Skills, Education and Canadian Provincial Disparity

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Summary
We derive synthetic time series over the 1951 to 2001 period of the skills of labour market entrants for the ten Canadian provinces from the 2003 ALL survey. The effect of the skills variable on regional income is significant and substantial. Skills acquired by one extra year of schooling result in an increase in per capita income of around 5 per cent which is close to microeconomic Mincerian estimates. Our literacy indicator does not outperform human capital indicators based on education. This contrasts sharply with recent cross-country evidence and suggests substantial measurement error in cross-country schooling data.

Keywords: Human capital, education, skills, regional disparity, measurement error

JEL classifications: I20, J24, O47, R11, and R15

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1. INTRODUCTION

What determines the differences in living standards across economies in the long run? The study of this central question regained the front stage of mainstream economics in the last two decades with the “growth revival” pioneered by the works of Baumol (1986), Romer (1986), and Lucas (1988). According to Glaeser et al. (2004), after years of empirical and theoretical studies and debate, two answers to this central economic question stand out as candidates: (A) human capital accumulation as pioneered by Mankiw, Romer, and Weil (1992); and (B) institutional improvements or investment in social infrastructure as emphasized by Hall and Jones (1999).¹

From an empirical point of view, testing candidates A and B using cross-country data is subject to some problems. First, it is very difficult to construct indicators of institutional quality that are comparable across countries and across time. According to Glaeser et al. (2004), the most often used indicators of institutional quality in cross-country growth studies are conceptually deficient. However, not using indicators of social infrastructure raises a second important problem in cross-country studies. Supporters of candidate answer B might interpret a positive estimated effect for the human capital indicator as a missing variable bias if the human capital indicator is positively correlated with the quality of institutions. An alternative empirical strategy that avoids both potential problems would be to focus on regional data sets. Since the social infrastructure is relatively similar across regions of homogeneous countries, the process of human capital accumulation should account for most differences in standards of living if candidate answer A is at least a part of the story. Empirical practitioners, however, have not used this approach as much because of the lack of reliable data on human capital and
standards of living at the sub-national level in most countries for a sufficiently long period of time.

In this paper, we follow the regional strategy using Canadian provincial data and test whether human capital accumulation can account for income differences across economies. To this end, we focus mainly on two measures of human capital. The first is university achievement, measured as the percentage of the working-age population holding a university degree. This measure, used in recent studies on Canadian provincial convergence (Coulombe and Tremblay, 2001; Coulombe, 2003), is available at 10-year intervals from census data since 1951. The second measure is a new direct indicator of skills based on literacy test scores. In collaboration with Statistics Canada, we computed and aggregated this new skills data for the 10 Canadian provinces for the 1951–2001 period from the 2003 Adult Literacy and Lifeskills Survey (ALL). Following the methodology proposed by Coulombe, Tremblay, and Marchand (2004), we provide the cross-sectional data with a time-series dimension inferred from the demographic structure of the ALL data. The data are intended to capture the mean skill level of labour market entrants aged 17 to 25 for each of the 10 Canadian provinces. Skills data might be viewed as a direct measure of human capital that is highly comparable across time and across economies. Our different measures of human capital are then used in pooled time-series and cross-sectional (the 10 provinces) empirical models (TSCS) to estimate the mean effect of human capital on aggregate provincial per capita income, minus government transfers.

Our empirical analysis provides support to the view that human capital matters substantially for income disparities. Human capital indicators — based on both education
and skill levels — are found to exert a positive and significant effect on per capita income levels when entered in separate TSCS regressions. But more importantly, analyzing the role of human capital accumulation on income disparities in a regional context allows us to make two important contributions to the growth literature.

First, by focusing on the Canadian provinces across which the level of social infrastructure is relatively homogeneous, we are able to derive a potentially more reliable estimate of the return to human capital accumulation. From our empirical results, we derive an estimate of the macroeconomic Mincerian rate of return to education of approximately 5 percent. This estimate is very close to the estimated return of education in terms of individual earnings typically found in microeconomic studies (Psacharopoulos, 1994). The fact that the aggregate return to education is virtually the same as the individual earnings return suggests that human capital externalities may be relatively small.

Of course, our analysis does not rule out the social capital explanation for income differences across a broad set of countries. The high level of social capital that is common to all Canadian provinces might well account for a large proportion of the living standards differences between Canada and less-developed countries. However, in our empirical TSCS analysis, the common level and improvements of social capital across Canadian provinces since 1951 are purged out of the analysis.

Second, our regional dataset allows us to compare the effects on income disparities of input (education) and output (skills) measures of human capital given that highly comparable schooling data is available for Canadian provinces over a long period of time. A large body of empirical work has recently focused on the role of human capital
accumulation in cross-country growth. Generally speaking, when the cross-country sample includes a large set of developed and developing countries, schooling achievement is found to generate a positive and significant effect on transitory growth and on the long-run level of labour productivity or per capita income in growth regressions (Barro, 2001). However, when the data set is restricted to developed countries, the effect of various schooling variables has not usually been significant and has sometimes even been negative (Islam, 1995; Barro, 2001). These divergent results might be interpreted in at least two different, but not necessarily incompatible, ways. First, as we argued before, in a broad set of heterogeneous countries, schooling indicators may be positively correlated with missing variables related to social infrastructure. The effect of education may vanish in a sample of OECD countries since developed countries are more homogeneous along this dimension (Coulombe, 2001). Second, measurement error on schooling data can be a big issue, especially in cross-country studies (Krueger and Lindahl, 2001; Fuente (de la) and Doménech, 2002).

Our result that both skills and education matter for income disparities contrasts sharply with the main result of Coulombe, Tremblay, and Marchand’s (2004) cross-country study, where the best schooling indicator was clearly outperformed by skills indicators, and raises the possibility that schooling data may be subject to serious measurement error biases at the cross-country level.

From a regional perspective, a key result of this paper is that both university achievements and skill levels are important to a strong regional economy. The fact that university achievement is significant after controlling for regional skill levels is consistent with the existence of ‘sheepskin effects’ and may suggest that the
complementarity of skills acquired by a college degree exerts a positive effect on individual and regional income. We also show that the accumulation of human capital, along with a limited set of structural variables such as the urbanization rate, can explain a very substantial portion of the evolution of differences in per capita income across Canadian provinces since 1951.

In Section 2, we present the data and explain the methodology used to construct the synthetic skill variable. In Section 3, we discuss the theoretical foundation of our analysis and the empirical methodology. Results are presented and discussed in Section 4 and Section 5 concludes.

2. MEASURES OF HUMAN CAPITAL

One of the main reasons why measurement error might be a serious issue with cross-country schooling data is that raw national data are assembled by various statistical agencies using different methodologies. Schooling data for the Canadian provinces should be much more comparable. However, as elegantly illustrated by Fuente (de la) and Doménech’s case study (2002, Section 3.1) most Canadian indicators of educational achievement are not consistent on a time-series basis. The census questionnaires have changed their format over time and the only official relevant and consistent data are those dealing with university attainment. More precisely, our benchmark schooling indicator is based on the percentage of the population in the 15-to-65 age group with at least one university degree. Our earlier studies dealing with the human capital accumulation process across Canadian provinces have shown well that university attainment data might
be viewed as appropriate proxies for the relative level of human capital across the provinces in TSCS analyses (Coulombe and Tremblay, 2001; Coulombe, 2003).

Our first human capital indicator, the percentage of the population aged between 15 and 65 with at least one university degree, is shown for each province in figure 1. The percentage of university graduates has grown faster in provinces that initially had a relatively low percentage of individuals with a university degree. Despite this convergence pattern, the relatively rich provinces of Ontario, Alberta, and British Columbia have had the highest percentage of university graduates throughout the period. Newfoundland, Prince Edward Island, and New Brunswick have been trailing behind. In contrast to the other Atlantic Provinces, Nova Scotia has been, and still is, relatively well endowed in university graduates. Finally, the percentage of university graduates in Quebec initially was substantially above the Canadian average but declined steadily during the 1960s and 1970s due to the exodus of the relatively well-educated Anglophone population.

INSERT FIGURE 1 HERE

Our second type of human capital indicator used in this study is based on literacy skills test scores and is intended to capture the mean skill level of labour market entrants. Literacy skills test scores are taken from the 2003 ALL, which tested the skills of individuals between 16 and 65 years of age. Four domains of literacy skills were tested (prose, document, numeracy, and problem solving). The skill level of an individual is equal to the average score over these domains. It is important to note that the tests were not designed to focus only on basic literacy skills. The tests were constructed to assess the ability of individuals to accomplish tasks of varying difficulty levels ranging from
simple to highly complex. For example, the most difficult tasks included in the tests required that individuals be able to ‘search for information in dense texts that contain a number of plausible distractors’, ‘to make high-level inferences or to use specialized knowledge’, ‘to process conditional information’ and ‘to perform multiple operations sequentially’ (OECD, 2000). Thus, some of the skills tested are quite advanced and are not typically acquired before post-secondary education.

Using the demographic profile of test scores, we constructed a synthetic time series of the mean skill level of individuals aged between 17 and 25 for each period starting in 1951 (1951, 1956, 1961, …, 2001). More precisely, we use as an indicator of the relative level of human capital investment made by a province in a particular period, the average score of individuals that would have been aged 17 to 25 years old in that period. For example, individuals that were aged between 17 and 25 years old in 1995 were aged between 25 and 33 years old when the skills tests were conducted in 2003, and so on.

Implicit in the construction of these indicators is the assumption that the skill level of individuals remains constant during their lives in the labour market. Hence, the indicators do not take into account the changes in skills that result from labour market training, learning-by-doing through labour market experience, and skills depreciation. This is obviously an important drawback of our skills indicators. However, if the process of human capital accumulation and depreciation over the lifetime of individuals is relatively similar across provinces, our results will be largely unaffected by this process given that, in our empirical analysis, skills indicators are expressed as deviations from the
cross-sectional mean. Nonetheless, this limitation should be kept in mind when interpreting the results.

On the other hand, our synthetic skills indicators provide a direct measure of the quality of human capital. In contrast to schooling, which is an input measure in the human capital production function, literacy skills are an output measure and literacy skills test scores have been found to be closely associated with income at the micro-economic level (Green and Riddell, 2001).

Of greater concern is the effect of migration on the construction of our synthetic indicator. The first skills indicator that we use does not take into consideration the migration flows that occurred over the period, which can potentially result in an important measurement error. By using the average score of a given cohort of individuals in 2003 as a proxy for the relative human capital investment of a province in the past, we incorrectly include in the sample of a given province individuals that were not living in that province earlier in the period. Therefore, this human capital indicator may well be biased by the processes of international and interprovincial migration. This will be the case if, for instance, international immigrants are not uniformly distributed across provinces. But more importantly perhaps, a significant bias may be introduced by interprovincial migration given the well-documented fact that interprovincial migrants tend to be relatively young and well-educated, and tend to migrate from the poor to the relatively rich provinces.

To address this issue, we also constructed a synthetic skills indicator by including only individuals that were living in 2003 in the same province as the one where they did their last year of high school education. We refer to these individuals as non-movers.
Based on the raw data from ALL 2003, this is the best measure that can be constructed to exclude the effects of migration and derive a potentially unbiased human capital indicator. However, this indicator is constructed from a subset of the population only. Non-movers represented 62.5 per cent of the population for Canada as a whole and 40 per cent, 48 per cent and 55 per cent of the population in the three richest and immigrants-receiving provinces of British Columbia, Alberta and Ontario, respectively. The correlation between the skills variables for the overall population and for the non-movers population is 0.85.

Figures 2 and 3 depict these indicators for each province, again expressed as logarithms of deviations from the provincial mean. Similar to the university graduate indicator, both skills indicators also exhibits a clear convergence pattern. Interestingly, however, there are notable differences in the university and skills indicators of some provinces. In particular, the skills indicators for Quebec have increased steadily over the period in sharp contrast to the evolution of its university graduates indicator. Ontario’s overall skills indicator has surprisingly been below average for all periods except for 1991 despite the province’s very high level of university graduates. In contrast however, the non-movers skills indicator for Ontario has been above average, except in 1951. This sharp difference between the two skills indicators suggests that on average immigrants to Ontario, including both interprovincial and international immigrants, have a relatively lower level of skills than the overall Ontario population. The opposite pattern holds for Nova Scotia where the skills of all individuals between 17 and 25 years old has been steadily above average while the skills of non-movers has been steadily below, except in 2001. Western provinces have generally had the best performance throughout the period.
with the labour market entrants of Saskatchewan and Alberta having the highest average score in 2001 among both the overall and non-movers populations. Finally, Newfoundland and New Brunswick have been trailing behind for most of the period.

INSERT FIGURES 2 AND 3 HERE

Figure 4 depicts the evolution of the standard deviation of the three human capital indicators. The dispersion across provinces of all three indicators has clearly been decreasing over the period. Interestingly, the relative decrease in the dispersion of the university indicator started somewhat earlier. Most importantly, however, the dispersion of the university graduates indicator, measured on the left axis, is approximately 10 times that of the skills indicators, measured on the right axis. The low dispersion of the skills indicators results from the arbitrary 0–500 scale that was chosen to report the performance of individuals. Although the pattern of dispersion in both skills indicators over time is remarkably similar, dispersion in the skills of non-movers is systematically larger than in the overall population.

INSERT FIGURE 4 HERE

Finally, we used another education indicator, constructed from the reported years of schooling of the non-movers in the ALL 2003 survey. We generated synthetic time series to capture years of schooling of labour market entrants, using the same procedure based on the demographic profile that was used to generate the time-series dimension in the skills variables.

Education and skills indicators will be used below to estimate the effect of human capital on the relative level of provincial per capita income minus government transfers to individuals. The relative income measures are shown for each province in figure 5.
Although there has been substantial convergence, Ontario and the western provinces (except for Saskatchewan) have had the highest levels of per capita income minus government transfers throughout the period; the Atlantic Provinces have stood at the lower end. The dispersion of per capita income across provinces is also presented in Figure 4 (measured on the left axis). It has decreased in all subperiods except during the 1970s when the per capita income in Alberta increased substantially with the oil shock.

3. THEORETICAL FOUNDATIONS AND EMPIRICAL METHODOLOGY

From the Production Function to TSCS Models

Our benchmark results of the effect of human capital accumulation on income differences come from an empirical framework that has many similarities with the traditional growth accounting framework. Both frameworks are based on the production function. Let us suppose that output $Y$ of economy $i$ at time $t$ is described by the following Cobb-Douglas production function:

$$Y_{i,t} = A_{i,t} K_{i,t}^\alpha H_{i,t}^\eta L_{i,t}^{1-\alpha-\eta}$$

with: $0 < \alpha < 1, 0 < \eta < 1$, and $\alpha + \eta < 1$

In this set-up, inputs $K$ and $H$ are respectively the stock of physical and human capital, input $L$ is “raw” labour, and $A$ is the state of the technology. Taking the logarithms on both sides of equation (1), the production function can be written:

$$\ln y_{i,t} = \ln A_{i,t} + \alpha \ln k_{i,t} + \eta \ln h_{i,t},$$

where: $y = \frac{Y}{L}, k = \frac{K}{L},$ and $h = \frac{H}{L}$
In growth accounting, assumptions are made regarding parameters $\alpha$ and $\eta$ in order to measure the Solow residual $A_{i,t}$. As pointed out in Topel (1999), the private return of human capital in the growth accounting approach is implicitly assumed to be equal to the social return. The macro-econometric literature on the effect of human capital, pioneered by Mankiw, Romer, and Weil (1992), is less restrictive; the effect of human capital is estimated freely in regressions based on (2) using (cross-country) macro-data in which the technology parameter $A_{i,t}$ is included in the error term:

$$\ln y_{i,t} = \beta_0 \ln k_{i,t} + \beta_1 \ln h_{i,t} + \beta_2 \ln A_{i,t} + \varepsilon_{i,t}$$

With appropriate indicators of the stock of human and physical capital, equation (3) can be estimated with TSCS data and the error term that embodies the technology parameter can be modelled in a much more general way than in a pure cross-sectional study.

The main complication in estimating parameter $\beta_1$ in (3) is finding reliable data on the stock of human capital and physical capital that have time-series and cross-sectional dimensions. If the physical capital stock is measured with error, the estimator of $\beta_1$ will generally be biased. We do not need data on the physical capital stock in a TSCS framework, however, if the physical capital/output ratio is assumed to be constant through time. This hypothesis is consistent with Kaldor’s (1963) stylized facts on growth and has been used in TSCS analysis of this type in Coulombe and Tremblay (2001) and Lange and Topel (2004). This stylized fact might be explained in a Cobb-Douglas production function framework by the assumption that the marginal product of capital is constant through time. Barro, Mankiw, and Sala-i-Martin’s (1995) model of a small open
economy with perfect (physical) capital mobility and a binding constraint for the
financing of human capital generates this result. In this case, \( \ln y_{i,t} - \ln k_{i,t} = c_t \), and
equation (3) simplifies to:

\[
\ln y_{i,t} = \beta_h \ln h_{i,t} + \overline{c}_i + \ln \overline{A}_{i,t}
\]

where \( \overline{c}_i \) and \( \ln \overline{A}_{i,t} \) are renormalizations of \( c_t \) and \( A_{i,t} \) and \( \beta_h = (\beta_t / 1 - \beta_o) \). In this
framework, \( \beta_h \) is the macroeconomic return to human capital under the assumption that
the physical capital/output ratio is constant.

The technology parameter \( \ln \overline{A}_{i,t} \) is decomposed in three components: the initial
technology levels \( A_{i,0} \) that are allowed to vary across provinces; a technological growth
component \( g(t) \) that is assumed to be the same across provinces but allowed to vary
through time; and idiosyncratic disturbances \( \varepsilon_{i,t} \):

\[
\ln \overline{A}_{i,t} = A_{i,0} + g(t) + \varepsilon_{i,t}
\]

The term embedding the growth rate of technological progress in (5) is treated as
an unobservable time-specific fixed effect \( \lambda_t \) in all TSCS models in this paper. With this
modelling, equation (4) can be written as:

\[
\ln y_{i,t} = \beta_h \ln h_{i,t} + \overline{c}_i + A_{i,0} + \lambda_t + \varepsilon_{i,t}
\]

As discussed in section 2, we used various proxy \( (p) \) variables \( h^*_{p,i,t} \) of \( h_{i,t} \) based
on education and skills indicators. The relationship between the proxy variables and the
true human capital concept might be viewed as:

\[
\ln h_{i,t} = \phi_p \ln h^*_{p,i,t} + \nu_{p,i,t}.
\]

With the proxy variables, equation (6) becomes:
\( \ln y_{i,t} = \beta_p \ln h^*_{p,i,t} + \ln c_i + A_{i,0} + \lambda_i + \eta_{i,t} \)

where \( \beta_p = \phi_p \beta_h \) and \( \eta_{i,t} = \epsilon_{i,t} + \nu_{i,t} \). The coefficient \( \beta_p \) is the main coefficient of interest in this study. It is important to bear in mind that various estimates of \( \beta_p \) cannot be interpreted in a straightforward way as a measure of the macroeconomic return of human capital since \( \beta_p \) is a function of the scale (\( \phi_p \)) of the various variables used as proxy for human capital. In the case of the skills variables, we will interpret the \( \hat{\beta}_p \) in a Mincerian way by computing the macroeconomic return of skills generated by one extra year of schooling. This is one of the main contributions of this paper.

In our first empirical TSCS model, \( c_i + A_{i,0} \) of equation (7) are amalgamated into an unobservable cross-sectional specific effect \( \gamma_i \):

\[
(R1) \quad \ln y_{i,t} = \beta_p \ln h^*_{i,t} + \gamma_i + \lambda_i + \eta_{i,t} \]

The fixed-effects transform procedure is the straightforward one to use if one is interested in getting estimates of only the \( \beta_p \). However, that procedure cannot be used for estimating the effect of time-invariant determinants of the technology level and the capital/output ratio in (7).

In line with previous studies (Coulombe, 2000; 2003), we also use a “structural” version of (7). In this version, a rural/urban structure variable, \( UR_i \), is used as a proxy variable for the time-invariant determinants (capital/labour ratios and initial technology levels) in the production function:

\[
(R2) \quad \ln y_{i,t} = \beta_p \ln h^*_{i,t} + \varphi_1 UR_i + \varphi_2 AB_{i,t} + \varphi_3 QU_{i,t} + \lambda_i + \eta_{i,t} \]
The $UR_i$ variable captures the relative (measured as the logarithm deviation from the cross-sectional sample mean) degree of urbanization of the 10 provinces. As shown in Coulombe (2000), even if the post-1950 period is characterized by a steady urbanization in all provinces, the relative degree of urbanization is quite stable for all provinces during the period for which these data are available. Also in line with our previous studies, we account for province-specific shocks that disturbed the growth patterns of Alberta in 1973 (the first oil shock) and Quebec around 1970 (the Anglophone exodus and the relative decline of Montreal). The $AB$ and $QU$ variables take the value zero for the other nine provinces and the value one for Alberta ($AB$) after the oil shock and Quebec ($QU$) after the Anglophone exodus. For these two provinces, their respective shock variables take also the value zero prior to the shock.\textsuperscript{89}

An alternative to equation (7) for estimating the macroeconomic effect of human capital is to use the convergence-growth framework (Barro and Sala-i-Martin, 1995). In this setting, the initial level of income is added to the list of controls in (7). Topel (1999) and Krueger and Lindahl (2001) have argued that the point estimate of the human capital variable in such a framework cannot be interpreted in a straightforward way. In this vein, Coulombe (2001) argues that in the open-economy framework of Barro, Mankiw, and Sala-i-Martin (1995) — certainly a model better able to account for the growth of Canadian provinces than the closed-economy version of the neoclassical growth model from which the convergence-growth equation is derived — the regression model is misspecified when both the initial human capital and the initial per capita output are included in the list of controls. In Coulombe and Tremblay (2006), we report some results with the initial level of income included in the regression. In this case, the effect of human capital
is not estimated precisely. We also show that the initial human capital variable can be used as an efficient instrument for the initial per capita income in IV estimations of the convergence-growth framework.¹⁰

**Details on Estimation Techniques**

We use appropriate econometric techniques to tackle the time-series and cross-sectional heteroscedasticity problems underlying this type of TSCS analysis. A set of results comes from pooled least squares (PLS) for which we report White heteroscedasticity consistent standard errors (HCCME). A second set of results comes from feasible generalized least squares (FGLS) that allow for a different residual variance for the each cross section. A cross-section weighting matrix is computed from the residual variance of a preliminary PLS regression. The weighted matrix is then used in a GLS regression and we used iterative techniques to update coefficients and the weighting matrix until convergence. For FGLS, we also report HCCME standard errors to allow for asymptotically valid inferences in the presence of the remaining time-series heteroscedasticity.¹¹

A third set of results was produced using instrumental variables (IV) estimations. We present results from two-stage least squares (TSLS) which is the IV analogue of PLS and from weighted two-stage least squares (WTSLS). WTSLS estimations are the IV analogue of FGLS and are designed to account for cross-sectional heteroscedasticity. For WTSLS, we also used iterative techniques for updating coefficients and the weighting matrix. In all IV estimations, the lagged skills data are used as the instrument for the contemporaneous skills variable. This procedure might help mitigate a possible endogeneity problem.¹² The skill of the young cohort might result from the current
income level. Instrumenting with the lagged variable is a common way to cope with the possible reverse causation. For all IV estimations, the other independent variables (such as the urban, the Alberta, and the Quebec variables) are used as their own instrument. Finally, in some tables, we also report results on beta coefficients using standardized variables (for skills, university achievement, years of schooling, per capita income, and the urbanization variable). These beta coefficients are reported within brackets in the same column as the associated usual estimation. The beta coefficients allow comparisons between point estimates dealing with skills and education since the two types of variables are not measured on the same scale.

4. RESULTS

The results are presented in three steps. First, we present the results of a simple cross-section between income disparities and our benchmark skill variable. Second, we use models R1 and R2 to analyse the relative empirical performance of our four candidate indicators of human capital. Finally, we consider regressions that include both skills and university achievement indicators as measures of human capital.

**Cross-Sectional Analysis**

The scatter diagram (Figure 6) provides a first look at the cross-sectional relationship between income per capita and the mean skill level for the non-mover population in the 16 to 65 age group for the ten observations available in 2003. This figure shows a clear positive relationship between income per capita and skills in each province, both measured relative to the cross-sectional mean. Moreover, the result of a simple cross-
section regression shows that skill disparities can potentially explain up to 48 per cent of income disparities. The slope coefficient of the skill variable is 2.2 and is highly significant. With the small number of cross-section observations at hand (10), it is not possible to estimate the effect of other variables. Consequently, the point estimate in the cross-section analysis will be biased as long as human capital is correlated with important variables omitted in this simple regression. In particular, our empirical analysis shows that the relative rate of provinces’ urbanization, which is positively correlated with skills, has a positive and significant effect on income per capita. As a result, the omission of urbanization in the simple regression presented in the figure below leads to an upward bias in the estimated effect of skills. Although admittedly too simple, this cross-section regression nonetheless provides a reference measure for the potential macroeconomic effect of skills which is not dependent on the synthetic cohort approach used to extend the number of observations in the TSCS analysis conducted in the remaining of the paper.

**Skills Versus Education as Indicators of Human Capital**

Results of TSCS estimations of regression models R1 and R2 when the skill or the education variables are used separately as indicator of human capital are presented in Tables 1 to 4. The results for the urbanization variable and the provincial dummies in Tables 2, 3 and 4 appear to be consistently estimated across the different models and with various human capital indicators. These results concur on qualitative and quantitative grounds with those found in Coulombe (2000) and will not be discussed further in this paper. The adjusted R$^2$ are very high ranging from 0.76 to 0.94. A substantial proportion
of the evolution of Canadian provincial disparities in per capita income since 1951 can be accounted for by the evolution of human capital disparities and a few structural factors such as the rural/urban structure. In the remaining of this section, we focus on the estimations of the various human capital indicators.

**Estimates of Human Capital Indicators.**

The first point that comes out of the results presented in Tables 1 to 3 is that the human capital indicator based on the skills of the non-mover population systematically outperforms the skill indicator derived from the overall population. In all cases, with comparable estimation techniques, the R², the degree of significance of the slope coefficient, and the beta coefficient, are larger when the synthetic skill variable is derived from the non-mover population only. These results suggest that the synthetic cohort methodology used in this paper to transform the pure cross-section data into TSCS data for the labour market entrants might be more appropriate if we abstract completely from the migrant population. As discussed in Section 2, the importance of interprovincial and international migration in Canada is such that applying the synthetic cohort approach to the overall population in 2003 might introduce substantial measurement errors. In the remainder of the paper, the results derived from the skills of the non-mover population are used as our benchmark skill variable.

The effect of skills derived from the non-mover population is positive and significant at least at the 5 per cent level in the 10 TSCS regressions presented in Tables 1 to 3. Note that the effect of all human capital indicators is estimated less precisely with PLS than with GLS. Furthermore, the effect of university achievement is also positive
and significant at least at the 5 per cent level in the four TSCS regressions from these
Tables. However, the effect of the years of schooling variable presented in Tables 1, 2
and 4, is always positive but is not significant at the 10 per cent level in three out of eight
regressions. As for our benchmark skill variable, the synthetic schooling is derived from
the non-mover populations and we get very comparable results when years of schooling
are derived from the overall population.\textsuperscript{14} With PLS, the schooling variable is only
significant with the structural model R2 in the regression using five-year periods in Table
4.

The relative lack of significance of the synthetic schooling variable, compared
with the data based on university attainment and skills, might be interpreted in at least
two ways. First, skills and university attainment matter more than years of schooling.
This may be explained by the fact that the skill variable is an output measure of human
capital. Furthermore, the signal contained in the university achievement variable might
be higher than for years of schooling since it also contain “sheepskin effects” that will be
discussed in detail below. Second, university achievement might perform better than the
years of schooling variable since, contrary to the later, the former is derived from the
overall population. Consequently, the university achievement variable captures the
accumulation of human capital across Canadian provinces generated by the
interprovincial and international migration processes. We will also come back to this
migration effect below.

Hence, human capital, whether measured from skills or university achievement,
appears to have a clear, positive effect on the relative level of per capita income across
provinces. Although not as robust as for these two variables, the effect of the years of
The schooling variable is always positive and is also significant in most regressions. In our view, the fact that human capital indicators derived either from skills or from education data have positive and significant effects on per capita income is one of the main results of this paper. It contrasts with our earlier cross-country study (Coulombe, Tremblay and Marchand, 2004) and suggests that measurement error in international schooling data may explain why education is often not found to be a significant predictor of cross-country income disparities.

Note however that, in addition to measurement error, a range of other reasons could also generate different results about the education and income disparity relationship at the sub-national and international levels. For example, the regions of particular countries, such as Italy, could exhibit greater variance in education attainment than groups of even heterogeneous countries. In the case of Canada though, skill differences across provinces are smaller than the differences between OECD countries reported in Coulombe, Tremblay, and Marchand (2004). Cross-border commuting could also weaken the spatial relationship between personal income and production in sub-national studies, although this issue is probably negligible for Canadian provinces as commuting is only important in the Ottawa-Gatineau area. No other important city is located near a provincial border. Finally, differences in results at the sub-national and international levels could also reflect the barriers to trade and migration that exist across countries. In the case of our analysis, constructing the skills variable for the non-movers population allows us to get around the migration issue.

INSERT TABLES 1 TO 4 AROUND HERE
From a quantitative point of view, the estimated effects of skills and university achievement on per capita income are quite different. The point estimate of the non-standardized skill variable is much larger than the point estimate of university achievement. This difference however is due to the fact that both indicators are measured on a different scale since the beta coefficients are very comparable across the two indicators. On average, a one standard deviation increase in skills in one province translates into an increase of 0.31 standard deviations in personal income (minus government transfers). For university achievement, the increase is 0.33 standard deviations. For the skill variable derived from the overall population, the mean beta coefficient is only 0.19. The mean beta coefficient for years of schooling variable derived from the non-mover population is only 0.16. In the remainder of this section, we focus on the results obtained from university achievement and the skills of the non-mover population.

The effect of skills appears to be consistently estimated across the 5-year and the 10-year data sets. The positive effect of skills remains highly significant when its lagged value is used as instrument in columns (7) and (8) of Table 3. Comparing columns (5) with (7) and columns (6) with (8) in Table 3, we see that the lagging procedure decreases the point estimate of the skill variable slightly when comparable estimation techniques are used. These results indicate that the potential reverse causation problem (endogeneity) is not driving the positive results of the synthetic skill variables.

Finally, it is worth pointing out that all the slope coefficients for the skill variable in the TSCS regressions are smaller than the slope coefficient of 2.2 estimated in the pure cross-sectional analysis above. Across the 10 TSCS regressions, the mean slope
coefficient of the skill variable is 1.34 which is 53 per cent smaller than the cross-section estimate. This result indicates that the variables that cannot be controlled for in the simple cross-section framework such as the initial technology levels, the urbanization structures, and the Alberta and Quebec shocks, are positively correlated with human capital. Consequently, the effect of human capital is over-estimated in a cross-section framework. In the next section, we show that the slope coefficient coming out of the TSCS approach is consistent with the Mincerian rate of return estimated across countries.

**Mincerian Interpretation of the Skills Effect.**

The mean point estimate of the skill variable is 1.34 across the 12 TSCS estimations in Tables 1 to 3. This number is the mean elasticity of per capita income (minus government transfers to individuals) to the skill variable coming out of our empirical investigation. A 1 per cent increase in the skills test in one province translates into an increase of 1.34 per cent in per capita income on average.

This point estimate can be interpreted in terms of Mincerian rate of return to education which is a common concept used in microeconomic labour studies. The Mincerian rate of return is the percentage increase in earning resulting from one extra year of schooling. According to Psacharopoulos’ (1994) extensive survey, Mincerian returns range from 5 to 15 per cent across countries. Mincerian rates also exhibit decreasing returns since the average for OECD countries is 6.8 per cent compared to 13.4 per cent for Sub-Saharan countries. The Mincerian rate of return reported for Canada by Psacharopoulos (1994) is 5.2 per cent.15
The first step for interpreting our skills point estimate in a Mincerian rate of return is by linking the arbitrary skills scale to schooling years. According to OECD (2000, p. xiv), one additional year of education increases the literacy skills score by 10 points on average across OECD countries. Second, using this OECD number, one additional year of schooling corresponds to a 3.8 per cent increase around the mean skills score (265) of the young cohorts across the Canadian provinces in our sample. Finally, our TSCS estimates imply that an increase in skills corresponding to one additional year of schooling increases per capita income at the provincial level in Canada by 1.34 times 3.8 per cent, or 5.1 per cent. This number is the inferred macroeconomic Mincerian rate of return derived from the mean slope coefficient of our 12 TSCS regressions. Our macroeconomic estimate is remarkably close to the microeconomic rate of return reported by Psacharopoulos (1994) for Canada and it locates at the lower end of the range for a broad set of countries. The fact that there is virtually no gap between the private individual return and the social aggregate return suggests that external effects associated with education may be relatively small which is consistent with the recent U.S. evidence of Acemoglu and Angrist (2000).

**Controlling for Both Skills and University Achievements**

Up to now, the skill and the university achievement indicators were viewed as alternative proxies of the true human capital concept. In this section, we extend the empirical framework to assess the complementarity between the two indicators by including both the skill ($S$) and the university achievement ($U$) variables in the same regression:

(R3) \[ \ln y_{i,t} = \beta_S \ln S_{i,t} + \beta_U \ln U_{i,t} + Z + \lambda_t + \eta_{i,t} \]
In this setup, the Z are the fixed effects of model R1 or the structural variables of R2.

Before interpreting the results, it is worth mentioning the dangers of collinearity. The two indicators are not perfectly correlated but a simple bivariate TSCS regression of the university achievement on our skill variable (non-movers) using PLS with the 60 ten-year TSCS observations yields a beta coefficient estimate of 0.55 and a \( t \)-statistics of 4.3.\(^\text{16} \) This is an indication that the two variables are strongly correlated and that the partial effect of the two indicators might not be estimated with great accuracy.

INSERT TABLE 5 HERE

The results of the regressions with both indicators included in the list of controls are presented in Table 5. In the two regressions with FGLS in models R1 and R2, the skill variable outperformed university achievement. The partial effect of skills is significant at the 1 per cent level and its beta coefficient is slightly larger. The partial effect of university achievement is only significant at the 10 per cent level. With PLS, the evidence is mixed. The coefficients of both variables are significant at the 10 per cent level in model R1 and at the 5 per cent level in R2 and the beta-coefficients are very comparable.

Overall, there is substantial evidence that the partial effect of skills remains positive and significant even after controlling for university achievement. This might not be surprising since the skill variable is a measure of output in the human capital production function. However, there is also some evidence that university achievement remains significant even after controlling for skills. This might result from two alternative, but not necessarily mutually exclusive phenomena: sheepskin effects and/or migration of human capital.
The basic way to interpret this result is to view the positive partial effect of university achievement as macroeconomic evidence of “sheepskin effects”. In the economics of education, sheepskin effects refer to the fact reported in many empirical studies that the earnings of individuals who have a diploma are typically larger than that of individuals who do not have a diploma after controlling for the years of schooling.\footnote{17} Sheepskin effects are interpreted in screening theories of education as evidence of the signalling hypothesis: a diploma, such as a college degree, sends a signal that is rewarded in the labour market. In these theories, the signal is interpreted by the employers as evidence of higher skills and productivity.

Our result might shed some light on the mechanism generating sheepskin effects. From a macro-regional perspective, university achievement appears to increase regional aggregate income even after controlling for a comprehensive measure of cognitive skills. This may be explained by the fact that university education provides individuals with a complementary set of skills. Consequently, the content of the signal that is valued in the labour market might be more related to skill complementarity for a given individual rather than to his skill level.

From a regional perspective, the sheepskin effects interpretation also suggests that the aggregations of university achievement and skills data both generate positive effects on regional income. The fact that the partial effect of aggregate university achievement is positive might be the result of the complementarity of particular skills across individuals in the same location. Consequently, the partial effect of university achievement might be viewed as a geographic agglomeration effect. It is often argued that the agglomeration of complementary skills, in aeronautics, computer engineering, economics, finance, design,
or biotechnology, for example, might be the best recipe for a robust regional economy. Again, this complementarity across individuals in the same region will not be measured by a cognitive skills test such as ALL. Even if the agglomeration effects from university achievement is not estimated precisely because of the multicollinearity problem, the results from Table 5 suggest that this effect is potentially substantial compared with the mere effect of skill level.

The sheepskin interpretation is based on the underlying assumption that the synthetic skill variable of the non-mover population, in our TSCS framework, is an unbiased proxy of the skills of the overall population. Relaxing this assumption allows us to provide another interpretation of the significance of the partial effect of both human capital indicators. Given the way both variables are derived, from the non-mover population only for skills and from census data for university achievement, one can view the partial effect of university achievement in R3 as being related to the contribution of the immigrant population to the human capital accumulation process at the provincial level. Along this line, empirical model R3 can be interpreted in the following way:

\[ \ln y_{it} = \beta_1 \ln (nm)_{it} + \beta_2 h(mig)_{it} + Z + \lambda_i + \eta_{it}, \]

where \( h(nm)_{it} \) and \( h(mig)_{it} \) are respectively the contributions of the non-mover and the immigrant populations to the human capital accumulation process. If we assume that \( h(mig)_{it} \) is proxied by \( U_{it} - S_{it} \) and \( h(nm)_{it} \) by \( S_{it} \) from R3, then, \( \beta_2 = \beta_U \) and \( \beta_1 = \beta_S + \beta_U \). In this framework, the partial effect of university achievement in R3 equals the contribution of the immigrant population to the human capital accumulation process and the sum of the coefficients of both human capital indicators from R3 captures the contribution of the non-mover population. Since the mean point estimates of skills
and university achievement are roughly equal in the four regressions reported in Table 5, one can argue that the investment in education of the non-mover population accounts, on average, for 2/3 of the human capital accumulation process and the remaining 1/3 is accounted for by the interprovincial and the international immigration processes.

Given data availability, it is not possible to sort out between the sheepskin and the immigration interpretations. Consequently, we have to conclude that the positive partial effect of university achievement found in R3 might result from either pure sheepskin effects, from the contribution of the immigrant population to the human capital accumulation process, or from both.

5. CONCLUSIONS

Our analysis makes an important contribution to the literature on the measurement of human capital and on macroeconomic returns from human capital accumulation at the regional level. It compares in a regional context the effects of two different types of human capital indicators based on education and skills, respectively. The main insights gained from our analysis are the following.

First, it consolidates our understanding of the regional growth process by showing that the accumulation of human capital has been an important determinant of the relative growth of Canadian provinces over the 1951–2001 period. To the extent that institutional quality and levels of social infrastructure are similar across Canadian provinces, our regional analysis allows us to derive a potentially unbiased estimate of the contribution of human capital to relative per capita income across economies. In cross-country studies, one may reasonably argue that estimates of the contribution of human capital to income
per capita may capture, at least to some extent, differences in the level of social infrastructure. Hence, our regional analysis may shed new light on this issue and provide support to the view that human capital does matter significantly for the relative long-run well-being of developed economies. Moreover, with only a few other structural variables, human capital disparities can explain a very large share of the evolution of income disparities since 1951.

Quantitatively, our mean estimate of the macroeconomic return from one additional year of education, in terms of skills acquired, is approximately 5 per cent. This number is remarkably close to Psacharopoulos’ (1994) microeconomic Mincerian estimates of 5.2 per cent and 6.8 per cent for Canada and for a set of OECD countries, respectively. The fact that the macroeconomic and microeconomic returns are almost the same suggests that human capital externalities may be quite small. At the same time, the fact that the aggregate return is not substantially smaller that the individual earnings return also indicates that education is not a pure signal (Spence, 1973).

Second, skills indicators do not appear to outperform education indicators based on university attainment at the Canadian provincial level. This contrasts sharply with the main result of the Coulombe, Tremblay, and Marchand (2004) study based on cross-country regressions. A potential explanation for this result is that skills indicators outperform schooling indicators at the cross-country level because skills test scores are more comparable than years of schooling. It is important to note that in the present study, the schooling indicator that performs better is not based on reported or computed years of schooling but on university achievement. It is also possible that the relative performance of university achievement data in our study comes from the fact that they are reported in
census data in a consistent way through time in Canada (see Fuente (de la) and Domenéch [2002] on this). At the cross-country level, however, data on years of education are often derived from raw data on benchmark educational level using correspondence that might not be consistent through time. The use of years of schooling at the cross-country level as the indicator of human capital — possibly motivated by the desire to link the macro results to the micro Mincerian literature that has focused on the return to an extra year of schooling — might exacerbate measurement errors. The fact that skills and university attainment data perform well suggests that both may be good proxies for human capital.

Third, we find that university attainment has a positive and significant effect on relative provincial income even after controlling for skills, which is consistent with the existence of ‘sheepskin effects’. The higher aggregate regional income resulting from higher university attainment, controlling for the level of skills may be explained by the fact that university education provides complementary sets of skills. Moreover, if the complementarity extends across individuals in a given location, university attainment data may capture human capital agglomeration effects at the regional level.

REFERENCES


### TABLE 1: Fixed-effects estimations of regression model R1

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**Notes:** Ten-year periods resulting in 60 panel observations. White heteroscedasticity standard errors are shown in parentheses. Beta coefficients are reported in brackets. a: significant at 1% level; b: at 5% level; c: at 10% level.
### TABLE 2: Estimations of structural regression model R2

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**Notes:** Ten-year periods resulting in 60 panel observations. White heteroscedasticity standard errors are shown in parentheses. Beta coefficients are reported in brackets. a: significant at 1% level; b: at 5% level; c: at 10% level.
### TABLE 3: Estimation results for the 5-year model, R1 and R2: Skills variables

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</tbody>
</table>

**Notes:** Five-year periods resulting in 110 panel observations in columns (1) to (6), and 100 panel observations in columns (7) and (8). FE: fixed-effects estimations in columns (1) to (4). In columns (7) and (8), the lagged literacy variable is used as instrument for the contemporaneous literacy variable. White heteroscedasticity standard errors are shown in parentheses below the estimated coefficients. a: significant at 1% level; b: at 5% level; c: at 10% level.
### TABLE 4: Estimation results for the 5-year model, R1 and R2: Years of schooling variable

<table>
<thead>
<tr>
<th></th>
<th>(1) PLS</th>
<th>(2) FGLS</th>
<th>(3) PLS</th>
<th>(4) FGLS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variables: per capita income minus government transfers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Years of schooling</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-movers</td>
<td>0.38</td>
<td>0.57</td>
<td>0.90</td>
<td>1.21</td>
</tr>
<tr>
<td></td>
<td>(0.29)</td>
<td>(0.12)</td>
<td>(0.33)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>Urban</td>
<td></td>
<td></td>
<td>0.83</td>
<td>0.63</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.08)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>Quebec</td>
<td></td>
<td></td>
<td>-0.12</td>
<td>-0.09</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.01)</td>
</tr>
<tr>
<td>Alberta</td>
<td></td>
<td></td>
<td>0.11</td>
<td>0.13</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>FE</td>
<td>YES</td>
<td>YES</td>
<td>NO</td>
<td>NO</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>.90</td>
<td>.90</td>
<td>.80</td>
<td>.85</td>
</tr>
<tr>
<td>DW</td>
<td>0.96</td>
<td>1.20</td>
<td>0.62</td>
<td>1.26</td>
</tr>
</tbody>
</table>

**Notes:** Five-year periods resulting in 110 panel observations. FE: fixed-effects estimations in columns (1) and (2). White heteroscedasticity standard errors are shown in parentheses below the estimated coefficients. a: significant at 1% level; b: at 5% level; c: at 10% level.

### TABLE 5: Regressions with both the skill and the university achievement indicators

<table>
<thead>
<tr>
<th></th>
<th>(1) PLS</th>
<th>(2) FGLS</th>
<th>(3) PLS</th>
<th>(4) FGLS</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variables: (standardized) per capita income minus government transfers</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Skills</td>
<td>0.22</td>
<td>0.35</td>
<td>0.28</td>
<td>0.31</td>
</tr>
<tr>
<td>Non-movers</td>
<td>(0.11)</td>
<td>(0.07)</td>
<td>(0.09)</td>
<td>(0.05)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>University</td>
<td>0.27</td>
<td>0.15</td>
<td>0.34</td>
<td>0.21</td>
</tr>
<tr>
<td>achievement</td>
<td>(0.14)</td>
<td>(0.08)</td>
<td>(0.17)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Observations</td>
<td>60</td>
<td>60</td>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>Adj. R²</td>
<td>.88</td>
<td>.93</td>
<td>.81</td>
<td>.90</td>
</tr>
<tr>
<td>DW</td>
<td>2.12</td>
<td>2.06</td>
<td>1.26</td>
<td>1.63</td>
</tr>
</tbody>
</table>

**Notes:** Ten-year model (R1 and R2). Statistics on structural parameters are not shown in columns (3) and (4). Beta coefficients reported for all regressions. White heteroscedasticity standard errors are shown in parentheses below the estimated coefficients. a: significant at 1% level; b: at 5% level; c: at 10% level.
FIGURE 1: Percentage of the Population Aged Between 15 and 65 with a University Degree (logarithm of deviations from the mean).
FIGURE 2: Average Skills of Population Aged Between 17 and 25
(logarithm of deviations from the mean).
FIGURE 3: Average Skills of Non-movers Aged Between 17 and 25  
(logarithm of deviations from the mean).
FIGURE 4: Standard Deviation of Human Capital and Per Capita Income Indicators.

Note: The standard deviation of the university indicator and of per capita income is measured on the left axis whereas the standard deviation of the literacy indicators is measured on the right axis.
FIGURE 5: Income Per Capita Minus Government Transfers (logarithm of deviations from the mean).

Note: Skills of non migrants and personal income (minus transfers to individuals) 10 provinces, 2003. Logarithm deviations from the cross-sectional sample mean.
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FIGURE 1: Percentage of the Population Aged Between 15 and 65 with a University Degree.

FIGURE 2: Average Skills of Population Aged Between 17 and 25.

FIGURE 3: Average Skills of Non-movers Aged Between 17 and 25.

FIGURE 4: Standard Deviation of Human Capital and Per Capita Income Indicators.

FIGURE 5: Income Per Capita Minus Government Transfers.


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1 In an open-economy growth model with physical capital mobility (Barro, Mankiw, and Sala-i-Martin, 1995), investment in physical capital is driven by human capital investment.

2 They are also available at 5-year intervals since 1976.

3 For a survey of empirical studies dealing with the growth effects of human and social capital across OECD countries, refer to Temple (2000). Also see Krueger and Lindahl (2001) for a broader discussion of empirical studies dealing with human capital and education.

4 The other measure of education attainment deals with the attainment of grade nine. However, given that virtually 100 per cent of the population attained this benchmark level of education in most provinces by the middle of our sample, we cannot use this indicator in the current study as a proxy of relative human capital across provinces.

5 This results from the pooling of time series and cross-section data and the use of time dummies in all regressions.

6 For a recent analysis of interprovincial migration in Canada, refer to Coulombe (2006).

7 See Topel (1999, Section 3.4).

8 In the working paper version of the paper (Coulombe and Tremblay, 2006), we also include a Nova Scotia dummy variable, as suggested in Coulombe (2003), in the regressions of the structural model. This variable was not significant in most structural regressions and was dropped from the model. The inclusion of this dummy does not change the point estimates of our variable of interest. Single dummy for
any of the other provinces are not significant when controlling for the urbanization variable. As discussed in Coulombe (2000), only Alberta and Quebec appear to have been hit by a structural break in the post 1950 period.

9 In Coulombe and Tremblay (2006), we also report results from a random-effects TSCS. Results from this empirical model concur with the ones reported in this study and a not reported for the sake of brevity.

10 See sections 3.3 and 4.4 of Coulombe and Tremblay (2006) for a complete analysis of including initial income level in the list of controls.

11 For more details on GLS and FGLS, refer to section 11.6.1 of Greene (2003).

12 We thank Angel de la Fuente for having suggested this point.

13 We also report in Coulombe and Tremblay (2006) results from alternative IV for the literacy variable.

14 Refer to Coulombe and Tremblay (2006) for results on years of schooling derived from the overall population of the ALL 2003 survey.

15 In Table A2, Psacharopoulos (1994) report Mincerian rate of returns for more than 60 countries.

16 The coefficient of 0.55 might be viewed as a reliability ratio from a measurement error analysis perspective. In this framework, both the university achievement and the skill variables are alternative proxies of the same true concept (human capital). Refer to Coulombe and Tremblay (2006) for an analysis of reliability ratios.

17 Refer to Jaeger and Page (1996) for a recent study on sheepskin effects.