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Quality of Work Experience and Economic Development—Estimates Using Canadian Immigrant Data.*

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Abstract

An issue that has been overlooked is the role of the quality of work experience in explaining differences in economic development. This paper argues why and shows how per capita GDP in an immigrant’s country of birth can be used—in a standard Mincerian model—as an indicator of the quality of schooling and work experience acquired in that country. Results obtained from regressions of immigrants’ earnings in Canada are then used to estimate the effects of differences in human capital quality on economic development. We find that while differences in the quality of schooling account for substantial differences in output per worker across countries, differences in the quality of work experience can account for even more. This suggests that the effects of improving the quality and the quantity of schooling in less-developed countries might be rather limited if labour-market institutions and ways of doing things are not changed at the same time to improve the quality of work experience. This study can be easily replicated using immigrant data from other countries than Canada to test whether the results are robust to changes in benchmark country.

Keywords: Quality of human capital, work experience, immigrant earnings, quality of schooling, economic development

JEL classifications: O15, J61, J24, O47, O57,

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1. **Introduction**

It is now generally recognized in the economic development literature that differences in the stock of human capital are an important determinant of differences in economic development across countries (see, for example, the seminal contribution of Mankiw, Romer and Weil, 1992). In empirical development accounting studies, those differences are typically defined in terms of gaps in input-based education measures such as school enrolment rates (Mankiw, Romer and Weil, 1992) and years of schooling (Barro and Lee, 1993, 2001; de la Fuente and Doménech, 2006). However, as it is usually acknowledged that the quality and efficiency of the education process can vary substantially with the development level of a country,\(^1\) a growing trend has been to also account for differences in quality of schooling when performing development accounting exercises.

In their development accounting exercises, Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999) recognize that the quality of schooling varies across countries. In particular, Klenow and Rodriguez-Clare (1997) link quality of schooling to a country’s GDP per capita and—using Borjas’s (1987) analysis—estimate a quality-of-schooling elasticity of 0.12. Concretely, this means that a country whose GDP per capita is one-twentieth that of the U.S., would be 36 percent richer if somehow it could increase its quality of schooling to the same level as that of the U.S. More recently, Schoellman (2012) finds that incorporating differences in education quality doubles the contribution of education in explaining cross-country differences in output per worker.

Despite the substantial amount of cross-country empirical research emphasizing differences in human capital, very little has been done on the role of the quality of work

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\(^1\) For studies showing that quality of schooling significantly varies across countries depending on their level of economic development, see Hanuskek and Kimko, 2000 and Coulombe and Tremblay, 2009. As argued in Hanushek and Woessmann (2008), education has both a quantity (years of schooling) and a quality (skills) dimension.
experience. There are indeed several reasons for the latter to vary across countries and to affect economic development, including differences in customs and managerial styles that may foster (or hinder) innovative thinking (as in Bloom and Van Reenem, 2007, 2010) and differences in learning-by-doing (as in Arrow, 1962 and Romer, 1986). One study was done recently, contemporaneously to ours, on that topic by Lagakos, Moll, Porzio and Qian (2012). The authors estimate earnings regressions on cross-sectional data from 36 countries and find that the returns to work experience are higher in rich countries than in poor countries; they conclude that human capital can explain a substantially larger fraction of cross-country income differences when the quality of work experience is taken into account than when it is not.

This paper addresses the same issue but with a different approach. We use the results obtained from regressions on immigrants’ earnings in Canada to measure differences in human capital quality across countries. The main advantage of using data on immigrants in one country as opposed to cross-sectional data from different countries is to allow isolating the impact of quality on returns to skills from other factors that can affect returns to skills and that vary across countries (e.g., the quantity of physical capital, the quantity of human capital, the technology, the industrial structure, the business cycle). Indeed, when an immigrant moves to another country, all those other factors are left behind and the immigrant brings only his or her human capital. Possible concerns with this approach though are that beside quality, immigrants’ returns to skills can be affected by other factors such as self-selection and skills not being transferable to the host country (see the discussion in Schoellman 2012). We address these concerns the way it is generally done in the immigrant earnings literature (see Friedberg 2000 and the body of the text for more discussion on this subject) and to the extent that data allows.
Our contribution is threefold. First, we adapt standard Mincerian regressions to allow for schooling quality and work experience quality to have different effects on returns to skills. Second, we show evidence that GDP per capita in an immigrant’s country of birth can be used as a proxy for the quality of human capital acquired in that country. Specifically, we show that GDP per capita is strongly correlated with the returns to schooling and work experience estimated through country of birth fixed effects and, through a more parsimonious model, we show that the returns to schooling and work experience statistically significantly increase with the GDP per capita of an immigrant country of birth. Third, on the more substantive side, using our regression results, we find that differences in human capital quality play an important role in explaining differences in economic development. For example, we estimate that a country whose GDP per capita is one-twentieth that of Canada (e.g., Kenya) would be almost 51 percent richer if it had the same human capital quality as that of Canada. Undoubtedly our most important finding, however, is that differences in work experience quality play an even bigger role than differences in the schooling quality in explaining differences in economic development. As a point of fact, we find that for a country like Kenya, the impact of work experience quality on output per worker is more than twice as large as that of schooling quality. Another interesting result that we find is that while between-country differences appear to be as important as within-country over-time differences for explaining differences in schooling quality, between-country differences are much more important for explaining differences in work experience quality than within-country over-time differences.

Our study builds on Borjas (1987), Hendricks (2002) and Schoellman (2012). Like Hendricks (2002) and Schoellman (2012), we use the results of Mincerian
regressions on immigrants’ earnings to estimate country differences in human capital quality. Further, like Borjas we assume that an immigrant’s quality of human capital is a function of the GDP per capita in his or her country of birth. However, unlike them, we differentiate between schooling quality and work experience quality and allow for cross-country differences in on-the-job human capital accumulation.

The rest of this paper is organized as follows. Section 2 presents the analytical framework. Section 3 describes the data and provides some descriptive statistics. Section 4 presents the empirical results of Mincerian regressions on immigrant earnings. Section 5 compares returns to skills across countries. The regression results are translated into comparative development accounting measures in Section 6. Section 7 concludes.

2. The analytical framework

As in Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999), assume that output $Y$ in country $j$ is produced according to the Cobb-Douglas production function

$$ Y_j = K_j^\alpha (A_j H_j)^{1-\alpha}, $$

where $K_j$ denotes the stock of physical capital, $H_j$ is the amount of skill-adjusted labour used in production and $A_j$ captures a labour-augmenting technology. In addition, assume that there are $L_j$ (homogenous) workers in country $j$ who are endowed with $s_j$ years of schooling and $x_j$ years of work experience on average, and that the quality of schooling and of work experience varies across countries. More specifically, assume that

$$ H_j = e^{d(s_j, x_j, q_j, q_s)} L_j $$

(2)
where \( q_{sj} \) and \( q_{sj} \) respectively denote schooling quality and work experience quality indices for country \( j \) and \( \phi(s_j, x_j, q_{sj}, q_{sj}) \) reflects the efficiency of \( s_j \) years of schooling and \( x_j \) years of work experience. For our purposes, we assume that all schooling and all work experience have been acquired in country \( j \). We will refer to \( \phi \) as the human capital generating function. Note that the derivatives \( \phi_x, \phi_s, \phi_{qs} \) and \( \phi_{qx} \) respectively correspond to the returns to schooling, work experience, schooling quality and work experience quality in a Mincerian regression wage equation framework (Mincer, 1974).

Given (1) and (2), output per worker, \( y \equiv Y / L \), can be expressed as

\[
y_j = A_j \left( \frac{K_j}{Y_j} \right)^{a/(1-a)} e^{\phi(s_j, x_j, q_{sj}, q_{sj})},
\]

and the percentage difference between output per worker in country \( j \) and output per worker in country \( k \), \( \Delta y(j,k) \equiv \ln y_j - \ln y_k \), can be decomposed into differences in technology, physical capital intensity (as a ratio of GDP), human capital quantity and quality:

\[
\Delta y(j,k) = \ln(A_j / A_k) + \{a/(1-a)\} \{\ln(K_j / Y_j) - \ln(K_k / Y_k)\} + \phi(s_j, x_j, q_{sj}, q_{sj}) - \phi(s_k, x_k, q_{sk}, q_{sk}).
\]  

(3)

Thus, the share of the percentage difference between output per worker in country \( j \) and output per worker in country \( k \) that is due to the difference in human capital quality can be approximated by

\[
\Delta y(j,k)_q \approx \phi_{qs} (q_{sj} - q_{sk}) + \phi_{qx} (q_{sj} - q_{sk}).
\]  

(4)

The first part of (4) is the Schooling-quality effect while the second part is the Work-experience-quality effect. Supposing that country \( k \) is the richer country, equation (4)

\footnote{The use of a linear approximation for \( \Delta y(j,k)_q \) is not absolutely necessary but greatly facilitates the development of the empirical model that follows.}
says that even if country \( j \) had the same technology, the same physical capital intensity and the same quantity of human capital as country \( k \), its output per worker would still be 
\[
\phi_{qs}(q_{sj} - q_{sk}) + \phi_{qs}(q_{sj} - q_{sk}) \text{ percent lower than country } k\text{'s output per worker. Or, put another way, given its current technology, its current physical capital intensity and its current quantity of human capital, country's } j\text{ output per worker would increase by about }
\phi_{qs}(q_{sj} - q_{sk}) + \phi_{qs}(q_{sj} - q_{sk}) \text{ percent if its quality of human capital increased to the level of that of country } k.
\]

### 2.1 Using immigrant data to estimate the impact of human capital quality on output per worker

Thus, according to (4), given some human capital quality indices \( q_s \) and \( q_x \), to estimate the impact of human capital quality on output per worker, one can specify a functional form for \( \phi \) and obtain \( \phi_{qs} \) and \( \phi_{qx} \) by estimating equation (3) by least-squares regression using a cross-section of countries. Another approach, which we follow in this paper, is to estimate \( \phi_{qs} \) and \( \phi_{qx} \) by comparing the wages of immigrant workers from different countries in the same competitive labour market using a Mincer-type regression model (thus following in the path of Hendricks, 2002 and Schoellman, 2012). Given that in such a market, workers have access to the same capital/output ratio, the same production function, and the same institutional framework, we should expect that immigrants with exactly the same human capital characteristics should earn the same wages. However, if we observe that the returns to schooling and work experience of immigrants endowed with the same level of schooling and work experience vary systematically with their

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3 Still another approach would be to estimate the function \( \phi \) by running a separate regression for each country (such as in Lagakos et al. 2012). However, this approach has a number of drawbacks including the necessary data being unavailable for many countries and the absence of control variables for factors affecting earnings beside human capital variables such as differences in industrial structures and business cycles.
country of birth, then this probably reflects differences in the quality of schooling and work experience they acquired in their country of birth.

Two possible concerns with this approach though are that difference in immigrants’ returns to skills could also reflect differences in human capital transferability and differences in self-selection (these concerns are discussed at length in Schoellman 2012). If these concerns are not somehow addressed in the estimation process, then the lack of transferability of human capital would result in our approach overestimating the role of quality in economic development, while the presence of positive self-selection would result in an underestimation of the role of quality in economic development—the net result being indeterminate.\(^4\)

2.1.1 Transferability of human capital issues

The human capital of immigrants may not be transferable from their country of birth to the host country for at least three reasons. One is because it may simply be of much lower quality than that in the host country. For example, being an expert at shovelling may have some market value in a country where power shovels are uncommon but has very little market value in a developed economy. This form of non-transferability is quality related and is therefore part of what we want to measure

Another reason why human capital may not be transferable is that immigrants may find difficult applying their skills into their new country because of a combination of language barriers and of lack of information about *ways of doing things* in the host

\(^4\) There are of course other factors that could possibly result in immigrants’ returns to skills varying across country of origin besides human capital quality, lack of transferability of skills and self-selection. For example, professional accreditation (*e.g.*, licensing for doctors) could be easier for immigrants without much experience than for immigrants with high levels of experience. Another possibility could be that immigrants who are young and have little experience are strongly selected, while those who are older and have more experience are weakly selected. However, since these other factors have not been identified as being important in the immigrant earnings literature and since it is not clear how they could be controlled for given the data available, they are ignored in this paper.
country. However, over time, as immigrants become more proficient in the host country working language and more knowledgeable about the host-country-specific knowledge (that is, as they assimilate) their returns to skills should improve. In the immigrant earnings literature, this issue is typically addressed by including language-fluency indicators and year-since-immigration second order polynomials in Mincer-type wage regressions (see, for example, Friedberg 2000).

A third reason why immigrants may have difficulty being rewarded in the host country for the skills they acquired in their country of birth is because the two countries may have different industrial structures or that the host country has labour market barriers (e.g., professional accreditation) that result in credentials from certain countries not being as recognized as credentials from other countries. The way this issue is dealt with in the immigration literature is by including country fixed effects in Mincer-type regressions.

2.1.2 Self-selection issue

Self-selection is a perennial issue when estimating the returns to skills of immigrants. A popular belief is that immigrants are positively selected in the sense that they are more able and more ambitious than the typical inhabitant of their country of birth (see, for example, Chiswick, 1978). However, Borjas (1987) shows that under certain circumstances, immigrants could be negatively selected. In the first instance, our approach would underestimate the effect of human capital quality on economic development, while in the second instance, it would overestimate it. Unfortunately, the literature on the labour market integration of immigrants has not found yet a fully satisfactory way of dealing with the issue of immigrant self-selection that would be
A practical, albeit imperfect way of dealing with the possibility of self-selection is to follow Borjas (1987) and include GDP per capita in an immigrant’s country of birth as an explanatory variable in the regressions.

2.2 Some empirical specifications for the human capital generating function

In this section, we look at different human capital generating functions that have been estimated in the immigrant literature. Our starting point is the ubiquitous Mincerian human capital generating function

\[ \phi(s_j, x_j) = \alpha s_j + \beta x_j + \beta^2 x_j^2 \]  

where the overscript ~ denotes variables measured in efficiency units and \( \alpha \) and \( \beta \) are coefficient vectors. If we assume that individuals are paid their marginal product in efficiency units of human capital, then, following Mincer (1974), \( \alpha \) and \( \beta \) can be estimated through a regression of the form

\[ \ln w_{ij} = \alpha s_j + \beta x_j + \beta^2 x_j^2 + z_{ij} \theta + \epsilon_{ij} \]  

where \( w_{ij} \) denotes the earnings of immigrant \( i \) from country \( j \); \( z_{ij} \) denotes a vector of determinants of human capital other than years of schooling and years of work experience that might vary across individuals or country of birth (e.g., language spoken, country of

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5 A theoretically satisfactory approach would be to treat the decision to immigrate as endogenous and estimate Heckit regression equations (Heckman 1976) but this would require for every country, information on a sample of those who decide not to immigrate, which is clearly not practical in our case.

6 There is some debate in the literature as to whether one should include, in a Mincer-type regression, a higher polynomial function (e.g., a quartic function) for work experience than just a quadratic one (see, for example, Lemieux 2006). Notwithstanding that debate, in this paper, we use the standard quadratic function as it is simpler and significantly more parsimonious (in our case, in some regressions, modeling work experience as a quartic function would increase the number of coefficients to be estimated by 25). Furthermore, we do not believe that this simplification introduces major biases since a quadratic function seems to be performing as well as a quartic function at estimating the returns to work experience at the means of the distribution, which is really what we are interested in measuring in this study (as opposed to estimating the returns to work experience at the tails of the distributions).
birth fixed effects); $\theta$ is a coefficient vector and $\epsilon$ denotes an error term with zero mean and constant variance.

When differences in human capital quality are ignored, then $\bar{x} = s$ and $\bar{x} = x$, and equation (5) simplifies to

$$\phi(s_j, x_j) = \alpha s_j + \beta_1 x_j + \beta_2 x_j^2. \quad (5a)$$

Accordingly, equation (6) simplifies to

$$\ln w_{ij} = \alpha s_{ij} + \beta x_{ij} + \beta_2 x_{ij}^2 + z_{ij} \theta + \epsilon_{ij}. \quad (6a)$$

### 2.2.1 Borjas (1987) human capital generating function

A simple human capital generating function that accounts for differences in human capital quality is the one used by Borjas (1987) in his work on immigrant self-selection:

$$\phi(s_j, x_j, q_j) = \alpha s_j + \beta x_j + \beta_2 x_j^2 + \gamma q_j, \quad (7)$$

where $\gamma$ is a coefficient and where the natural logarithm of real GDP per capita (denoted by $GDPc$ henceforth) is used as a measure of human capital quality,\(^7\) that is

$$q_j \equiv \ln GDPc_j.$$

Thus, using U.S. immigrant data, Borjas (1987) estimates the parameters of (5) through a regression equation of the form

$$\ln w_{ij} = \alpha s_{ij} + \beta x_{ij} + \beta_2 x_{ij}^2 + \gamma \ln GDPc_{ij} + z_{ij} \theta + \epsilon_{ij}. \quad (8)$$

Borjas’s results have since often been used to estimate the impact of human capital quality on economic development (see, for example, Rodriguez-Clare, 1997).\(^8\)

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\(^7\) The last point is not strictly correct as Borjas (1987) actually used real GNP per capita (as opposed to real GDP per capita) as a measure of human capital quality.
However, there are two issues with this formulation that arise in the context of
devolution accounting. One issue is that it does not distinguish between the impact of
schooling quality and work experience quality. Another issue is that GDP per capita is an
indirect measure of human capital quality that may reflect factors that explain immigrant
wages (such as self-selection, for example, which was the original intent of Borjas’
specification), but that are irrelevant for explaining differences in economic development
across countries.

2.2.2 Human capital generating functions in the literature on the labour market
integration of immigrants
Since the pioneering work of Chiswick (1978), researchers have recognized that the
quality of human capital acquired in an immigrant’s country of birth is different from that
acquired in the host country. For example, Friedberg (2000) essentially sets
\[ \tilde{s}_{ij} = \delta_i s_{Bij} + s_{Hij} \] and \[ \tilde{x}_{ij} = \omega_i x_{Bij} + x_{Hij} \] in (5), where \( \delta_i \) and \( \omega_i \) are unknown coefficients
and the \( H \) and \( B \) subscripts respectively refer to host country (Israel in her case) and birth
country, and estimates a regression equation of the form
\[
\ln w_{ij} = \alpha_i s_{Bij} + \alpha_2 s_{Hij} + \beta_1 x_{Bij} + \beta_2 x_{Bij}^2 + \beta_3 x_{Hij} + \beta_4 x_{Hij}^2 + \beta_5 x_{Bij} x_{Hij} + z_i \theta + \epsilon_{ij}.
\] (9)

2.3 Proposed specifications
Our specifications of the human capital generating function bridge the development
literature and the immigrant earnings literature in that regard. In particular, drawing from
the immigrant earnings literature, we build on the development literature by assuming

\[ \Delta y(j,k) = \gamma (\ln GDP_j - \ln GDP_k) \]

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8 Given (4), (6), (7) and an estimate of \( \alpha \) obtained from regression (8), the share of the percentage
difference in output per worker between two countries that is due do the difference in the quality of human
capital can then be estimated as
that not only the quality of schooling varies across countries, but also the quality of work experience. However, unlike what is typically done in the immigrant earnings literature (e.g., Friedberg 2000), we assume that the quality of schooling and of work experience varies across countries of birth. While the assumption that the quality of work experience varies across countries is quite novel in the economic development literature, it is highly intuitive. Indeed, just as the quality of work experience enhances human capital and, by extension, earnings at the individual’s level, one should expect that it would do the same at the aggregate level. We test two specifications: the first specification allows for the quality of human capital to vary freely across countries but not over time while the second specification imposes some structure on the way human capital quality varies both across countries and over time.

2.3.1 Flexible functional form for the quality of human capital across countries

In this specification, we estimate the schooling quality and work experience quality indices through country of birth schooling and work experience fixed effects. Explicitly, we set

\[ \tilde{s}_{ij} = s_{Bij}(1 + q_{sj}) \]  

(10)

and

\[ \tilde{x}_{ij} = x_{Bij}(1 + q_{sj}) + x_{Hij}, \]  

(11)

where we have further assumed for simplicity that immigrants acquire all their schooling in their birth country\(^9\) and that the quality indices \(q_{sj}\) and \(q_{sj}\) are constructed in such a way that they are equal to, smaller than or greater than zero if the schooling quality and the

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\(^9\)This assumption means that we will have to restrict our sample to immigrants who have acquired all their schooling in their country of birth. It also means that we will not have an estimate of the return to schooling acquired by immigrants in the host county, but this is not something we need to have to carry out our accounting exercise.
work-experience quality in country $j$ are respectively the same, lower than or higher than that in some benchmark country (to be defined as the U.S. in our analysis). Given this set-up and (5), and assuming that the curvature of the earnings’ growth profile is constant across all countries (to have a manageable number of coefficients in the regression), then the generating function for the human capital acquired in country $j$ (different from the host country, that is, setting $x_H \equiv 0$ in (11)) is

$$
\phi(s_j, x_j, q_j, q_{ij}) = \alpha_s s_j + \alpha_q q_j + \beta x_j + \beta^2 x_j^2 + \beta^3 x_j^3.
$$

(12)

where $\alpha_{sq} \equiv \alpha_q q_{sq}$ and $\beta_{sq} \equiv \beta q_{sq}$.

Given (6), (10) and (11), and some labour market information on immigrants (e.g., wages, human capital variables) from $N$ countries, the coefficients in (12) can be estimated through a regression equation of the form

$$
\ln W_{ij} = \alpha_s s_{Bij} + \sum_{n=2}^{N} \alpha_{sq} D_n s_{Bij} + \beta x_{Bij} + \beta^2 x_{Bij}^2 + \sum_{n=2}^{N} \beta_{sq} D_n x_{Bij}
$$

$$
+ \beta x_{Hij} + \beta^2 x_{Hij}^2 + \beta^3 x_{Hij}^3 + z_j \theta e_j
$$

(13)

where $D_n$ is a dichotomous variable that takes the value of one when $n = j$ and zero otherwise. One advantage of this specification is that it allows the identification of the human capital quality indices from the data itself, without having to impose any functional form on the way human capital quality varies across countries. Indeed, given estimates of the coefficients in (13), we estimate for country $j$, the schooling quality index as $\hat{q}_{sj} = \hat{\alpha}_{sq} / \hat{\alpha}_s$ and the work experience index as $\hat{q}_{qj} = \hat{\beta}_sq / \hat{\beta}_s$. There are however two disadvantages with this specification. One is that the estimation results can be used to measure the impact of human capital quality on economic development for only the countries in the regression sample. Another disadvantage is that it assumes that the
human capital quality of immigrants coming from a given country is the same irrespective of the time they immigrate. In other words, this specification assumes that human capital quality does not vary within a country over time, which is highly debatable. For example, most people would agree that the quality of schooling should improve as a country gets richer. However, this specification is useful if one wants to compare the average impact of between-country differences in human capital quality on economic development.

2.3.2 Parsimonious functional form for the quality of human capital across countries

In this specification, we assume that the quality of schooling and the quality of work-experience are related to an index of human capital quality $q_{ij}$. In other words, we set

$$\tilde{s}_{ij} \equiv s_{Bij}(1 + \delta q_{ij})$$

and

$$\tilde{x}_{ij} \equiv x_{Bij}(1 + \omega q_{ij}) + x_{Hij},$$

and as for the previous specification, we assume that immigrants acquire all their schooling in their birth country and that the quality index $q_{ij}$ is constructed in such a way that they it is equal to, smaller than or greater than zero if the quality of human capital in country $j$ is respectively the same, lower than or higher than that in the benchmark country. Given this set-up and (5), and assuming a direct quality effect (à la Borjas, 1987), then the generating function for the human capital acquired in country $j$ (different from the host country, that is, setting $x_H \equiv 0$ in (15)) is

$$\phi(s_j, x_j, q_j) = \alpha s_j + \alpha_2 s_j q_j + \beta x_j + \beta_2 x_j^2 + \beta_3 x_j q_j + \beta_4 x_j^2 q_j + \gamma q_j.$$

Given (6), (14) and (15), and some labour market information on immigrants, the coefficients in (16) can be estimated through a regression equation of the form
\[
\ln w_{ij} = \alpha_1 s_{Bij} + \alpha_2 s_{Bij} q_{ij} + \beta_1 x_{Bij} + \beta_2 x_{Bij}^2 + \beta_3 x_{Bij} q_{ij} + \beta_4 x_{Bij}^2 q_{ij} + \beta_5 x_{Bij}^3 q_{ij} ^2 \\
+ \rho_0 x_{Hi} + \beta_6 x_{Hi}^2 + \beta_7 x_{Hi} q_{ij} + \beta_8 x_{Hi}^2 q_{ij} + \gamma_{ij} + z_{ij} + \epsilon_{ij}.
\] (17)

Three observations are in order.

First, note that with regards to human capital quality, the formulation in Borjas (1987) and Hanushek and Kimko (2000) is a special case of (17) when 
\[
\alpha_2 = \beta_3 = \beta_4 = \beta_5 = \beta_8 = \beta_9 = 0; \quad \beta_1 = \beta_6; \text{ and } \beta_2 = \beta_7.
\]

Second, to estimate (17), we will use GDP per capita (smoothed to eliminate business cycles) as an indicator of an immigrant country of birth’s human capital quality. Specifically, setting Canada as the human capital quality benchmark country, we will use the index:

\[
q_{ij} = \ln \left( \frac{GDP_{c_{ij}}}{GDP_{c_{Canada}}} \right).
\] (18)

The advantages of this specification are that being a logarithm, it can easily be interpreted and that it is comparable to the index used by Borjas (1987) and Klenow and Rodriguez-Clare (1997). Note that \(q_{ij}\) meets the conditions that it is less than zero if country \(j\) is poorer than Canada, equal to zero if country \(j\) has the same standard of living as Canada and greater than zero if country \(j\) is richer than Canada. Note also that \(q_{ij}\) will be measured at the time of graduation. In other words, \(q_{ij}\) will represent the relative quality of human capital in country \(j\) in the year individual \(i\) from that country obtained his highest diploma, and will therefore vary over time (as we should expect). As a result, unlike the previous specification, this specification allows for measuring the impact of changes of human capital quality within a country and over time on economic development. We further expand on the rationales for using GDP per capita as an indicator of human capital quality in Section 2.3.3 below.
A third observation concerns the interpretation of the coefficient $\gamma$. Because $\gamma$ measures the human capital quality effect when *Years of schooling* and *Years of work experience* are zero, it may reflect the quality effect of unobservable skills of immigrants (e.g., motivation, ambition). If our estimate of $\gamma$ turns out positive, then this could suggest that immigrants from poorer countries are not the most able and the most ambitious persons in their country of birth (as postulated by Borjas, 1987) or that they are willing to settle for lower wages than immigrants from richer countries simply because of poorer labour market alternatives. On the other hand, if our estimate of $\gamma$ turns out negative, then it could suggest that immigrants from poorer countries have better unobservable skills than immigrants from richer countries. Either way, our estimate of $\gamma$ would reflect immigrant self-selection effects, which means that the value of this coefficient should not be used to infer about the quality of human capital of residents in foreign countries.

### 2.3.3 GDP per capita as an indicator of human capital quality

There are several reasons for using GDP per capita as an indicator of human capital quality. One is practicality. A measure of human capital quality that has been often used in the development accounting literature is the average score of a country on cognitive tests conducted by the *International Association for the Evaluation of Educational Achievement* and *the International Assessment of Educational Progress* (see, for example, Hanushek and Kimko 2000, Coulombe, Tremblay and Marchand 2004, and Coulombe and Tremblay 2006). While cognitive tests provide direct measures of human capital quality, they have the disadvantage of being available for far fewer countries and for much shorter periods of time than GDP per capita. For example, test scores from *the International Adult Literacy and Skills Survey* are available for only 27 countries while
data on GDP per capita are available for 188 countries and for as many as 55 years in Heston, Summers, and Aten (2009). Furthermore, and probably more importantly in our case, cognitive tests are not appropriate measures of experience quality—they really are measures of education quality.\textsuperscript{10}

Other reasons for using GDP per capita as an indicator of human capital quality are more conceptual. While the relationship between GDP per capita and quality of schooling and work experience may be complex, we explore here some of the more obvious reasons why we think that the former is an appropriate proxy for the latter. Countries with high GDP per capita generally have more monies to spend on schools, teachers and the like. As a result, one should expect that the quality of schooling in a country would increase with that country’s GDP per capita.

Another reason for using GDP per capita as an indicator of human capital quality is the link between the quality of work experience and economic development as an outcome of \textit{learning-by-doing}. Across countries, differences in customs, in employer-employee relationships/labour relations and differences in managerial styles may foster (or hinder) innovative thinking as in, for example, Bloom and Van Reenen (2007, 2010). Further, it could be that more developed economies use more physical capital such that there is more \textit{learning-by-doing} in rich countries. Indeed, since the seminal work of Arrow (1962) and its introduction into endogenous growth models by Romer (1986), learning-by-doing at the firm level is often assumed to be a function of the capital/labour ratio of the overall economy. In the framework of this paper, we can think of the value of the work experience that an individual has acquired in his or her birth country to be

\textsuperscript{10} For example, Cawley, Heckman and Vytlacil (2001) find that “measured cognitive ability and schooling are so highly correlated that one cannot separate their effects without imposing strong, arbitrary parametric structure in estimation which, when tested, is rejected by the data.”
determined in part by the physical capital intensity of that country. In this context, a country’s GDP per capita, itself a function of the capital intensity of that country, is a straightforward proxy for its quality of work experience. It is well known that cross country GDP data are much more reliable than capital stock data.\textsuperscript{11}

Still another reason to assume that GDP per capita is a good proxy for quality of human capital comes from the works of Erosa, Koreshkova and Restuccia (2010) and Manuelli and Seshadri (2010). In their Ben-Porath type models (see Ben-Porath 1967), total factor productivity (TFP) and human capital accumulation are complementary: the higher the TFP in a country, the more incentive there is to accumulate human capital. As a result, according to these models, the quality of human capital varies systematically with the level of economic development.

At the aggregate level, GDP per capita is determined by a variety of institutional, geographical, sociological, and political factors. However, when individuals migrate to another country, they bring with them their human capital and leave behind most of the other determinants of their country’s GDP per capita.

Finally, it is worth mentioning that since in an immigrant earnings regression, an immigrant’s country of birth GDP per capita is a strictly exogenous variable, any correlation with earnings is an indication of a causal link that runs from GDP per capita to earnings, and not the other way around.\textsuperscript{12}

2.3 \textit{Estimation considerations}

As is common in labour market studies of immigrants, not all coefficients of equation (13) and (17) are well-identified. However, the coefficients of interest (that is, the returns

\textsuperscript{11}The problems of comparability of capital stock data are well illustrated in Pritchett (2000).

\textsuperscript{12}Of course, this assumes that there is no other form of mis-specifications in the regressions which could result in coefficients being biased (\textit{e.g.}, omitted variables).
to country of birth’s schooling and work experience) are. It is well-known in the immigrant literature that one cannot distinguish between a cohort effect (that is the returns to skills of immigrants varying over time because of changing quality), an assimilation effect and a host country work experience effect when performing regressions like (13) and (17) on a simple cross-section data set (Borjas, 1999). In our case, the coefficients that are not well identified are the coefficients in $x_H$ because given our set-up, years of experience in the host country (that is $x_H$) is equal to years since immigration, which is a determinant of assimilation. In other words, the estimates of coefficients $\beta_6$, $\beta_7$ and $\beta_8$ in (13) and (17) will pick-up an assimilation effect. However, this is not a problem for us as these coefficients are not related to the skills acquired in an immigrant’s country of birth (see equations (12) and (16)) and are therefore not needed for our development accounting exercise.

Lastly, we will include in the vector $z$ knowledge-of-language indicators and country of birth fixed effects, which, in addition to the inclusion of the variable years of experience in host country in the regression, should mitigate to a large extent identification problems associated with immigrant assimilation and the lack of transferability of skills.

3. Data and summary statistics

Canada provides an ideal ground to test our model for two major reasons. One reason is that it has one of the largest and most culturally diverse intake of immigrants among the world developed economies. For example, Statistics Canada estimates that in 2006, almost 20 percent of all Canadians were born abroad (Statistics Canada, 2009). Canada
receives annually more than 250,000 immigrants, distributed among three major classes: economic immigrants, family reunification, and refugees.

The other reason why Canada is particularly well suited for this study stems from its immigration selection policy. In Canada, economic immigrants (the majority of immigrants) are admitted through a Point System, which evaluates candidates based on their schooling, age, work experience, language skills and other factors. Because of that particular policy, Canadian immigrants tend to be less economically self-selected than immigrants in other countries, notably the United States.

The data used for our analysis come from the Statistics Canada 2006 Census Microdata Masterfile, which provides a very large sample of immigrants, with very detailed information on their countries of birth. To eliminate as many extraneous factors as possible, the sample is restricted to working age men who worked full-time full-year in 2005, who were not self-employed and who obtained their highest certificate, degree or diploma in their country of birth. Working age is defined as ages 18 to 64, Full-time is defined as 30 hours or more a week and Full-year is defined as 49 weeks or more. The number of years of schooling is not available directly from the data and is defined on the basis of the highest certificate, degree or diploma (see Table A1 in appendix). Potential work experience is defined as Age minus Years of schooling minus 6.

Data on GDP per capita come from Heston, Summers, and Aten (2009) and is adjusted for purchasing power parity. To eliminate the effects of business cycles, GDP per capita is first smoothed through a five-year moving average. Then, for a given immigrant, Relative GDP per capita is measured as the ratio of his country of birth’s smoothed real GDP per capita and that of Canada in the year when he obtained his highest diploma. Countries for which there are fewer than 50 observations are dropped.
from the sample. The final sample is comprised of 80 countries (see Table 4 for the complete list of countries included in the sample). Appendix A provides further details on the variables used in our analysis.

Table 1 provides summary statistics on Canadian born and immigrant workers in our sample. It is interesting to note that despite being endowed with more years of schooling and work experience, immigrants earn on average about 10 percent less than Canadian born individuals. A number of labour economists have argued that one reason for the existence of this gap is that the human capital quality of immigrants in Canada is lower than that of Canadian born individuals (see, for example, Sweetman, 2004, and Bonikowska, Green and Riddell, 2008).

(Table 1 approximately here)

Table 2 illustrates the diversity of immigrant source countries in our sample. They are diverse not only in terms of geography but also in terms of level of economic development. Among the fifteen most important countries of origin, seven are Asian, six are European and two are American. Some are very rich (e.g., the U.S. and U.K.), while some others are developing (e.g., India and China). No group of source countries clearly dominates our sample, which means that our empirical results will not pick-up the effects of only a few countries.

(Table 2 approximately here)

4. Empirical results

In this section, we report estimates of nested versions of the immigrant earnings equations (13) and (17), from the most restricted to the least restricted. This allows for
the examination of changes in coefficient estimates following the removal of restrictions. The estimated coefficients of the human capital generating function are reported in Table 3. As a point of comparison, we also include the estimated coefficients of an earnings regression on Canadian born individuals. A key finding is that an immigrant’s returns to schooling and work experience significantly depend on his country of birth’s level of economic development.

(Table 3 approximately here)

4.1 Base case: No control for human capital quality

From a human capital point of view, the most restricted case of (13) and (17) is when it is assumed that the quality of one year of schooling or work experience acquired in an immigrant’s country of birth is the same as that acquired in Canada, which corresponds to equation (6a). The results in the column labelled Model 1 in Table 3 show that if such assumption was correct then the returns to human capital would significantly be lower for immigrants than for Canadian born individuals. For example, the Mincerian returns to years of schooling and years of work experience (evaluated at zero years of work experience) would respectively be 5.2 percent and 2.6 percent per year for immigrants compared with 8.6 percent and 5.6 percent per year for Canadian born individuals.

4.2 Work experience acquired in Canada vs. work experience acquired abroad

Model 2 in Table 3 is a first step towards distinguishing between the quality of human capital acquired in different countries. This model makes a distinction between work experience acquired in Canada and work experience acquired in an immigrant’s country of birth. This model corresponds to equation (13) and (17) with the restriction $\alpha_2 = \beta_3 = \beta_4 = \beta_5 = \beta_6 = \gamma = 0$. The results strongly support the notion that
human capital quality varies across countries and in particular that the quality of work experience is perceived by Canadian employers to be lower if the work experience has been acquired outside Canada. Indeed, all other things equal, immigrants earn roughly 2.2 percent more per year of work experience acquired in Canada than that acquired in their country of birth (3.8 percent per year compared with 1.6 percent per year).

4.3 Flexible functional form for the human capital quality indices

Model 2 is a rather crude way of modeling the effect of quality of schooling and work experience on earnings as it pre-supposes that it is the same for all countries of birth, which is clearly untenable, especially in light of results in international standardized literacy tests. Therefore, it is not useful for estimating the impact of human capital quality on economic development along the lines discussed in Section 2. Model 3 is our first attempt to correct for that by allowing the returns to schooling quality and work-experience quality to vary freely across countries (see Equation (13)). In this model, the U.S. is set as the reference/benchmark country. In other words, the estimates of $\alpha_i$ and $\beta_i$ for Model 3 in Table 3 respectively correspond to the returns to schooling and work experience acquired in the U.S. of a U.S. immigrant to Canada. The estimates of the $\alpha_2$’s and $\beta_3$’s in (13) are depicted in Figures 1a and 1b in relation with GDP per capita in the country of birth and respectively represent the differences between the returns to schooling and work experience of U.S. immigrants and those of immigrants from other countries, which in our model reflects differences in schooling quality and work experience quality. Three observations are in order.

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13 Note however that as discussed previously, the coefficients of variables that are functions of work experience in the host country are capturing both cohort and assimilation effects.
First, the hypotheses that the $\alpha_{2n}$'s and that the $\beta_{2n}$'s are jointly significantly equal to zero are strongly rejected (at levels of significance of less than $10^{-88}$ and $10^{-23}$ respectively). This is consistent with the theory that the quality of schooling and of work experience varies across countries.

Second, we observe that the $\hat{\alpha}_{2n}$'s and $\hat{\beta}_{2n}$'s are overwhelmingly negative. As a point of fact, 47 $\hat{\alpha}_{2n}$'s (out of 79) and 54 $\hat{\beta}_{2n}$'s (out of 79) are statistically significantly negative at the five percent level, while only two $\hat{\alpha}_{2n}$'s and one $\hat{\beta}_{2n}$'s are statistically significantly positive. According to our model, this suggests that the quality of human capital in the U.S. is significantly higher than that in most other countries in the world (at least, it is perceived by Canadian employers as being so).

Third, the estimated regression lines provide strong evidence that the quality of human capital varies with the level of economic development (as argued in Section 2.3.3). Indeed, we find that the correlation coefficient between this regression’s estimate of the schooling quality index and average GDP per capita over the time period studied is 0.61 (t-stat of 6.61) while the equivalent figure for the work-experience quality index is 0.46 (t-stat of 4.53). This result is striking—especially if we consider that the correlation coefficients between the “true” human capital quality indices and GDP per capita is probably even higher than those reported here because this regression’s estimates of human capital quality indices are measured with errors as they are based on estimated regression coefficients.

4.4 Parsimonious functional form—GDP per capita as a proxy for human capital quality

Model 4 allows for GDP per capita in the birth country to affect earnings only directly (à la Borjas, 1987 and Hanushek and Kimko, 2000) while Model 5 allows for GDP per
capita in the birth country to affect earnings both directly and indirectly through the returns to years of schooling and years of work experience. Specifically, Model 4 corresponds to equation (17) but with the restriction \( \alpha_2 = \beta_1 = \beta_3 = \beta_4 = 0 \), and Model 5 corresponds to equation (17) without restriction.

Looking at the coefficient estimates of Model 4 in Table 3, we find that Relative GDP per capita has a highly statistically significant and economically substantial impact on an immigrant’s earnings. Specifically, we find that an immigrant’s earnings elasticity with respect to this variable is 0.093. This is close to the value of 0.116 found in Borjas (1987) and Klenow and Rodriguez-Clare (1997) using U.S. data. It suggests, for example, that an immigrant from a country whose GDP per capita is 5 percent that of Canada earns about 28 percent less than another immigrant who comes from a country whose GDP per capita is comparable to that of Canada, but who is similar in all other respects.\(^1\)

While the results of Model 4 clearly show that Relative GDP per capita has a positive direct impact on immigrants’ earnings, we are concerned that Relative GDP per capita may be capturing more than a human capital quality effect. Indeed it could be capturing the effects of a host of other factors besides quality of schooling and of work experience, such as, for example, an immigrant self-selection effect (Borjas, 1987).

The coefficient estimates of Model 5 in Table 3 provide a more convincing argument that Relative GDP per capita is an appropriate indicator of human capital quality. Indeed, we find that the effects of Relative GDP per capita on immigrants’ earnings seem to be mostly operating through the Years of schooling and Years of work experience variables: the interaction effects of Relative GDP per capita are globally

\(^1\) All percentage changes in this paper are computed using natural logarithmic differences.
highly statistically significant\textsuperscript{15} and the first order effects are of the expected (positive) signs. However, the direct impact of Relative GDP per capita is now negative (and statistically significant at the 0.1 percent level). If we use Borjas (1987) interpretation of this coefficient, this would suggest that the quality of the unobserved skills (e.g., ambition, motivation) would increase the wages of immigrants from countries poorer than Canada and lower the wages of immigrants from countries richer than Canada. In other words, this would suggest that immigrants from countries poorer than Canada would be positively selected while immigrants from countries richer than Canada would be negatively selected.\textsuperscript{16}

5. Returns to skills across countries

While the flexible functional form of Model 3 is useful for giving us a sense of the wages-human capital quality relationship across countries, the parsimonious functional form of Model 5 is more convenient for several exercises that we perform in this paper (e.g., measuring the impact of human capital quality on economic development for countries not in the regression samples) and for comparing our results with those in the existing economic development literature. Also, as mentioned before, the parsimonious

\textsuperscript{15} The null hypothesis that all interaction effects of Relative GDP per capita are jointly equal to zero is rejected at a level of significance of less than $10^{-18}$ (using an F-test). While the cross-terms in Equation (17) are difficult to interpret, they show up to be statistically very significant and are therefore kept in the regression: the null hypothesis that $\beta_4 = \beta_5 = \beta_q = \beta_9 = 0$ is rejected at a level of significance below $10^{-31}$ (using an F-test).

\textsuperscript{16} Other variations of Model 5 in Table 3 were estimated to test the robustness of our model but the results are not reported here. For example, we tested an alternative specification for our human capital quality index than the one specified in equation (15). The alternative specification was $q_j = \frac{GDP_{c, j}}{GDP_{c, \text{canada}}} - 1$. We also tried relative life expectancy at birth instead of Relative GDP per capita as an indicator of quality of skills (the rationale being that life expectancy at birth is another widely available statistics related to well-being). In all these cases, the results were generally similar to those in Table 3, while their interpretation was not as intuitive.
functional form allows for the quality of human capital within a country to vary over time, as a country’s fortune changes, which seems reasonable. Thus in much of the remainder of the paper, we focus on the estimates of the parsimonious functional form of Model 5.

If we assume that immigrants are paid their marginal product of labour, that skills acquired in an immigrant’s birth country are transferable to the host country over time as immigrants assimilate and that self-selection is not too important —assumptions whose suitability we discussed earlier, then, given adequate GDP per capita data, we can use the coefficients estimated under Model 5 to infer the returns to schooling and work experience acquired in different countries at various points in time. Accordingly, in this section, we apply our methodology to a few selected countries. Our objective is to put figures on the extent to which the returns to skills acquired in poor countries are lower than the returns to skills acquired in rich countries, and to see how these returns to skill evolve over time as the level of economic development changes.

Figure 2 and Figure 3 respectively present estimates of returns to years of schooling and to years of work experience in six countries relative to the U.S., and at two points in time: 1954 and 2004. The countries are Argentina, China, India, Japan, Kenya and South Korea. They were selected because they are fairly representative of the growth paths experienced throughout the world over the years: some countries grew relative to the U.S. (e.g., China, Japan and South Korea), some declined (e.g., Argentina and Kenya) and some remained about the same (e.g., Canada and India). These estimates provide four main insights. First, they show that, as expected, the returns to schooling and to work experience are lower in poor countries than in rich countries. Further, we find that our estimated returns to work experience are not completely out of line with those
estimated by Lagakos et al. (2012). For example, they estimate that the average returns per year of work experience in China and India for 2005 (calculated over twenty years of work experience) are respectively approximately 70 percent and 35 percent that in the U.S., while we estimate that they are respectively 43 percent and 32 percent for 2004.

(Figures 2 and 3 approximately here)

A second insight provided by our regression estimates is that the returns to work experience are more sensitive to the level of economic development than the returns to schooling, especially for poor countries. For example, we estimate that in 2004, the return on one year of schooling in Kenya was 59 percent that of the U.S. while the return on one year of work experience was at best 17 percent that of the U.S.

Third, according to our regression estimates, the rich-poor country differential return on years of work experience increases with the number of years of experience. For example, we estimate that in 2004, the average rate of return on five years of work experience in China was 48.7 percent that in the U.S. while on 30 years of experience, it was 24.7 percent that in the U.S.

A fourth insight is that our estimated rates of return on human capital are consistent with the existence of human capital cohort effects, which is simply another way of saying that the quality of human capital in a country varies over time. In our model, because we assume that the quality of human capital depends on GDP per capita, we have that the quality of human capital in a country will evolve over time with the level of economic development in that country. For example, GDP per capita in Japan relative to that in the U.S. almost tripled between 1954 and 2004. As a result, we estimate that compared to the U.S., schooling quality in Japan increased by about 17 percent in relative
terms between 1954 and 2004, while average work experience quality (calculated over 20 years of work-experience) increased by about 40 percent in relative terms.

**Between-country differences vs. over-time differences**

An interesting question is whether or not in reality, human-capital quality differences should be dominated by between-country differences or by within-country over-time differences. An implicit assumption in *Model 5* is that within-country over-time differences have as much impact on human-capital quality differences as between country differences. In other words, whether the relative GDP per capita of a country *A* grows by \( x \) percent between \( t_1 \) and \( t_2 \), or its relative GDP per capita is \( x \) percent higher than that of country *B*, then the portion of the difference between GDP per capita at time \( t_1 \) and that at time \( t_2 \) explained by human capital quality is the same as the portion of the difference between its GDP per capita and that of country *B*. This is a strong assumption. One implication is that in a country that grows faster than some benchmark country, the U.S. for example, the quality of human capital of young workers (relative to the U.S.’ quality of human capital) will be above that of old workers while in a country that grows slower than the U.S., the quality of human capital of young workers (relative to the U.S.’ quality of human capital) will be lower than that of old workers. For example, for Japan, we estimate that the quality of schooling for those who graduated in 1954 is 73 percent that of the U.S. compared to 91 percent that of the U.S. for those who graduated in 2004 (see Figure 2).

One way of testing whether human-capital quality differences are dominated by between-country differences or by within-country over-time differences, is to add
Country of birth schooling and work experience fixed effects to Model 5 to estimate the regression equation

\[ \ln w_{ij} = \alpha_i s_{Bij} + \alpha_s s_{Bij} q_{ij} + \beta_1 x_{Bij} + \beta_2 x_{Bij}^2 + \beta_3 x_{Bij} q_{ij} + \beta_4 x_{Hij} + \beta_5 x_{Hij}^2 + \beta_6 x_{Hij} q_{ij} + \beta_7 x_{Hij} x_{Bij} \]

\[ + \sum_{n=2}^{N} \lambda_{n} D_{n} s_{Bij} + \sum_{n=2}^{N} \lambda_{n} D_{n} x_{Bij} + \gamma q_{ij} + \zeta \theta + \epsilon_{ij}, \]  

(19)

which is a mixture of equations (13) and (17) where we have assumed that the curvature of the estimated earnings’ growth profiles is constant across all countries of birth (in order to have a manageable number of coefficients in the regression). Since the estimates of \( \alpha_z \) and \( \beta_z \) capture both the between-country and the over-time effects, while the estimates of the \( \lambda \)'s capture only the between-country effects, if the estimates of \( \alpha_z \) and \( \beta_3 \) turn out to be statistically non-significantly different from zero in this regression, then it will suggest that the between-country effects are much more important than the within-country over-time effects. On the other hand, if the estimates of \( \alpha_z \) and \( \beta_3 \) turn out to be statistically significantly greater than zero in this regression, then it will suggest that the within-country over-time effects is as (if not more) important than the between-country effects. The results of this regression are reported under Model 6 in Table 3.

Interestingly, \( \hat{\alpha}_z \) remains statistically (highly) significantly positive while \( \hat{\beta}_3 \) becomes not statistically significant at all. This suggests that within-country over-time differences are important for explaining differences in schooling quality, but between-country differences are much more important for explaining differences in work experience quality than within-country over-time differences.

6. Human capital quality and economic development

The regressions results presented in Table 3 come from the analysis of earnings of Canadian immigrant individuals. In this section, we return to the macroeconomic
development accounting framework outlined in Section 2 and use the coefficients estimated under Model 5 to estimate the impact of human-capital quality on economic development. To perform this task, we use the fact that if the representative worker in country $j$ is endowed with a level of schooling $s_j$ and a level of work experience $x_j$, then given (3) and (16), the portion of the percentage difference between output per worker in country $j$ and that in country $k$ explained by the difference in human capital quality from the point of view of country $j$ is

$$
\Delta \gamma(j,k) = \phi(s_j, x_j, q_j) - \phi(s_j, x_j, q_k),
$$

which can be decomposed into two parts:

a Schooling-quality effect: $\alpha_s s_j (q_j - q_k)$, \hspace{1cm} (20a)

and

a Work-experience-quality effect: $(\beta_s x_j + \beta_x x_j^2) (q_j - q_k) + \beta_s x_j^2 (q_j^2 - q_k^2)$. \hspace{1cm} (20b)

The figures in Table 4 show for 92 countries, how these countries’ output per worker would increase if these countries had the same schooling quality and work-experience quality as that of Canada. These countries were selected based on the availability of data on schooling in Morrisson and Murtin (2009) and Barro and Lee (2013). Further information on the definition of the variables and the sources of the data is provided in the footnotes to Table 4.

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17 The $\gamma(q_j - q_k)$ effect is ignored in analyzing the impact of differences in human-capital quality on economic development because as previously discussed, the coefficient $\gamma$ really reflects self-selection effects, not human-capital quality effects.

18 The number of countries listed in Table 4 (92) is greater than the number of countries in the regression sample (80). As pointed out earlier, an advantage of imposing some structure on the way human capital quality varies both across countries and over time (such as we do in Model 5 by modelling human capital
The figures in Table 4 clearly demonstrate that differences in human capital quality matter a lot for explaining differences in output per worker between rich and poor countries. For example, if we assume that the representative worker in Kenya has 6.5 years of schooling and 21.9 potential years of work experience, then we estimate that Kenya’s output per worker would increase by 51.0 percent if it had the same human capital quality as that of Canada. Under such circumstances the ratio of Canada’s output per worker to that of Kenya’s would decrease from 20:1 to 13.2:1.

It also interesting to see that for more developed countries such as India and Argentina, differences in human capital quality also account for substantial differences in output per worker. For example, we estimate that India’s output per worker would increase by 39.2 percent if India’s human capital quality was the same as Canada’s. The equivalent figure for Argentina is 19.0 percent.

Of course the difference is much smaller for economies that are relatively similar to each other (such as Canada and the U.S.). For example, assuming that workers in both Canada and the U.S. have on average the same number of years of schooling and the same number years of work experience, then Table 4 suggests that if Canada had the same human capital quality as the U.S., Canada’s output per worker would increase by 6.0 percent. In other words, we estimate that human capital quality accounts for about 21 percent of the difference in standard of living between these two countries.

quality as a function of GDP per capita) is that we can perform economic development analyses for countries that are not included in the regression sample.
6.1 Decomposition of the impact of human capital quality

Table 4 also reports the decomposition of the impact of differences in human capital quality on output per worker into a Schooling quality effect and Work-experience quality effect—as per equations (20a) and (20b). The results are striking. In all cases, the quality of work experience plays a much greater role in explaining differences in output per worker than the quality of schooling. For example, if we take the case of Kenya, the Work-experience quality effect is about twice as large as the Schooling quality effect. In the case of Argentina, the Work-experience quality effect is about 80 percent larger than the Schooling quality effect. Overall, on average, for the countries listed in Table 4, we find that the Work-experience quality effect is about twice that of the Schooling quality effect. These results are in some respect the most revealing of this study. Up to now, the economic development literature has focused primarily on schooling when studying the impact of human capital quality on standards of living. In this paper, we show that a country’s quality of schooling is indeed a key determinant of its standards of living. However, our bottom line is that the quality of work experience is an even more important determinant from a quantitative point of view. This might not be surprising ex-post since we know that the average number of years of work-experience in a country is generally larger than the number of years of schooling. Nevertheless, normalizing our estimates for the number of years of schooling and the number of years of work experience, we find that on average for the countries listed in Table 4, the quality impact on output per worker of one year of work experience is still substantial compared to that of one year of schooling—about 66 percent of the latter in fact.

Clearly, further research is needed to better understand the factors that determine the quality of work experience in countries at different stages in their economic
Development. In the basic Mincerian framework (as in the Ben-Porath 1967 framework) returns to work experience are explained by the fact that workers invest in human capital on the job to become more productive later. Our results show that the return to such investment is higher if this investment is made in a rich country than if it is made in a poor country. An obvious explanation is that from an economic development point of view, on-the-job training is more valuable if it is acquired while working with sophisticated tools and within complex organizations than it is otherwise. For example, most would agree that from an economic development point of view, working with computers provides more valuable training than working with abaci. Another explanation could be that potential work experience in poor countries is less intensive than in rich countries because of higher unemployment and shorter working time.

6.2 How do our results compare?

It is noteworthy that we find that human capital quality has a greater impact on economic development than that reported in Klenow and Rodriguez-Clare (1997), but smaller than that estimated by Schoellman (2012). Klenow and Rodriguez-Clare find that Borjas (1987) estimates imply that the difference in human capital quality between Kenya and Canada would account for 36 percent of Kenya’s output per worker, while we estimate that it would account for 51.0 percent (see Table 4). For Canada compared to the United States, our estimate of 6.0 percent is more than twice as large as what would be obtained using Klenow and Rodriguez-Clare (1997)’s methodology.

Comparing our results with those of Schoellman (2012) provides another perspective. Schoellman finds that controlling for differences in human capital quality (which he totally assigns to differences in schooling quality) doubles the impact of differences in human capital on economic development. Using the parameter estimates
of Model 5, we find that indeed for a poor country (e.g., Kenya), the impact of differences in human capital quality slightly more than double the impact of human capital quantity on output per worker. But this comes mostly from accounting for the quality of work experience: under such circumstances, we estimate that by taking into account quality, the impact of human capital on output per worker increases by about 115 percent with about two-third of the increase due to the impact of work experience quality. On the other hand, for a richer country, our estimate of the impact of human capital quality is much smaller than that found by Schoellman (2012): for Argentina, for example, we estimate that controlling for human capital quality increases the impact of differences in human capital on output per worker by about 66 percent (with about 64 percent of the increase due to the impact of work experience quality).

The only study to which we can compare our estimates of the effects of work experience quality on economic development is that of Lagakos et al. (2012). Our estimates of these effects are generally much smaller. For example, they estimate that GDP per capita in Argentina would be between 100 and 130 percent larger if Argentina’s work-experience quality was the same as that of the U.S., while, using figures in Table 4, we estimate that it would be approximately 15.4 percent higher. Figures for India are even more dramatic: they estimate that India’s GDP per capita would be between 300 and 400 percent larger if India had the same work-experience quality as that of the U.S., while we estimate that it would be approximately 32.1 percent larger. On the other hand, in a few cases, their estimate is quite similar to ours: for example, they estimate that

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19 Our estimates are based on the following formulas. Since Canada is the benchmark country, \( q_k = 0 \), and from (3) and (16), the contributions of the differences in schooling endowments, schooling quality, work experience endowments and work experience quality to the difference in income per capita between country \( j \) and country \( k \) respectively are: 

\[ S = \alpha_j (s_j - s_k); \quad \Delta q_s = \alpha_j s_j q_j; \quad X = \beta_s (x_j - x_k) + \beta_e (x_j^2 - x_k^2); \] 

and, 

\[ Xq = (\beta_s x_j + \beta_e x_j^2) q_j + \beta_e x_j^2 q_j^2. \]
Canada’s GDP per capita would be between 2.5 and 4.5 percent larger if Canada had the same work-experience quality as that of the U.S., while we estimate that it would be approximately 3.2 percent larger.

7. Conclusion

In this paper, we present a methodology to analyze the effects of schooling quality and work-experience quality on economic development. In that vein, we argue that GDP per capita is a good indicator of human capital quality across countries and provides empirical evidence to that effect using Canadian census data on immigrant earnings. When this insight is incorporated into an economic development accounting exercise by allowing schooling quality and work-experience quality to vary across countries according to their GDP per capita, we find that combining quality adjustments for both schooling and work experience leads to human capital quality adjustments that are in between those previously found in the literature (e.g., Klenow and Rodrigues-Clare, 1997; Schoellman, 2012 and Lagakos et al. (2012). Perhaps more importantly though, we document a new fact: quantitatively speaking, the quality of work experience plays a much bigger role in explaining differences in output per worker than the quality of schooling. Another interesting result we find (and that probably needs to be further investigated) is that while between-country differences appears to be as important as within-country over-time differences for explaining differences in schooling quality, between-country differences is much more important for explaining differences in work experience quality than within-country over-time differences.

As emphasized by Hanushek and Woessmann, (2008), one of the key facts revealed by recent economic development experiences is that improvements in the
quantity of education have not always yielded the expected progress in terms of economic well-being. They convincingly argue that the quality of schooling should also be improved. The results of our analysis confirm their diagnostic: differences in the quality of schooling are substantial between rich and poor countries. However, our analysis also highlights another potential explanation for the weak impact of improving schooling on economic well-being in poor countries: the low quality of work experience in those countries. Indeed, while improving schooling quantity and quality would certainly enrich the stock of human capital in poor countries, improving the quality of work experience might achieve even more. Our results thus introduce the notion that, ideally, from a human capital point of view, an economic development process should be balanced: it should be characterized by simultaneous improvements in both schooling and labour market experience.

Finally, our results might shed new light on our understandings of the international transferability of human capital (see for example, Chiswick and Miller, 2009). The returns to education and work experience of Canadian immigrants appear to be affected by the degree of economic development in their country of birth. The weak transferability of human capital (abstracting from language skills) might result from quality differences in the human capital formation process.

The next step for this study would be to replicate the methodology using data from other countries that have large and diverse populations of immigrants such as the U.S. and Israel. The objective of such exercise would be to test whether the development accounting results obtained in this study are robust to changes in benchmark countries.
References


APPENDIX A
DATA DESCRIPTION

Dependent variable

Our dependent variable is the natural logarithm of weekly earning. Weekly earning is calculated as wages and salaries reported for 2005 divided by the number of weeks worked in 2005.

Some restrictions were applied to eliminate very small and very large values of earnings. Observations with annual wages less than $1000 and less than $2 per hour were removed. The sample was also restricted to men who had obtained their (post-secondary) highest certificate, diploma or degree in their country of birth according to the Location of study variable in the 2006 census. For individuals without post-secondary certificate, diploma or degree, we assumed that they had acquired their education in their country of birth except if they had immigrated to Canada before they turned 18, in which case we assumed they had completed their education in Canada (and therefore were excluded from the sample).

Independent variables

We allow earnings to vary by a fixed effect across Canada. We control for six regions: the Atlantic Provinces, Quebec, Ontario (the reference category), the Prairies, Alberta and British Columbia.

The 2006 census does not provide a value for Years of schooling. To compute this value we use the information provided on the highest certificate, degree or diploma obtained in the way described in Table A1. In the census, the variable location of study is
reported only for individuals who have completed a postsecondary certificate, diploma or degree.

*Potential experience* is defined as *Age minus Years of schooling* minus 6. *Foreign experience* is measured as potential experience minus *Years since migration*, where *Years since migration* is calculated as 2005 minus the year the individual’s year of immigration (that is, the year landed immigrant status was first granted). Work experience in the host country labour market is defined as potential experience minus *foreign experience*.

For language skill, we use the variable *Knowledge of the official languages* (as evaluated by the respondents). The categories are (1) English only (the reference), (2) French only, (3) Both English and French, and (4) None of English and French.

**Table A1: Construction of Number of Years of Schooling Variable**

<table>
<thead>
<tr>
<th>Highest certificate, degree or diploma obtained</th>
<th>Estimated years of schooling</th>
</tr>
</thead>
<tbody>
<tr>
<td>No certificate</td>
<td>8</td>
</tr>
<tr>
<td>High school certificate</td>
<td>12</td>
</tr>
<tr>
<td>Trade, apprenticeship, college or CEGEP certificates or diploma from a program of three months to less than one year</td>
<td>13</td>
</tr>
<tr>
<td>Trade, apprenticeship, college or CEGEP certificates or diploma from a program of one year to two years</td>
<td>14</td>
</tr>
<tr>
<td>University certificate or diploma below bachelor level</td>
<td>15</td>
</tr>
<tr>
<td>University bachelor level</td>
<td>16</td>
</tr>
<tr>
<td>University certificate or diploma above bachelor level</td>
<td>17</td>
</tr>
<tr>
<td>Masters</td>
<td>18</td>
</tr>
<tr>
<td>Doctorate (including medicine, dentistry and similar programs)</td>
<td>22</td>
</tr>
</tbody>
</table>
Data on real GDP come from Heston, Summers, and Aten (2009) and is available for 188 countries (including Canada). *Relative GDP per capita* is measured as the ratio of a *five-year moving average* of an immigrant’s country of birth real GDP per capita and of a *five-year moving average* of Canada’s real GDP per capita, at the year when individuals obtained their highest diploma. Countries for which there are fewer than 50 observations are dropped from the sample.
Table 1
Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Canadian Born Individuals</th>
<th>Immigrants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weekly earnings</td>
<td>1155.3</td>
<td>1039.6</td>
</tr>
<tr>
<td>Ln weekly earnings</td>
<td>6.9</td>
<td>6.7</td>
</tr>
<tr>
<td>Years of schooling</td>
<td>13.2</td>
<td>13.7</td>
</tr>
<tr>
<td>Total potential experience (years)</td>
<td>21.6</td>
<td>26.9</td>
</tr>
<tr>
<td>Host country</td>
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<td>14.5</td>
</tr>
<tr>
<td>Foreign</td>
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<td>14.4</td>
</tr>
<tr>
<td>Real GDP per capita ratio*</td>
<td>n.a.</td>
<td>0.35</td>
</tr>
<tr>
<td>Sample size</td>
<td>552,175</td>
<td>52,615</td>
</tr>
</tbody>
</table>

\*Full-time, full-year working males between 18 and 64. Immigrants are defined as having obtained their highest diploma in their country of birth.
\*Ratio of five-year moving averages measured at the time of obtention of highest diploma.
Source: Calculations from Statistics Canada 2006 census data.

Table 2
The Fifteen Most Common Countries of Birth of Canadian Male Immigrants in 2006

<table>
<thead>
<tr>
<th>Country of Origin</th>
<th>% of Immigrant Male Population</th>
</tr>
</thead>
<tbody>
<tr>
<td>India</td>
<td>13.2</td>
</tr>
<tr>
<td>Philippines</td>
<td>10.7</td>
</tr>
<tr>
<td>China</td>
<td>9.3</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>9.0</td>
</tr>
<tr>
<td>Sri Lanka</td>
<td>3.7</td>
</tr>
<tr>
<td>Poland</td>
<td>3.4</td>
</tr>
<tr>
<td>Hong Kong</td>
<td>3.4</td>
</tr>
<tr>
<td>U.S.</td>
<td>3.4</td>
</tr>
<tr>
<td>Romania</td>
<td>3.1</td>
</tr>
<tr>
<td>Pakistan</td>
<td>3.0</td>
</tr>
<tr>
<td>Portugal</td>
<td>2.2</td>
</tr>
<tr>
<td>France</td>
<td>2.0</td>
</tr>
<tr>
<td>Jamaica</td>
<td>1.8</td>
</tr>
<tr>
<td>Italy</td>
<td>1.8</td>
</tr>
<tr>
<td>Iran</td>
<td>1.4</td>
</tr>
</tbody>
</table>

\*Full-time, full-year working male immigrants between 18 and 64 who obtained their highest diploma in their country of birth.
Source: Calculations from Statistics Canada 2006 census data.
Table 3

Returns to Years of Schooling and Years of Work Experience\(^a\)

<table>
<thead>
<tr>
<th>Immigrants ((n = 52,615))</th>
<th>Canadian Born Individuals ((n = 552,175))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimated Coefficients(^b)</td>
<td>Model 1(^c) (no difference in human capital quality)</td>
</tr>
<tr>
<td>(\alpha_1 (s_B))</td>
<td>0.086 (279)</td>
</tr>
<tr>
<td>(\alpha_2 (s_Bq))</td>
<td></td>
</tr>
<tr>
<td>(\beta_1 (x_B))</td>
<td>0.026 (21.)</td>
</tr>
<tr>
<td>(\beta_2 (x_B^2))</td>
<td>-0.040 (18.)</td>
</tr>
<tr>
<td>(\beta_3 (x_Bq))</td>
<td></td>
</tr>
<tr>
<td>(\beta_4 (x_B^2q))</td>
<td></td>
</tr>
<tr>
<td>(\beta_5 (x_B^2q^2))</td>
<td></td>
</tr>
<tr>
<td>(\beta_6 (x_H))</td>
<td>0.056 (210)</td>
</tr>
<tr>
<td>(\beta_7 (x_H^2))</td>
<td>-0.090 (147)</td>
</tr>
<tr>
<td>(\beta_8 (x_Hx_B))</td>
<td>-0.050 (9.8.)</td>
</tr>
<tr>
<td>(\beta_9 (x_Hx_Bq))</td>
<td></td>
</tr>
<tr>
<td>(\gamma (q))</td>
<td></td>
</tr>
<tr>
<td>(R^2)</td>
<td>0.285</td>
</tr>
</tbody>
</table>

\(^a\)Absolute t-ratio in parentheses. The dependent variable is ln (weekly earnings). Also included in regressions are five regions of residence indicators, three language spoken indicators and 79 immigrant country of birth dummy variables.

\(^b\)Associated independent variables are between parentheses. The estimated returns to variables in \(x^2\) have been multiplied by 100.

\(^c\)In Model 1, the return to foreign work experience is assumed to be the same as the return to domestic work experience.

\(^d\)In Models 3 and 6, in order to have a manageable number of coefficients in the regressions, we assume that the curvature of the estimated earnings’ growth profiles is constant across all countries of birth.
Table 4
Impact of Differences in Human Capital Quality on Output per Worker

<table>
<thead>
<tr>
<th>Country</th>
<th>GDP per Capita of Country of Birth (relative to Canada)</th>
<th>Average Number of Years of Schooling</th>
<th>Average Number of Years of Work Experience</th>
<th>Quality Effects of... (as a percent of GDP)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Schooling</td>
</tr>
<tr>
<td>Afghanistan</td>
<td>0.02</td>
<td>3.7</td>
<td>23.7</td>
<td>12.8</td>
</tr>
<tr>
<td>Algeria</td>
<td>0.20</td>
<td>7.2</td>
<td>23.1</td>
<td>9.8</td>
</tr>
<tr>
<td>Argentina</td>
<td>0.40</td>
<td>8.8</td>
<td>23.1</td>
<td>6.8</td>
</tr>
<tr>
<td>Australia</td>
<td>0.99</td>
<td>13.3</td>
<td>20.3</td>
<td>0.1</td>
</tr>
<tr>
<td>Austria</td>
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<td>22.5</td>
<td>-0.1</td>
</tr>
<tr>
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<td>0.07</td>
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<td>23.9</td>
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<tr>
<td>Barbados</td>
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<td>9.6</td>
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<td>4.4</td>
</tr>
<tr>
<td>Belgium</td>
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<td>11.4</td>
<td>23.0</td>
<td>0.7</td>
</tr>
<tr>
<td>Benin</td>
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<td>2.7</td>
<td>25.1</td>
<td>7.1</td>
</tr>
<tr>
<td>Brazil</td>
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<td>23.5</td>
<td>7.7</td>
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<td>Country</td>
<td>Schooling-quality effect</td>
<td>Work-experience-quality effect</td>
<td>Average age of the workforce</td>
<td>Average number of years of schooling</td>
</tr>
<tr>
<td>------------</td>
<td>--------------------------</td>
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<td>Morocco</td>
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Notes:
a Figures in the table are natural logarithm percentage points and correspond to the sum of the Schooling-quality effect (equation 20a) and the Work-experience-quality effect (equation 20b) estimated using the coefficients of Model 5 in Table 3 and multiplied by -100. Countries that were part of the regression samples but are not listed in this table because of lack of reliable information on years of schooling are Grenada, Somalia and St. Vincent.
b Ratio of five-year moving averages; 2004 figures.
c Source: Morrisson and Murtin (2009) unless otherwise specified.
d Calculated as the difference between the estimated Average age of the workforce minus the Average number of years of schooling minus 6. The Average age of the workforce is estimated from the age structure provided in Central Intelligence Agency (2013) for the age groups 15-24, 25-54 and 55-64.
e The source for the variable Average number of years of schooling for this country is Barro and Lee (2013).
f This country was not part of the regression samples because there were too few observations.
Figure 1a: Country of Birth Schooling Fixed Effects
(Estimates of the $\alpha_2$’s in Equation 13)

Figure 1b: Country of Birth Work Experience Fixed Effects
(Estimates of the $\beta_3$’s in Equation 13)
Figure 2: Returns to Years of Schooling
(per-year of schooling, U.S. = 1, selected countries)

Figure 3: Returns to Work Experience
(per year of work experience, U.S. = 1, selected countries)