diploma	0.1499 (17.24)	0.1546 (17.67)	-----	0.152 (17.21)	-----	0.1508 (16.76)	-----
College (cegep) certificate/diploma	0.1897 (10.10)	0.2079 (11.34)	-----	0.1972 (10.52)	-----	0.1986 (10.54)	-----
University < bachelor level	0.2435 (7.96)	0.2569 (8.27)	-----	0.2466 (8.09)	-----	0.2489 (8.05)	-----
Bachelor degree(s)	0.3568 (17.22)	-----	-0.2632 (-10.43)	0.3669 (17.44)	-----	0.3473 (16.57)	-0.1879 (-6.97)
University > bachelor level	0.3538 (9.70)	-----	-0.2601 (-7.10)	0.3634 (10.41)	-----	0.3824 (9.51)	-0.2516 (-7.33)
Medicine/Dentist/vet/Optomety	0.6138 (16.18)	-----	Omitted category	-----	0.1026 (1.88)	0.9016 (3.76)	Omitted category
Master degree(s)	0.4432 (13.29)	-----	-0.1811 (-6.12)	-----	-0.0306 (-0.84)	0.4699 (15.86)	-0.163 (-3.43)
Earned Doctorate	0.4572 (10.26)	-----	-0.156 (-3.12)	-----	Omitted category	0.3119 (5.18)	-0.0608 (-0.84)
CMA human capital measure:							
Average Education	0.2529 (6.60)	-----	-----	-----	-----	-----	-----
Average Experience	0.0683 (5.29)	-----	-----	-----	-----	-----	-----
Share of workers with university degree	-----	0.0132 (2.78)	0.0216 (3.81)	-----	-----	-----	-----
Share of workers with postgraduate degree	-----	-----	-----	0.0561 (2.40)	0.0813 (2.78)	-----	-----
Share of scientists and engineers	-----	-----	-----	-----	-----	0.0307 (1.77)	0.0304 (2.67)
N	180304	156408	23896	176170	4134	172272	8032
R ²	0.46	0.44	0.5	0.45	0.49	0.45	0.49

²⁸ Higher administration staff is an omitted category

²⁹ “Less than high school certificate” is an omitted category

Bibliography

Acemoglu, D. and J. Angrist (2000), “ How Large Are Human Capital Externalities? Evidence from Compulsory Schooling Laws”, NBER macro Annual

Guellec, D. and B. van Pottelsberghe de la Potterie(2001), “Recherche-développement et croissance de la productivité : Analyse des données d’un panel de 16 pays del’OCDE”, *Revue économique de l’OCDE*, no 33, pp. 111-36.

Moretti, E. (2004) “Estimating the social return to higher education: evidence from longitudinal and repeated cross-sectional data”, *Journal of Econometrics*, vol 121, pp 175-212.

Rauch, J. E. (1993) “Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities”, *Journal of Urban Economics*, vol 34, pp 380-400.

Rudd, J. (2000) “Empirical Evidence on Human Capital Spillovers”, Federal Reserve Board, Finance and Economics Discussion Paper 2000-46, October

Statistics Canada (2004), *Estimates of Canadian research and development expenditures, Canada, 1993 to 2004, and by province 1993 to 2002*, Cat. No. 88F0006XIF2004020, URL: <http://www.statcan.ca/bsolc/english/bsolc?catno=88F0006X2004020>