Experience Matters for Development Accounting* (Preliminary)

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Abstract

This study uses newly available large-sample micro data to document that the wage increase associated with increasing worker experience is lower for poorer countries. By taking this fact into account when calculating aggregate human capital, we find that human capital can explain a substantially larger fraction of cross-country income differences than in previous studies.

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1 Introduction

Why are some countries so much richer than others? What fraction of cross-country income differences can be attributed to differences in factors of production? These are central questions in development and macroeconomics and development accounting attempts to answer them. For instance, establishing the importance of factors for explaining income differences would allow researchers to focus their efforts on explaining the differences in factor accumulation across countries, and policy makers to focus on designing policies to improve the stocks of physical and human capital. Good measures of capital stocks are key for development accounting and researcher have made significant efforts to improve such measures. For studies of human capital, this includes allowing for differences in the quality of schooling and the health status of workers in addition to the traditional measure of formal schooling (Barro and Lee, 2001, Bils and Klenow, 2000, Hanushek and Kimko, 2000, Klenow and Rodriguez-Clare, 1997, Weil, 2007, and Shastry and Weil, 2003).[1] While these improvements increase the role of human capital in explaining cross-country differences, the total contribution of human capital is nevertheless limited (Caselli, 2005).[2]

In this study, we argue that the existing literature underestimates the true contribution of human capital to cross-country income differences because past studies have not taken into account the differences across countries in returns to experience when computing human capital. Specifically, our accounting exercise has three innovations. First, we allow the returns to experience to vary fully flexibly for each additional year of experience rather than use the more restrictive functional form imposed by Mincerian estimates that have been used in existing studies. Second, we allow the level of experience to vary across countries and across individuals within a given country. Finally, we account for the possibility that cross-sectional estimates of returns to experience may be biased and control for time or cohort effects.

We document that experience-earnings profiles in poor countries tend to lie below those in rich countries. The most widely accepted explanation for the fact that earnings increase with experience

[1]Klenow and Rodriguez-Clare (1997) and Bils and Klenow (2000)account for the possibility that the quality of education is positively associated with the human capital of older cohorts. Barro and Lee (2001) account for differences in pupil-student ratios and government spending on education. Hanushek and Kimko (2000) measure quality with test scores. Weil (2007), and Shastry and Weil (2003) provide evidence that health, which they measure as adult mortality rate, accounts for a significant gap in cross-country differences.

[2]Caselli (2005) reviews the literature on development accounting and finds that there is little empirical evidence to support the belief that the stocks of human or physical capital play a large role in explaining cross-country income differences.

is the accumulation of human capital on the job (Ben-Porath, 1967; Rosen, 1976; Heckman, 1976). That returns to experience are lower in poor countries then suggests that there is less on-the-job human capital accumulation in these countries. Traditional development accounting exercises, which either completely ignore human capital due to experience or assume that all countries have the same experience-earnings profiles, will therefore over-estimate the stock of human capital in poor countries relative to rich ones. This will, in turn, cause one to under-estimate the explanatory power of human capital for cross-country income differences.

The main difficulty for our study is the same as for most development accounts studies: data availability. Accurately estimating experience-profiles requires large samples of micro-data that report wages, schooling and age for each country. For the estimates to be comparable across countries, the data should ideally be for similar sub-populations within each country (e.g. males). Historically, such data have been limited, especially for poor countries, and the estimates for returns to schooling and experience have been based on data drawn from different sub-populations and different time periods across countries.[3]

A second difficulty for explaining cross-country income differences with human capital is that traditional cross-sectional estimates may produced biased results because they do not adequately control for changes in worker cohorts or changes in variables such as TFP over time. Since experience (e.g., age) is a linear combination of time and cohort (e.g., birth year), empirical estimates of the returns to experience cannot simultaneously control for year and cohort effects. We show in section 3.3 that one can provide estimates of the upper- and lower-bound of the returns to experience by controlling for either year or cohort effects.

The main contribution of our study is to address the difficulties we discuss above. We address the issue of data limitation by using newly available large-sample micro-data from population censuses or nationally representative labor surveys. The large sample size of micro-data for each country allows our estimates to be flexible such that we can examine the entire experience-earnings profile. This turns out to be important for calculating human capital stocks because the differences in returns to experience between poor and rich countries are not constant across experience levels. The main limitation of our data is that they are only available for a few countries (Canada, China,

[3]For example, see the studies by Psacharopoulos (1994) and Krueger and Pischke (1992) among others that Bils and Klenow (1998) extract their cross-country estimates shown in their Appendix Table B from.

India, Mexico, and the United States). Nonetheless, because the countries in our sample span a large part of the world income distribution, we believe that our results plausibly generalize outside the specific contexts for which we have data.

Moreover, our data are also available for many years. Thus, we can construct a panel for each country to allow our estimates to alternatively control for cohort or year fixed effects and provide bounds for human capital stocks.

Our study adds to recent development accounting exercises that are cited at the beginning of the introduction that attempt to improve the estimates of human capital stocks. It is particularly closely related to two studies that allow the level of experience to vary across countries. Klenow and Rodriguez-Clare (1997) find that accounting for experience reduces the relative level of human capital stocks in poor countries and therefore, reduces the explanatory power of human capital for explaining cross-country differences. This finding is due to the fact that the positive effect of longer life expectancy, later retirement and higher levels of experience in rich countries is dominated by the negative effect of the fact that workers in rich countries obtain more schooling, which causes them to enter the labor force later, and hence have less experience. Our paper differs from theirs in that we not only allow the level of experience to vary across countries, but we also allow the slopes of the earnings profile to vary.

Our study is more similar to Bils and Klenow (1998), which allows both the returns to and the level of experience to vary across countries.[4] However, they find that returns to experience, which they obtain from various studies, do not systematically differ across income levels. The most likely causes of the difference between our estimates and those that they use are that we allow the returns to experience to vary fully flexibly across experience levels, and that our data are more comparable across countries. We discuss this in more detail in the paper. Finally, our work is related to that of Jones (2011) who points out that one critical assumption of traditional development accounting is that different skill types are perfect substitutes in production and argues that relaxing this assumption can substantially amplify the role of human capital in accounting for cross-country income differences (and even close the entire income gap between rich and poor countries if high and low skill types are sufficiently complementary). Our work is complementary but differs in an

[4] In the published version Bils and Klenow (2000), the authors assume that all countries have similar returns to experience.

important dimension: we argue that, even under the assumption that different skill types are perfect substitutes in production, taking into account cross-country differences in on-the-job human capital accumulation can make a big difference for development accounting exercises.

The paper is organized as follows. Section 2 describes the data. Section 3 presents a simple model to motivate the empirical exercise and estimates returns to experience across countries. Section 4 uses these returns to experience to calculate implied human capital stocks and conduct our development accounting exercise. Section 5 summarizes the results and offers concluding remarks.

2 Data

Our main analysis examines the United States, Canada, Mexico, India and China. These countries are chosen to reflect different parts of the world income distribution, and also to be comparable to other recent studies that have examined cross-country productivity differences.[5] Our data comprise of population censuses (for the U.S. and Canada), labor force surveys (for Mexico) and household consumption expenditure surveys (for India and China). These data provide large-sample micro data that report income, schooling and age of workers. We focus on data from after the end of the Cold War, which may have had differential effects on rich and poor countries. This means that our time period coincides with economic liberalization in India and the transition from a centrally planned to a market-oriented economy in China. It is important to note that the countries we examine are broadly speaking, politically and economically stable during this period. The years of data coverage are listed in the Data Appendix. Note that since the census extracts are extremely large, we create a randomly chosen sample of these data for our analysis for computational ease.

For comparability, we impose similar restrictions across countries when we construct the samples used for analysis. Our empirical estimates aim to assess the differences in worker productivity across countries. Thus, we restrict the sample to male workers to address the fact that selection into the labor force and the quality of training can be very different between rich and poor countries for female workers. For example, a flatter experience-profile in poor countries could reflect wage discrimination towards women rather than lower productivity. Second, we follow the standard in the literature and calculate *experience=age-schooling-6*. This assumes that children begin primary school at age

[5] For example, Hsieh and Klenow (2009) compare firm size and TFP between the United States, Mexico, India and China.

seven in all countries. To address the fact that children who obtain no schooling do not work when they are very young, we also assume that the earliest a person can begin working is age fifteen such that *experience=age-15* if a worker has less than nine years of education. Finally, we restrict the sample to individuals older than fifteen and younger than seventy years of age.

We measure wages with wage income. Data on labor supply (hours worked) is not available for most countries. Therefore, interpretation of our estimates assumes that labor supply is not increasing with experience in rich countries relative to poor countries. Otherwise, our estimates will over-state the difference in experience profiles between rich and poor countries.

There are several facts to keep in mind for the empirical analysis. First, the labor force and consumption surveys for India and China typically only include information of the household head and spouse, while census data include all household members. This should not affect representativeness of our estimates since the households are randomly chosen to be nationally representative. However, it does reduce the sample size for countries with survey data, which are a 0.01% sample of households. In particular, it disproportionately reduces the sample size for young and very inexperienced workers in poor countries since these workers are likely to be living with their parents.

Second, the data for China include only urban areas because the concept of individual wages are not meaningful in rural China, where workers typically work in coordination with their entire household in agriculture and home production. It is also important to note that the period of our study coincides with urban economic transition from a socialist to a capitalist economy. Thus, one may be concerned that wages in this context may not reflect marginal production. To address this, we restrict the sample to workers that work in the private sector.

A related concern exists for the data from India, which include both urban and rural workers. While Indian agricultural workers do not face the same institutional constraints as their counterparts in China, one may still doubt the quality of wage income data from poor rural areas, where much of agriculture is for subsistence. If survey remunerators do not carefully account for the value of subsistence farming, then the data will under-state the productivity of rural workers.

Finally, note that for each country, we have two or more repeated cross-sections of data. This means that we can alternatively control for year or cohort effects in our estimates. However, it is also important to note that our data covers a much larger range in terms of the birth cohorts than in terms of time (e.g., calendar years). We return to discuss this later in the paper.

3 Returns to Experience Across Countries

3.1 Conceptual Framework

A simple model of human capital, similar to that proposed by Bils and Klenow (1998) motivates the empirical estimation. Human capital of individual i in country j at time t, h_{ijt}, depends on schooling, s_{ijt} and experience, x_{ijt}:

$$h_{ijt} = \exp(g_j(s_{ijt}) + f_j(x_{ijt})). \tag{1}$$

We further impose $f_j(0) = g_j(0) = 0$ for all j, meaning that we normalize the human capital of a worker with zero years of both schooling and experience to be one. In effect then, we *define* human capital as that part of earnings that is only due to schooling or experience. Further, assume that individuals are paid their marginal products in efficiency units of human capital up to a mean zero error term. Hence an individual's earnings are just their human capital times a skill price, w_j, and an error term, ε_{ijt}:

$$y_{ijt} = w_j h_{ijt} \exp(\varepsilon_{ijt}). \tag{2}$$

Combining and taking logs, we obtain

$$\log y_{ijt} = \log w_j + g_j(s_{ijt}) + f_j(x_{ijt}) + \varepsilon_{ijt}. \tag{3}$$

The main goal of our paper is to estimate the function $g_j(\cdot)$ and assess how it varies across countries. Our main empirical result is that this function in poor countries lies below that in rich countries.

3.2 Baseline Results

For comparison with the existing literature, we first estimate a standard quadratic Mincer equation:

$$y_{ijt} = \alpha_j + \theta_j s_{ijt} + \phi_{1,j} x_{ijt} + \phi_{2,j} x_{ijt}^2 + \varepsilon_{ijt}, \tag{4}$$

where the log wage of individual i living in country j during year t is a function of the years of schooling, s_{ijt}; and the years of experience, x_{ijt}. This is the special case of the model presented in the previous section with $g_j(s) = \theta_j s$ and $f_j(x) = \phi_{1,j}x + \phi_{2,j}x^2$. The return to an additional year of experience conditional on schooling is $f_j'(x) = \phi_{1,j} + 2\phi_{2,j}x$.

The estimates are presented in Table 1 panel A. Each column shows an estimate for one country. The Table shows that the highest returns to experience are experienced by workers in the United States, Canada and China. At the bottom of panel A, we present the implied returns to experience for workers with twenty years of experience. We find that Canada, the United States and China have the three highest implied returns. Since the United States and Canada are the two riches countries in our sample and China (along with India) is one of the poorest countries in our sample, these estimates show that there is no obvious pattern between income levels and the Mincer returns to experience.

The main drawback of the mincer estimation is that it forces the returns to experience to have a linear-quadratic functional form. This could be misleading if the difference between rich and poor countries differs over experience levels. To address this, we estimate a more flexible specification that can be written as:

$$y_{ijt} = \alpha_j + \theta_j s_{ijt} + \sum_{k=2}^{6} \phi_{k,j} D_{ijt}^k + \varepsilon_{ijt}, \tag{5}$$

where we divide workers into six groups according to their work experience and D_{ijt}^k is a dummy variable that takes the value of one if a worker is in group k. The six groups are workers that have worked: 0-1 year, 2-10 years, 11-20 years, 21-30 years, 31-40 years and 40 or more years. The reference group that is omitted from the equation are the first group of workers that have worked for 0-1 year.

Note that ideally, for ease of interpretation, we would like for the reference group to comprise only of workers with zero years of experience. In that case, the only assumption required to compare the results across countries is that workers with zero years of experience obtain no returns to experience in any country. However, we have very few observations of such workers in several of the poorer countries in our sample. Thus, we categorize the reference group as workers that have worked 0-1 years. Interpreting the evidence across countries then assumes that workers with 0-1 years of experience gain the same returns across countries. In the case that the returns for the first year of experience is higher in richer countries, then this grouping will cause our estimates to understate the difference in returns to experience between rich and poor countries.

The estimated effects are shown in Table 2 panel A. These estimates present a very different pattern from the Mincer estimates. For each experience group, the estimates show that the returns are lower for poorer countries. Moreover, these estimates show that the returns are not monotonic across experience levels and the degree of non-monotonicity differs across countries. For example, the returns to experience for those with 40 or more years of experience are lower than those with less experience for all countries. But the decline is most pronounced in poor countries such as India and China. These differences are important because they illustrate why the quadratic Mincer equation is inappropriate for capturing the differences in returns to experience across countries.

To fully account for changes in the slope of the experience-earnings profile, we estimate the following equation:

$$y_{ijt} = \alpha_j + \theta_j s_{ijt} + \sum_{x=1}^{50} \phi_{x,j} D^x_{ijt} + \varepsilon_{ijt}, \tag{6}$$

where D^x_{ijt} is a dummy variable for a worker's number of years of experience. The reference group comprises of individuals who have up to three years of experience. The coefficient ϕ_x estimates the earnings that workers receive on average for workers with x years of experience relative to the average earnings of workers in the reference group. Note that interpreting these estimates requires the assumption that workers with three or fewer years of experience have similar returns to experience across countries. If the returns are higher for such workers in rich countries, a comparison of our estimates will under-state the relative human capital of rich countries. In terms of our notation from the previous section, $\phi_{x,j} = f_j(x)$. That is, the coefficient estimate corresponding to each experience level, x, identifies the experience-earnings profile evaluated at that point x.

The coefficients and their standard errors are presented in Appendix Table A.1. The coefficients are plotted in Figure 1. These estimates confirm the previous findings and show that the experience profiles are too complex to be captured by a Mincerian linear-quadratic specification. Specifically, returns increase for inexperienced workers but decline for very experienced workers. Moreover, the initial increase for inexperienced workers is much steeper for rich countries and the decline for experienced workers is more pronounced for poorer countries. The most extreme case is China, where workers with approximately forty or more years of experience earn less than younger and less experienced workers. We will discuss this in greater detail later in the paper.

The key point to take away from the results thus far is that Mincer estimates can be misleading and understate the difference in returns to experience between rich and poor countries because returns vary across experience levels in a way that cannot be captured with a linear-quadratic specification.

3.3 Controlling for Cohort and Time Effects

In this section, we will show that the estimates for returns to experience and aggregate human capital stocks can differ substantially for certain countries when we control for cohort effects. We extend our simple model to interpret these differences. We further use the model to illustrate the biases generated by traditional cross-sectional estimates relative to panel estimates controlling for year or cohort effects. Specifically, we show that under the assumption that cohorts improve over time, not including cohort effects and only year effects results in downward-biased estimates. In contrast, under the assumption that year effects grow over time, not including year effects and only cohort effects results in upward-biased estimates.

We extend the simple model in section 3.1 to allow for cohort and time effects. We continue to assume that individual human capital depends on schooling and experience as in (1). However, in contrast to section 3.1, we now allow the skill price, w_{ijt}, to differ across cohorts and time periods:

$$w_{ijt} = \bar{w}_j \exp(\Gamma_j(t) + \Omega_j(c_{ij})). \tag{7}$$

We also continue to assume that an individual's earnings are their human capital times this skill price and an error term, ε_{ijt}, $y_{ijt} = w_{ijt} h_{ijt} \exp(\varepsilon_{ijt})$.[6] Substituting in for (1) and (7) and taking logs, we obtain

$$\log y_{ijt} = \log \bar{w}_j + g_j(s_{ijt}) + f_j(x_{ijt}) + \Gamma_j(t) + \Omega_j(c_{ij}) + \varepsilon_{ijt}. \tag{8}$$

The model in section 3.1 is the special case in which time and cohort effects are identically zero,

[6] An alternative formulation would have been to let human capital instead of skill prices depend on cohort quality: $h_{ijt} = \exp(g_j(s_{ijt}) + f_j(x_{ijt}) + \Omega_j(c_{ij})), w_{jt} = \bar{w}_j \exp(\Gamma_j(t))$. This would have some different implications for estimating human capital stocks. However, note that with this specification, it is no longer true that the human capital stock of an invidual with $s = x = 0$ is one, a normalization we imposed above. We prefer to work with this normalization because it effective *defines* human capital to be that part of earnings that is only due to schooling or experience.

$\Gamma_j(\cdot) = \Omega(\cdot) = 0$.

Ideally, we would be able to identify the functions $g_j(s_{ijt})$ and $f_j(s_{ijt})$ and use them to compute our measure of human capital (1). However, it is impossible to simultaneously control for year and cohort effects due to the familiar problem that schooling, experience, year and birth year are collinear.[7]

Instead, we can estimate the returns to experience either controlling for *i*) cohort fixed effects or *ii*) calendar year (e.g., time) fixed effects. If cohorts are improving over time and there is economic growth, as in the case for developing countries such as China and India, the estimates with cohort effects only provide an upper bound on the returns to experience; and those with year effects only provide a lower bound. See Appendix 5 for the derivation.

Since some of our countries have data for only every ten years, we construct birth-cohort categories of ten birth-year intervals. Our cohort fixed effects are therefore dummy variables that take the value of one if a worker belongs to a birth-cohort category. The estimates with cohort or year controls are presented in Table 1 panels B and C (for the Mincer returns to experience from equation (4)) and Table 2 panels B and C (for the estimates for the returns to ten-year experience categories from equation (5)). For brevity, the discussion will focus on the fully flexible estimates from equation (6). The coefficients and standard errors are presented in Appendix Table A.1. However, for interpretational purposes, we will focus on the figures that plot the estimated coefficients.

Figure 2 presents the coefficients for the returns to experience when birth-cohort fixed effects are included in equation (6). As with the cross-sectional estimates shown in Figure 1, these estimates show that the experience-earnings profile is relatively complex: the returns to experience increase until workers reach a certain level of experience, and then the returns decrease such that the experience-earnings. In some countries, the profiles are concave for low levels of experience whereas in others they are concave – in either case, they are too complex to be captured by a simple linear-quadratic specification. However, unlike the cross-sectional estimates, the addition of cohort controls causes the very experienced workers in India and China to have higher wages relative to the reference group. The difference between Figures 1 and 2 show that although Indian and Chinese workers of any given cohort earn higher wages as they become more experienced, there is little dif-

[7] In particular, schooling, experience, year and birth year are linked through the identity $t = age_{ijt} + c_{ij} = s_{ijt} + x_{ijt} + 6 + c_{ij}$.

ference in earnings across workers of different experience levels in the cross-section. This indicates that younger cohorts earn relatively more than older cohorts for a given level of experience such that when we examine all workers in the cross section, inexperienced workers from younger cohorts earn similar wages to experienced workers from older cohorts.

The influence of cohort controls is most prominent for China, where these controls cause the returns to dramatically increase and the experienced earnings profile to rotate counter-clockwise and change from being relatively flat to being hump-shaped. The results indicate that the relative earnings of young to old cohorts at a given point is so much higher that experienced workers from older cohorts receive lower wages than inexperienced workers from younger cohorts. This is despite the fact that there are positive returns to experience for each cohort.

In Figure 3, we plot the estimates for equation (6) when year controls are included. There is little difference from the cross-sectional estimates shown in Figure 1. These results indicate that there are not too many changes over time, which is not altogether surprising since our data covers a relatively short time period (between ten and fifteen years).

The estimates in this section show that the cross-sectional estimates presented in the previous section are reasonably accurate measures of the true returns to experience for the United States and Canada (e.g. they are similar to the upper- and lower-bound estimates). However, the cross-sectional estimates for India and China are likely to understate the true returns due to the rapid improvements in worker cohorts.

3.4 Returns to Experience Estimates from Earlier Studies

Before moving forward, we note that Bils and Klenow (1998) collected cross-sectional Mincer estimates from various studies for a large number of countries and found no relationship between the returns to experience and income. This naturally begs the question of why our estimates differ. Given the small number of countries in our sample, a natural concern is that we examine select countries that exhibit a correlation. To address this, we examine the estimates that Bils and Klenow (1998) used for our countries (from Appendix B of their paper) and calculate the implied returns to experience for workers with twenty years of experience as they do in their study (see Table 1 panel D). There is no relationship. This alleviates the concern that our main result that returns to experience is higher for higher countries is an artifact of our choice of countries.

Another obvious difference between our study and the earlier studies (e.g. Psacharopoulos, 1994; and Krueger and Pischke, 1992) from which Bils and Klenow (1998) extract their estimates is the underlying data. However, we do not believe that the difference in data is the sole cause in the difference in results. To see this, note that our Mincer estimates in Table 1 Panel A do not exhibit a relationship with country income levels. It is only when we allow the estimates to vary flexibly across experience levels (Table 2), that a pattern emerges. Hence, the difference in the data is important mostly in that the large samples allow us to conduct estimates that require larger samples. The fact that we allow for returns to experience to vary across experience levels according to a specification that is much more flexible than the simple Mincerian linear-quadratic one is key for our results.

4 Aggregate Human Capital and Development Accounting

Having estimated returns to experience across countries, we now calculate individual and aggregate human capital stocks that fully take into account cross-country differences in returns to experience. We then conduct a standard development accounting exercise with our improved measures of aggregate human capital stocks, and show that taking into account experience substantially increases the fraction of cross-country income differences that can be explained by human and physical capital stocks.

4.1 Human Capital Based on Experience

We find it useful to decompose individual human capital stocks into the components due to experience and schooling: $h_{ijt} = h^S_{ijt} h^X_{ijt}$ where

$$h^X_{ijt} = \exp(f_j(x_{ijt})),$$

$$h^S_{ijt} = \exp(g_j(s_{ijt})).$$

Analogously, the part of aggregate human capital due to experience only is just the average of the individual stocks across individuals and over time

$$H_j^X = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{T}\sum_{t=1}^{T}h_{ijt}^X.$$

Our estimates for aggregate human capital stocks due to experience therefore simply integrate under the experience-earnings profiles estimated in the previous section, using the distribution of work experience from the data. The distributions of work experience in our five countries are displayed in Figure 10 which shows that there are some cross-country differences in experience distributions, but these are certainly not dramatic. Our resulting estimates of human capital stocks due to experience are presented in Table 3 panel A1 columns (1)-(3). These are based on the fully flexible returns to experience estimates from equation (6) for when we use cross-sectional estimates of returns to experience, include cohort controls, and alternatively, year controls. These estimates show that human capital due to experience is higher in richer countries. This is shown clearly in panel A2, where we present the ratios of the implied human capital from experience for each country relative to that of the United States.

Similarly, we can plot the implied human capital from experience against average per capita GDP for each country during this period. We obtain GDP data from the World Bank Development Indicators. GDP is measured in constant 2000 USD. For China, we calculate urban per capita GDP by normalizing national GDP by the ratio of urban-to-rural real wages, which we obtain from the *China Statistical Yearbooks*. Figures 4-6 plot the implied human capital from experience against per capita average GDP for when we use cross-sectional estimates of returns to experience, include cohort controls, and alternatively, year controls. These figures show clearly that there is a strong positive relationship between human capital from experience and income levels.

For comparison, we show the implied human capital from experience based on the Mincer estimates of returns to experience (equation (4)) in columns (4)-(6) of panel A1 and plot these estimates against income levels in Figures 7-9. The y-axes of these figures cover the same range as the y-axes in figures 4-6. Consistent with our earlier findings that Mincer estimates of returns to experience cannot fully capture the shape of the experience-earnings profile, a comparison of the two sets of figures show that the relationship between human capital from experience and income levels is much weaker when using Mincerian returns to experience.

Recall from section (2) that one concern over interpreting the estimates for poor countries is that wage earnings data may not accurately reflect productivity for rural workers, where subsistence production is difficult to value. Since our data from China only include urban areas, this potential difficulty applies to India and Mexico. To address this, we restrict the data to urban workers and re-estimate the returns to experience using equation (6) and calculate human capital from experience. Panels B1 and B2 show that this makes little difference to our results. Hence, our main results are not driven by data issues from agricultural workers in poor countries.

4.2 Total Human Capital Stocks and Development Accounting

To facilitate comparison with the existing literature, we use the same accounting method as in the review by Caselli (2005). That is, our accounting procedure uses a Cobb-Douglas aggregate production function $Y_j = K_j^{\alpha}(A_j H_j)^{1-\alpha}$ where Y_j is country j's real GDP, K_j its physical capital stock, A_j is total factor productivity and H_j is our measure of the human capital stock. The capital share is assumed to equal $\alpha = 1/3$. In his benchmark exercise, Caselli takes into account cross-country differences in schooling but not experience or returns to experience. Since adding experience to the accounting exercise is the main contribution of this paper, we use his estimates that do not take into account experience as the benchmark against which to evaluate our measures of the human capital stock. To this end, we assume that the part of a country's total human capital stock that is due to schooling only is given by Caselli's estimates, and denote them by H_j^S. These estimates as well as his estimates for output and physical capital are shown in Table 4 rows (1)-(3).

Rows (4) to (7) restate our measures of human capital due to experience when using the fully flexible returns to experience estimates from equation (6) for each of our three ways of measuring returns to experience: using cross-sectional estimates, controlling for cohort effects and controlling for time effects (these are the same numbers as in Table 3 panel A1 columns (1)-(3)).

We then calculate our measure of aggregate human capital as the product of Caselli's estimates and our aggregate human capital stocks due to experience from rows (4)-(7), $H_j = H_j^S H_j^X$. This way of calculating aggregate human capital stocks clearly isolates the contribution of returns to experience vis-à-vis the existing literature. Rows (9) to (11) report the resulting aggregate human capital stock.

Rows (12) to (15) show the fraction of the gap between each of our countries and the United States that can be explained by differences in human capital stocks. For instance, the United States is approximately ten times richer than India in terms of GDP per capita. Caselli's human capital estimates can explain nineteen percent of this gap if experience is not taken into account. In contrast, if experience is taken into account, this fraction increases to between 31 and 32 percent, depending on which of our estimates we use. The estimates thus imply that taking experience into account allows human capital to explain twelve to thirteen percentage points more of the U.S.-Indian income difference. Similarly, it explains an additional one to three percentage-points of the U.S.-Canadian income difference, 45-65 percentage points more of the U.S.-Mexican income difference, and three to nineteen percentage-points more of the U.S.-Chinese income differences. Since human capital explains 59 (U.S.-Mexico), 19 (U.S.-India) and 15 (U.S.-China) percent of income differences when not taking experience account, our results imply that taking experience into account increases the contribution of human capital to the income difference between the poor countries in our sample relative to the United States by over 77% $((1.04-0.59)/0.59)$ for Mexico, 65% $((0.31-0.19)/0.19)$ for India, and 20% $((0.18-0.15)/0.15))$ for China.

Finally, we take differences in physical capital stocks into account. We do this by re-constructing Caselli's "Success-2" measure which is defined as

$$success_2 = \frac{Y_{KH}^{US}/Y_{KH}^{Poor}}{Y^{US}/Y^{poor}}$$

where $Y_{KH} = K^{\alpha}H^{1-\alpha}$ is the component of output explained by factors of production. That is, "Success-2" measures the fraction of the GDP gap between the US and one of our "poor" countries (Mexico, India, China or Canada) that can be explained by factors of production only. The estimates for "Success-2" are presented in rows (16)-(19). Results are similar as before: taking into account cross-country differences in returns to experience when calculating aggregate human capital stocks allows one to account for a substantially larger fraction of cross-country income differences than the existing literature. Specifically, accounting for experience allows Success-2 to explain zero to two percentage-points more of the U.S.-Canadian income gap, 33-46 percentage-points more of the U.S.-Mexican income gap, sixteen to seventeen percentage-points more of the U.S.-Indian income gap, and 4-23 percentage-points more of the U.S.-Chinese income gap.

Note that for Mexico, our estimates even modestly over-predict the GDP gap to the United States when taking experience into account. That is, we estimate that Mexican human capital is so low relative to the US, that the only way of accounting for the observed GDP gap is for Mexico to have higher TFP than the US.

5 Conclusion

Why are some countries so much richer than others? How much do human capital stocks matter? We attempt to address these questions by conducting a development accounting exercise which takes experience into account. By using recently available large sample microdata from five large economies on very different parts of the world income distribution, we document several novel facts. First, we show that the returns to experience differ greatly across countries. Specifically, the experience-earnings profiles of poor countries lie below those of rich countries. Previous studies, which had less data and estimated the returns to experience with restrictive Mincerian functional forms, could not fully capture the subtle and complex differences in experience-earnings profiles across countries. In contrast, our completely flexible estimates allow the returns to experience to vary for each year of experience.

Second, we show that controlling for cohort effects can have a significant influence on the estimated experience-earnings profiles for economies where workers are rapidly improving. Specifically, for such contexts, cross-sectional estimates that do not include such controls offset the wage gains due to experience with the fact that younger cohorts are more productive (and receive higher wages). This causes cross-sectional estimates of returns to experience to underestimate true returns to experience, and the implied human capital estimates to be too low.

Our results show that taking experience into account increases the contribution of human capital to the income difference relative to the United States by over 77% for Mexico, 65% for India, and 20% for China.

Note that our study also differs from previous studies by allowing the level of experience to vary across countries. This is interesting because poorer countries have lower levels of educational attainment, and thus higher levels of experience, on average (recall that $experience = age - schooling - 6$). Because higher levels of experience imply higher human capital, this creates a counteracting effect to the one we stress in our paper, namely that returns to experience are lower in poor countries. In fact, past studies such as Klenow and Rodriguez-Clare (1997) have found that the positive effect on human capital in poor countries due to higher average levels of experience is sufficiently large to offset the negative effect from lower returns to experience. We instead find that returns to experience are so much lower in poor countries that the latter effect outweighs the former. The difference between our estimates from Klenow and Rodriguez-Clare (1997) may be due to the different ways in which we estimate returns to experience or the underlying data used.

The next steps for this study are to expand the data to include more countries and examine potential mechanisms. The main analysis requires countries that have repeated cross-sections of large samples of microdata on wage income, age and schooling from 1990 and afterwards. We are in the process of collecting data from Indonesia, Russia and Germany, which fulfill these criteria. Data are available for many more countries if we only estimate cross-sectional returns to experience with no cohort of time controls. We are in the process of cleaning such data, which include data from countries in Africa. While the quality of these data are less reliable than those for the main analysis and we will not be able to estimate the upper- and lower-bounds of human capital stocks, having many more countries will allow us to more rigorously examine the relationship between human capital and income levels.

Our findings provoke two questions. First, why do cohort controls have so much influence for estimating the returns to experience. In China, the most extreme case, controlling for cohort effects almost doubles the implied human capital stock (see Table 4 rows (6)). We believe that the most plausible explanation for this stems from China's rapid economic growth during this period and the fact that productivity was increasing rapidly across cohorts. If that were the case, then the cross-sectional estimates confound the positive returns to experience with the fact that younger workers, who are less experienced and from a newer cohort, are more productive. To consider whether our argument is plausible, note that during 1990-2005, the period of our study, China experienced a phenomenal average annual income growth rate of approximately twenty percent per year in urban areas (which comprise our sample). Consistent with our belief that younger cohorts of workers became increasing more productive, the average educational attainment for the urban labor force increased by 1.5 years during this period from approximately eleven to almost thirteen years. Moreover, it is widely believed that production technologies and physical capital greatly improved during this period. This can increase the worker productivity of younger cohorts if human capital is vintage-specific as argued by theoretical studies such as Chari and Hopenhayn (1991).[8]

The second question that follows from our findings is more difficult to answer: why are return to experience lower in poor countries? We speculate that one possible explanation resides in differences in worker composition across countries. For example, returns to experience may be lower for less educated workers. To investigate this further, the next stop of our study is to stratify our data by education levels and examine whether the profiles of workers with similar levels of educational attainment differ across countries.

There are also other possibilities. For example, it could be that more developed economies use more advanced technology (e.g. machines) such that there is more learning-by-doing in rich countries.[9] Alternatively, workers in richer countries may have more access to on-the-job training or opportunities to obtain part-time education such that they continue to accumulate human capital after they enter the labor force.[10] It will be beyond the scope of this paper to provide a conclusive answer for this question. Our results point to understanding the determinants of the returns to experience as an important next step for explaining cross-country income differences.

[8]Chari and Hopenhayn (1991) argue that human capital is technology specific and experiences diminishing returns. If rapidly growing economies introduce more new technology over time, then younger cohorts will be more productive than older ones, and this will cause the experience-earnings profile in fast-growth countries to be flat even if the returns to experience is postive for a given cohort.

[9]That is, learning which arises as a *by-product* of working as in Arrow (1962) may be more productive in richer countries.

[10]That is, learning which is *rivalrous* to working as in Ben-Porath (1967) may be more productive in richer countries.

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Data Appendix

Our data come from nationally representative samples for the following countries and years. The data for Canada, India, Mexico and the United States are available at https://international.ipums.org/international/

Canada: *Census of Canada,* 1991 (3% Sample) and 2001 (2.7% Sample).

China: *Urban Household Surveys* (0.01% of urban households), 1988-2005, .

India: *Socio Economic Survey* by National Sample Survey Organization, 1993 (0.07% of households), 1999 (0.07% of households), 2004 (0.06% of households)

Mexico: *XI General Population and Housing Census*, 1990 (10% sample); *Population and Dwelling Count*, 1995 (0.4% of sample); *XII General Population and Housing Census*, 2000 (10.6% of sample).

USA: *Census of Population and Housing* 1990 (5% Sample) , 2000 (5% Sample) ; *American Community Survey*, 2005 (1% Sample)

Biases from the Omission of Cohort and Time Effects

To illustrate how the omission of cohort or time effects biases our estimates of human capital stocks, we work with a special linear case of the model presented in section 3.1. We further drop j (country) subscripts for notational convenience. More precisely, we assume in this section only that

$$f(x) = \phi x, \quad g(s) = \theta s, \quad \Gamma(t) = \gamma t, \quad \Omega(c) = \omega c.$$

While we have not worked out the more general non-linear case, we believe that biases would be similar qualitatively. Our main estimating equation (3) then specializes to

$$\log y_{it} = \log \bar{w} + \theta s_{it} + \phi x_{it} + \gamma t + \omega c_i + \varepsilon_{it}. \tag{9}$$

Ideally, we would be able identify the coefficients θ and ϕ and use them to compute our measure of human capital $h_{it} = \exp(\theta s_{it} + \phi x_{it})$. However, it is impossible to simultaneously control for year and cohort effects due to the familiar problem that schooling, experience, year and birth year are collinear. In the presence of this identification problem we can still examine the direction of the bias, in each of three cases: estimates with (i) neither cohort nor year effects, (ii) year effects, (iii) cohort effects. The discussion will focus on the case in which there is economic growth, $\gamma > 0$ and that cohorts are getting better over time, $\omega > 0$. The biases simply go in the opposite direction when countries or cohorts get worse over time. It also turns out that the biases in cases (ii) and (iii) are easier to derive analytically than that for case (i), and so we start with those cases.

Case (i): Estimates with year effects but without cohort effects. The true model is (9), but we instead estimate

$$\log y_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 x_{it} + \alpha_3 t + \varepsilon_{it} \tag{10}$$

Using that $c_i = t - age_{it} = t - (x_{it} + s_{it} + 6)$ in (9),

$$\log y_{it} = \log \bar{w} + \omega 6 + (\theta - \omega)s_{it} + (\phi - \omega)x_{it} + (\gamma + \omega)t + \varepsilon_{it}.$$

Hence the coefficient estimates are $\alpha_1 = \theta - \omega, \alpha_2 = \phi - \omega$. If cohorts are getting better over time, $\omega > 0$, estimated individual human capital stocks will be lower than their true values

$$\hat{h}_{it} = \exp(\alpha_1 s_{it} + \alpha_2 x_{it}) = \exp((\theta - \omega)S_{it} + (\phi - \omega)x_{it}) < \exp(\theta s_{it} + \phi x_{it}) = h_{it}$$

Hence, estimates with year effects are a lower bound on true human capital stocks.

Case (ii): Estimates with cohort effects but without year effects. The true model is (9), but we instead estimate

$$\log y_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 x_{it} + \alpha_3 c_i + \varepsilon_{it} \tag{11}$$

Using that $t = age_{it} + c_i = s_{it} + x_{it} + 6 + c_i$ in (9),

$$\log y_{it} = \log \bar{w} + \gamma 6 + (\theta + \gamma)s_{it} + (\phi + \gamma)x_{it} + (\omega + \gamma)c_i + \varepsilon_{it}.$$

Hence the coefficient estimates are $\alpha_1 = \theta + \gamma, \alpha_2 = \phi + \gamma$. If there is growth, $\gamma > 0$, these coefficients are biased upwards. Note also that this bias is higher the higher is a country's growth rate. Therefore also estimated individual human capital stocks will be higher than their true values

$$\hat{h}_{it} = \exp(\alpha_1 s_{it} + \alpha_2 x_{it}) = \exp((\theta + \gamma)s_{it} + (\phi + \gamma)x_{it}) > \exp(\theta s_{it} + \phi x_{it}) = h_{it}$$

Hence, estimates with cohort effects are an upper bound on true human capital stocks.

Case (iii): Estimates with neither cohort nor year effects The true model is (9), but we instead estimate

$$\log y_{it} = \alpha_0 + \alpha_1 s_{it} + \alpha_2 x_{it} + \varepsilon_{it} \tag{12}$$

To derive an expression for the bias, it is convenient to write (9) in deviations from the mean

$$\log \tilde{y}_{it} = \theta \tilde{s}_{it} + \phi \tilde{x}_{it} + \gamma \tilde{t} + \omega \tilde{c}_i + \varepsilon_{it}$$

where $\tilde{y}_{it} = y_{it} - \bar{y}$ and similarly for the other variables. Denote by N the number of observations and by Y the $N \times 1$ vector of observations $\tilde{y}_{it}$. Define S, X, T and C in the same way. Further define

$$W = \begin{bmatrix} S & X \end{bmatrix}, \quad \beta = \begin{bmatrix} \theta \\ \phi \end{bmatrix}, \quad Z = \begin{bmatrix} T & C \end{bmatrix}, \quad \delta = \begin{bmatrix} \gamma \\ \omega \end{bmatrix}$$

Then, the true model is $Y = W\beta + Z\delta + \varepsilon$ but we estimate the parameter vector $\hat{\beta}$ omitting the term $Z\delta$. We have that

$$\hat{\beta} = (W'W)^{-1}(W'Y) = (W'W)^{-1}W'(W\beta + Z\delta + \varepsilon) = \beta + (W'W)^{-1}W'Z\delta + (W'W)^{-1}W\varepsilon$$

Under the assumption $\mathbb{E}[\varepsilon|W] = 0$, we have

$$\mathbb{E}[\hat{\beta}|W] = \beta + \text{bias}, \qquad \text{bias} = (W'W)^{-1}(W'Z)\delta \tag{13}$$

Further $t = s_{it} + x_{it} + 6 + c_i$. In deviations from the mean, this is $\tilde{t} = \tilde{s}_{it} + \tilde{x}_{it} + \tilde{c}_i$ and in vector form $T = S + X + C$. Therefore $Z\delta = \gamma T + \omega C = (\gamma + \omega)T - \omega(S + X)$. Substituting into (13), we obtain

$$\text{bias} = (\gamma + \omega)(W'W)^{-1}W'T - \omega(W'W)^{-1}W'S - \omega(W'W)^{-1}W'X$$

Three observations can be made. First, the bias depends in a non-trivial way on the variance-covariance structure of the data as captured by the variance-covariance matrix of schooling and experience $W = [S, X]$ and the correlation of these variables with time. Second, the sign of the bias depends on how many cohorts relative to years our data span. For instance, consider the special case of only one cross-section, which implies $\tilde{t} = 0$ and hence $T = 0$. In this case $W'T = 0$, and hence the bias is always negative as in case (i) above where we control only for year effects. Similarly, if the number of cross-sections is small relative to the number of birth years, $W'T$ is likely to be "small" and hence the bias is "more likely" to be negative than positive. Third, it is possible for the estimate in case (iii) to be larger or smaller than both the estimate in case (i) and the estimate in case (ii). This is because the elements of the 2×1 vectors $(W'W)^{-1}W'T, (W'W)^{-1}W'S$ and $(W'W)^{-1}W'X$ do not necessarily lie between zero and one.

Table 1: Returns to Experience – Mincer Estimates

	Dependent Variable: Ln Wage														
	A.Cross-Sectional Estimates					B. Control for Cohort Effects					C. Control for Time Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	USA	Canada	Mexico	India	China	USA	Canada	Mexico	India	China	USA	Canada	Mexico	India	China
Schooling	0.088	0.052	0.085	0.092	0.061	0.088	0.050	0.083	0.092	0.095	0.088	0.053	0.086	0.092	0.051
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Experience	0.049	0.051	0.013	0.031	0.044	0.046	0.046	-0.003	0.024	0.051	0.049	0.051	0.013	0.031	0.038
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Experience^2	-0.001	-0.001	-0.000	-0.000	-0.001	-0.001	-0.001	-0.000	-0.000	-0.001	-0.001	-0.001	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	240930	157615	109756	103887	97651	240930	157615	109756	103887	97651	240930	157615	109756	103887	97651
R-squared	0.183	0.099	0.261	0.432	0.129	0.184	0.100	0.269	0.433	0.175	0.183	0.100	0.267	0.434	0.226
Returns to Exp (Exp=20)	0.96	1	0.26	0.62	0.86	0.9	0.9	-0.06	0.48	1	0.96	1	0.26	0.62	0.74
Relative to the USA	1.00	1.04	0.27	0.65	0.90	1.00	1.00	-0.07	0.53	1.11	1.00	1.04	0.27	0.65	0.77
	D. Estimates from Previous Studies**														
Experience	0.032	0.025	0.084	0.041	0.019										
Experience^2	-0.00048	-0.00046	-0.00100	-0.00050	0.00000										
Returns to Exp (Exp=20)	0.63	0.49	1.66	0.81	0.38										
Relative to the USA	1.00	0.78	2.63	1.28	0.60										

Notes: In panel B, we include categorical controls for birth cohorts (e.g., dummy variables indicating ten-year intervals for birth year). In panel C, we include controls for calendar year dummy variables.* * In panel D, the estimates for the USA are taken from Krueger & Pischke (1992). The estimates for Canada, Mexico, India and China are taken from Psacharopoulos (1994). These estimates are used by Bils and Klenow (1998) and reported in their Appendix B.

Table 2: Returns to Experience – Flexible Estimates

	Dependent Variable: Ln Wage														
	A. Cross-Sectional Estimates					B. Control for Cohort Fixed Effects					C. Control for Time Fixed Effects				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	USA	Canada	Mexico	India	China	USA	Canada	Mexico	India	China	USA	Canada	Mexico	India	China
Schooling	0.0917	0.0543	0.0864	0.109	0.0501	0.0906	0.0509	0.0843	0.109	0.0751	0.0916	0.0553	0.0879	0.108	0.0406
	(0.000606)	(0.000751)	(0.000618)	(0.000448)	(0.000921)	(0.000616)	(0.000773)	(0.000623)	(0.000472)	(0.000938)	(0.000609)	(0.000756)	(0.000616)	(0.000447)	(0.000857)
Experience = 2-10 Years	0.711	0.759	0.266	0.179	-0.127	0.688	0.720	0.241	0.179	-0.121	0.711	0.758	0.264	0.175	-0.0370
	(0.0168)	(0.0224)	(0.0432)	(0.0451)	(0.189)	(0.0170)	(0.0224)	(0.0430)	(0.0452)	(0.181)	(0.0168)	(0.0224)	(0.0429)	(0.0449)	(0.175)
Experience = 11-20 Years	1.177	1.197	0.471	0.559	0.0510	1.080	0.973	0.203	0.534	0.463	1.176	1.202	0.479	0.550	0.0823
	(0.0166)	(0.0221)	(0.0432)	(0.0446)	(0.188)	(0.0184)	(0.0247)	(0.0452)	(0.0463)	(0.181)	(0.0166)	(0.0221)	(0.0428)	(0.0444)	(0.174)
Experience = 21-30 Years	1.172	1.213	0.477	0.682	0.0611	1.065	0.955	0.0560	0.661	0.788	1.170	1.220	0.487	0.671	0.0260
	(0.0167)	(0.0223)	(0.0434)	(0.0447)	(0.188)	(0.0189)	(0.0257)	(0.0462)	(0.0471)	(0.181)	(0.0167)	(0.0223)	(0.0431)	(0.0445)	(0.174)
Experience = 31-40 Years	0.975	1.045	0.416	0.569	-0.543	0.866	0.774	-0.0597	0.568	0.493	0.973	1.049	0.426	0.559	-0.534
	(0.0171)	(0.0230)	(0.0439)	(0.0453)	(0.188)	(0.0197)	(0.0269)	(0.0472)	(0.0482)	(0.181)	(0.0171)	(0.0230)	(0.0436)	(0.0451)	(0.174)
Experience = 4+ Years	0.492	0.643	0.320	0.297	-1.398	0.380	0.365	-0.158	0.301	-0.239	0.490	0.651	0.334	0.284	-1.299
	(0.0238)	(0.0344)	(0.0469)	(0.0495)	(0.190)	(0.0259)	(0.0372)	(0.0500)	(0.0524)	(0.183)	(0.0238)	(0.0344)	(0.0466)	(0.0493)	(0.176)
Observations	172807	109845	69996	73968	77971	172807	109845	69996	73968	77971	172807	109845	69996	73968	77971
R-squared	0.192	0.111	0.236	0.460	0.139	0.192	0.115	0.246	0.460	0.208	0.192	0.113	0.248	0.465	0.264

Note: The reference group for each estimate comprises of workers with 0-1 years of experience. In panel B, we include categorical controls for birth cohorts (e.g., dummy variables indicating ten-year intervals for birth year). In panel C, we include controls for calendar year dummy variables.

Table 3: Aggregate Human Capital from Experience

	Fully Flexible Estimation of Returns to Experience			Mincer Estimates of Returns to Experience		
	Cross-Section	Cohort Controls	Time Controls	Cross-Section	Cohort Controls	Time Controls
Country	(1)	(2)	(3)	(4)	(5)	(6)
			A1. Full Sample			
USA	2.60	2.55	2.60	1.80	1.72	1.80
Canada	2.62	2.46	2.63	1.84	1.70	1.85
Mexico	1.47	1.21	1.47	1.19	0.91	1.20
India	1.57	1.50	1.57	1.51	1.33	1.50
China	1.13	2.05	1.15	1.42	2.60	1.27
			A2. Relative to the United States			
Canada	*1.01*	*0.97*	*1.01*	*1.02*	*0.98*	*1.03*
Mexico	*0.57*	*0.47*	*0.57*	*0.66*	*0.53*	*0.67*
India	*0.61*	*0.59*	*0.60*	*0.84*	*0.77*	*0.84*
China	*0.44*	*0.80*	*0.44*	*0.79*	*1.51*	*0.71*
			B1. Urban Only			
Mexico	1.47	1.23	1.47	1.16	1.17	0.91
India	1.77	1.72	1.77	1.57	1.56	1.41
China	1.13	2.05	1.15	1.42	2.60	1.27
			B2. Relative to the United States			
Mexico	*0.57*	*0.48*	*0.57*	*0.65*	*0.68*	*0.50*
India	*0.68*	*0.68*	*0.68*	*0.87*	*0.91*	*0.79*
China	*0.44*	*0.80*	*0.44*	*0.79*	*1.51*	*0.71*

Notes: The aggregate human capital estimates in columns (1)-(3) panels A1 and B1 are based on returns to experience estimates from fully flexible specifications (e.g., years of experience dummies). Those in columns (4)-(6) are based on returns to experience estimates from mincer estimates (e.g., experience and experience-squared). In columns (2) and (5), we include categorical controls for birth cohorts (e.g., dummy variables indicating ten-year intervals for birth year). In columns (3) and (6), we include controls for calendar year dummy variables.

Table 4: Aggregate Total Human Capital

			Country				
			USA	Canada	Mexico	India	China
Data from Caselli (2005)	(1)	*Y*	57259	45304	21441	5420	4908
	(2)	*K*	125227	122348	44206	5631	7407
	(3)	*H*	3.40	3.18	2.17	1.74	1.98
Human Capital Due to Experience	(4)	No Experience	1	1	1	1	1
	(5)	Cross-Section	2.60	2.62	1.47	1.57	1.13
	(6)	Cohort Controls	2.55	2.46	1.21	1.50	2.05
	(7)	Time Controls	2.60	2.63	1.47	1.57	1.15
Human Capital Due to Both Schooling and Experience	(8)	No Experience	3.40	3.18	2.17	1.74	1.98
	(9)	Cross-Section	8.84	8.32	3.19	2.73	2.25
	(10)	Cohort Controls	8.66	7.82	2.62	2.60	4.06
	(11)	Time Controls	8.84	8.34	3.20	2.72	2.28
$(H^{US}/H^{poor})/(Y^{US}/Y^{poor})$	(12)	No Experience	1	0.85	0.59	0.19	0.15
	(13)	Cross-Section	1	0.84	1.04	0.31	0.34
	(14)	Cohort Controls	1	0.88	1.24	0.32	0.18
	(15)	Time Controls	1	0.84	1.03	0.31	0.33
Success2 from Caselli (2005):	(16)	No Experience	1	0.83	0.71	0.42	0.32
$(Y\_HK^{US}/Y\_HK^{poor})/(Y^{US}/Y^{poor})$	(17)	Cross-Section	1	0.83	1.04	0.58	0.55
	(18)	Cohort Controls	1	0.85	1.18	0.59	0.36
	(19)	Time Controls	1	0.83	1.04	0.58	0.54

Figure 1: Returns to Experience for Each Year of Experience – Cross-Sectional Estimates

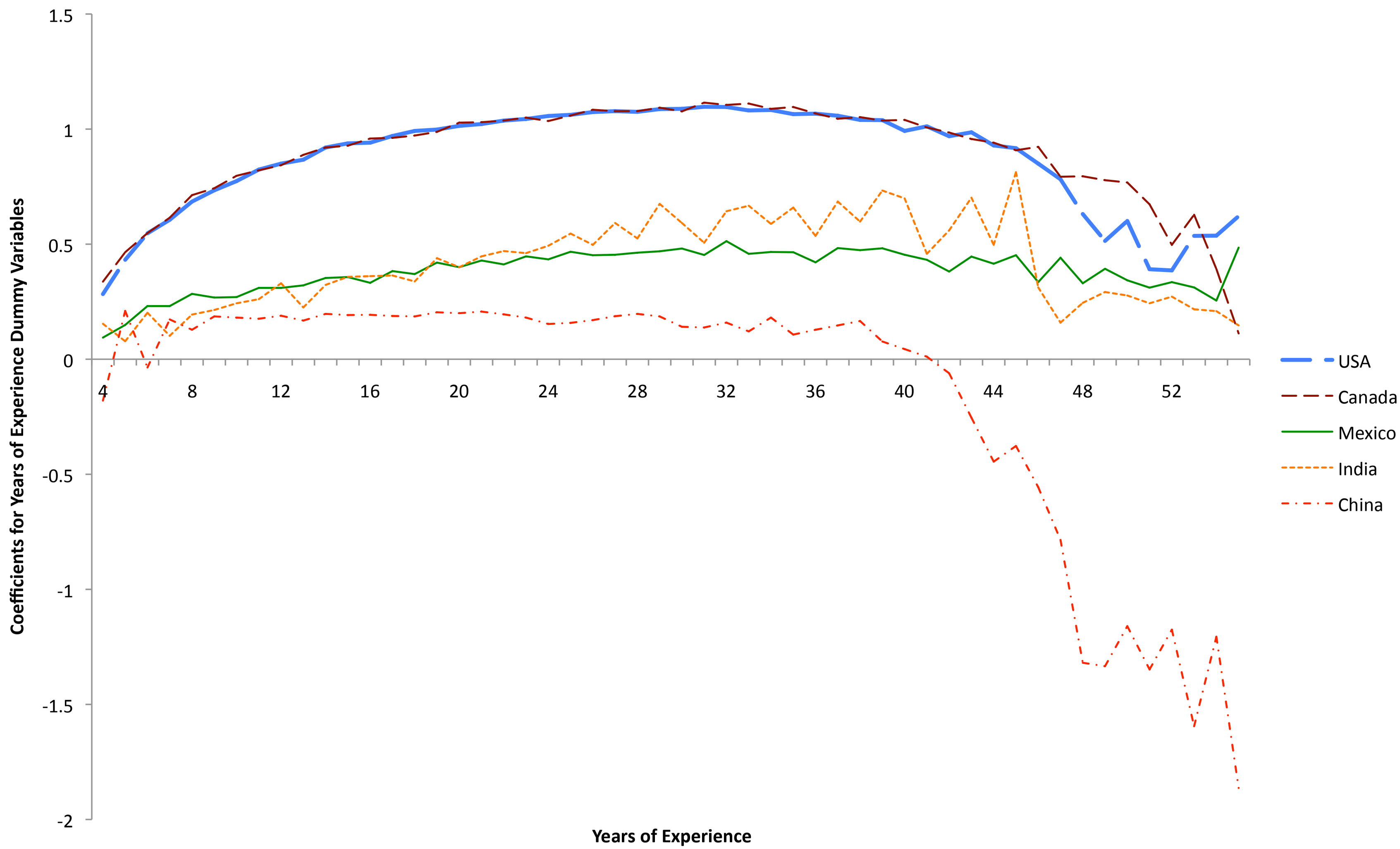


Figure 2: Returns to Experience for Each Year of Experience – Control for Cohort Effects

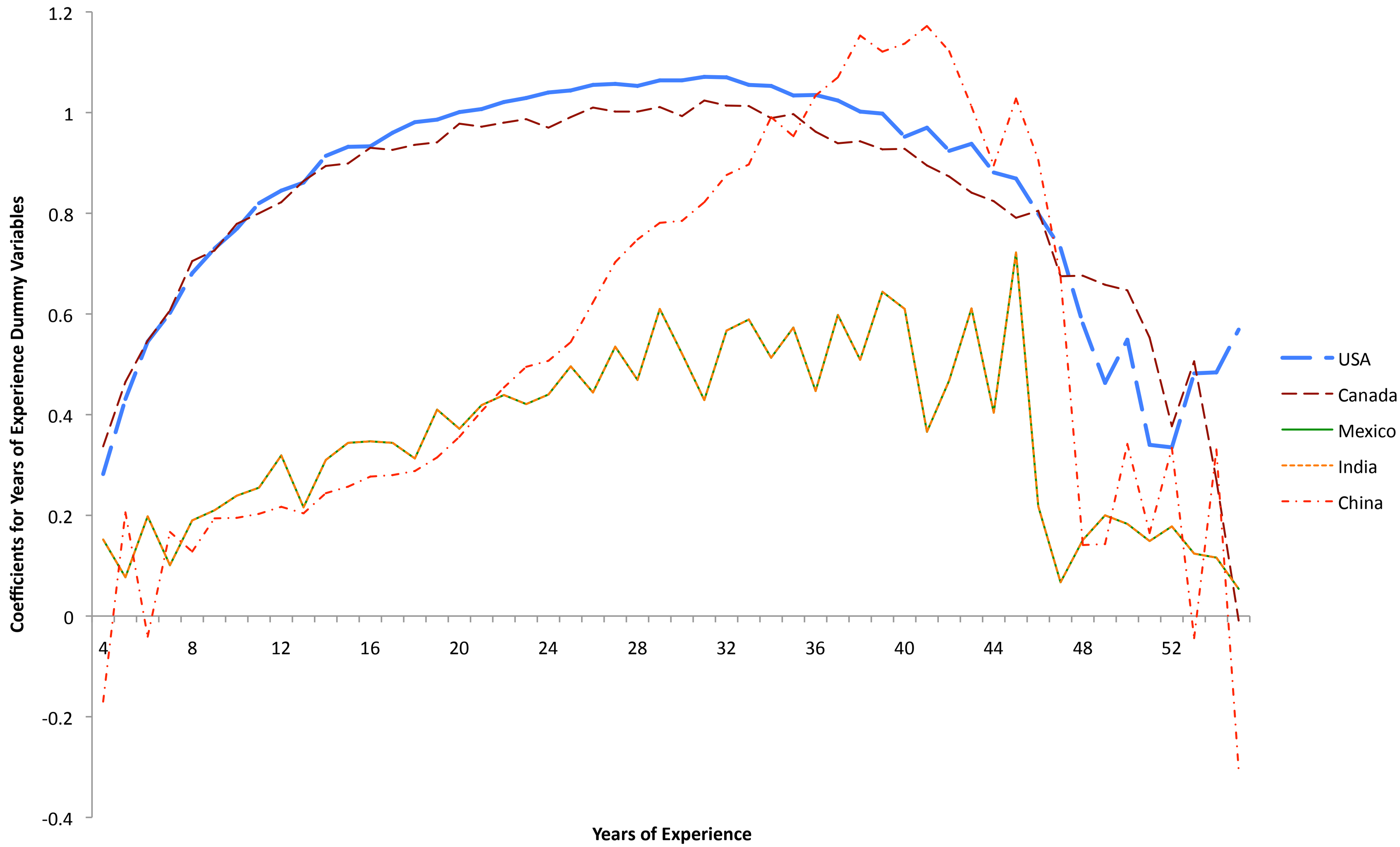


Figure 3: Returns to Experience for Each Year of Experience – Control for Time Effects

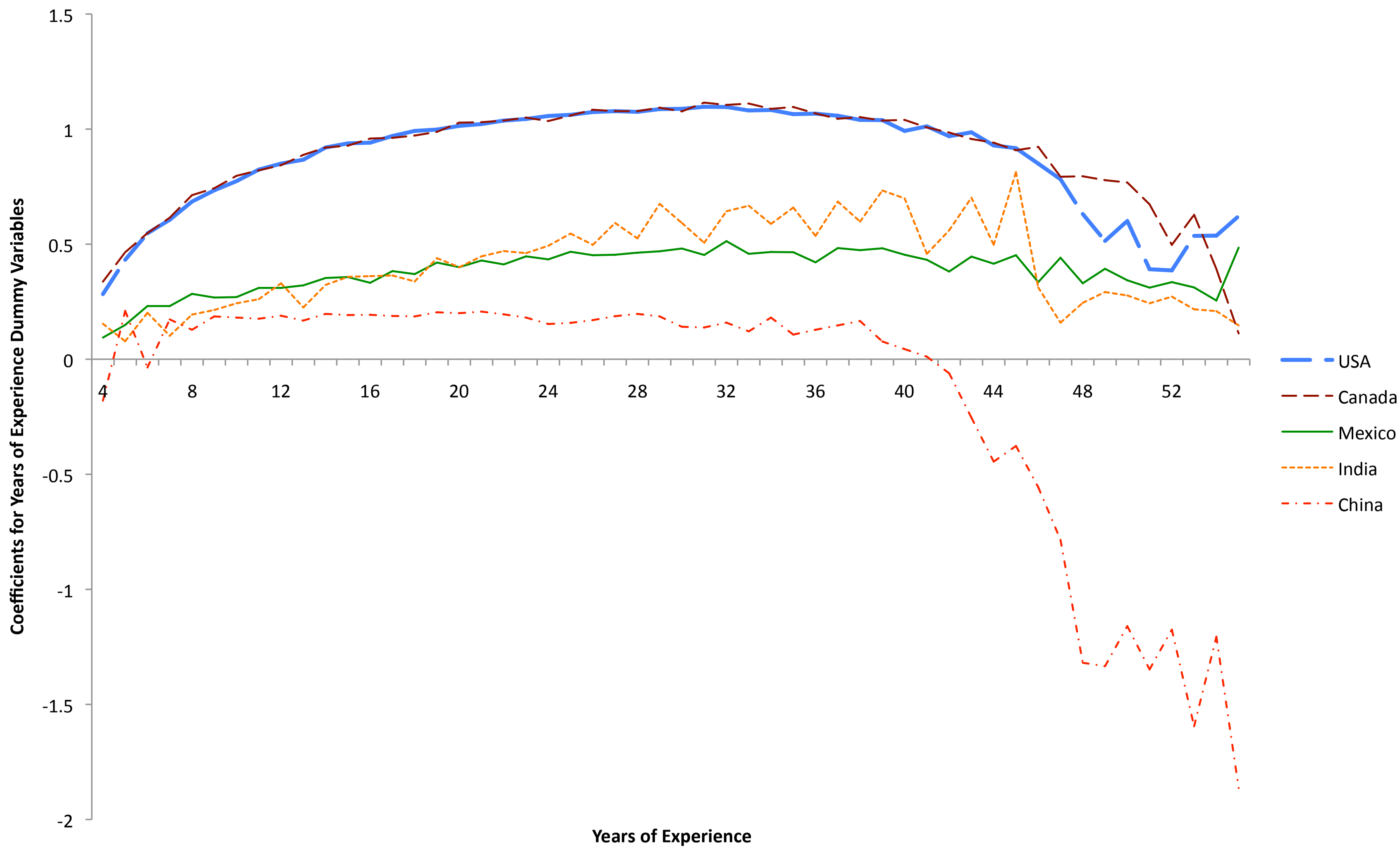


Figure 4: Implied Human Capital from Experience and Per Capita GDP (Based on cross-sectional estimates of the returns to experience)

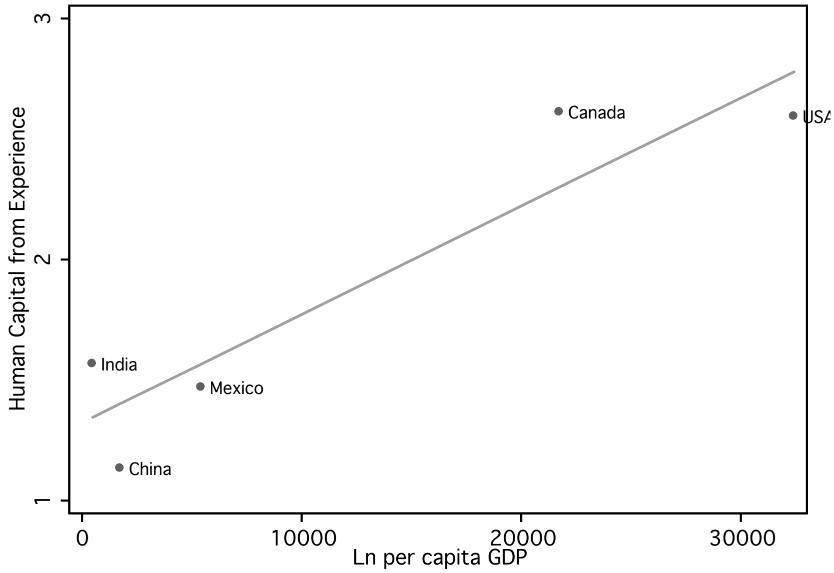


Figure 5: Implied Human Capital from Experience and Per Capita GDP (Based on estimates of the returns to experience with cohort controls)

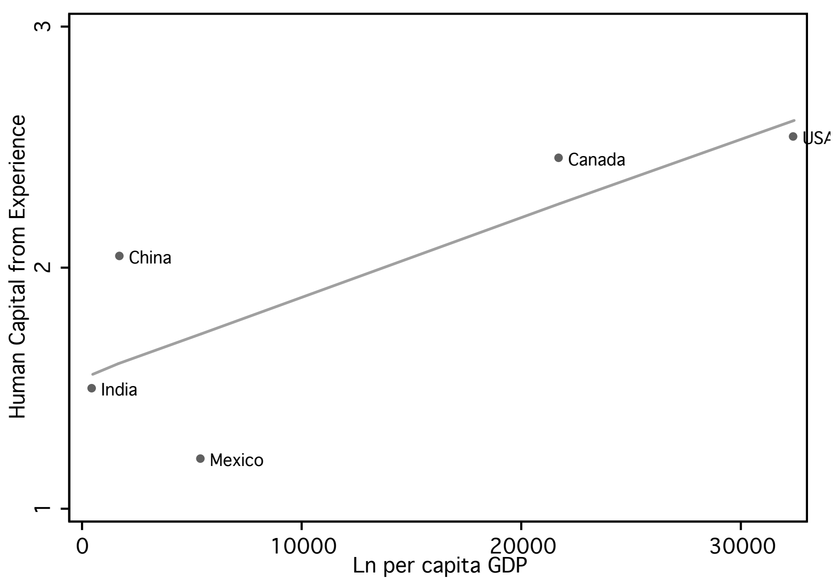


Figure 6: Implied Human Capital from Experience and Per Capita GDP (Based on estimates of the returns to experience with time controls)

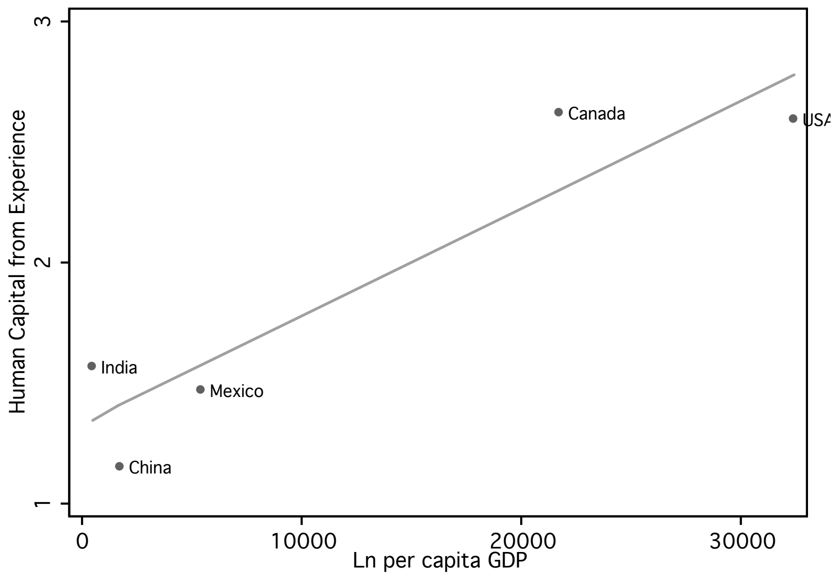


Figure 7: Implied Human Capital from Experience and Per Capita GDP (Based on cross-sectional Mincer estimates of the returns to experience)

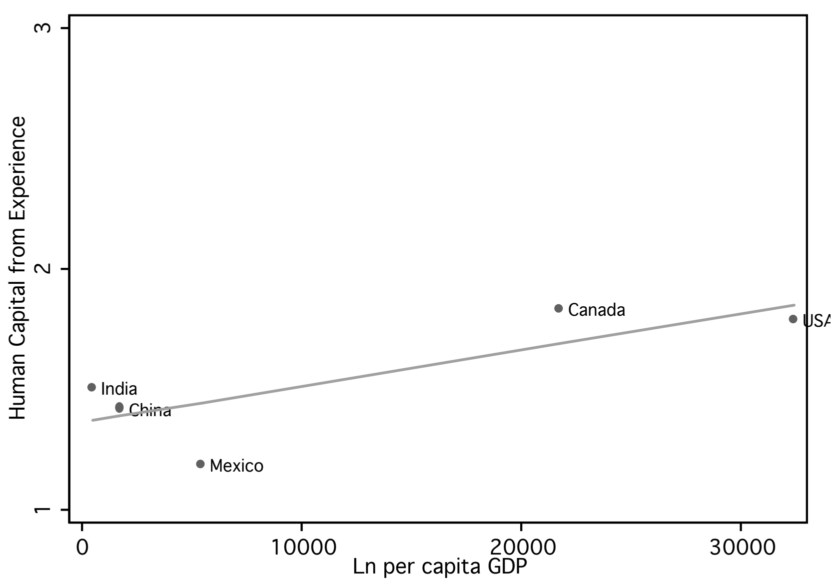


Figure 8: Implied Human Capital from Experience and Per Capita GDP (Based on Mincer estimates of the returns to experience with cohort controls)

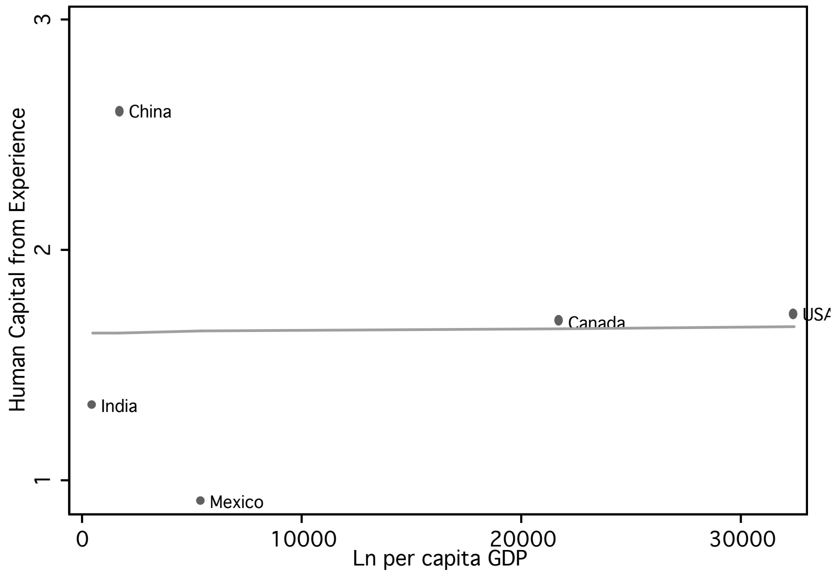


Figure 9: Implied Human Capital from Experience and Per Capita GDP (Based on Mincer estimates of the returns to experience with time controls)

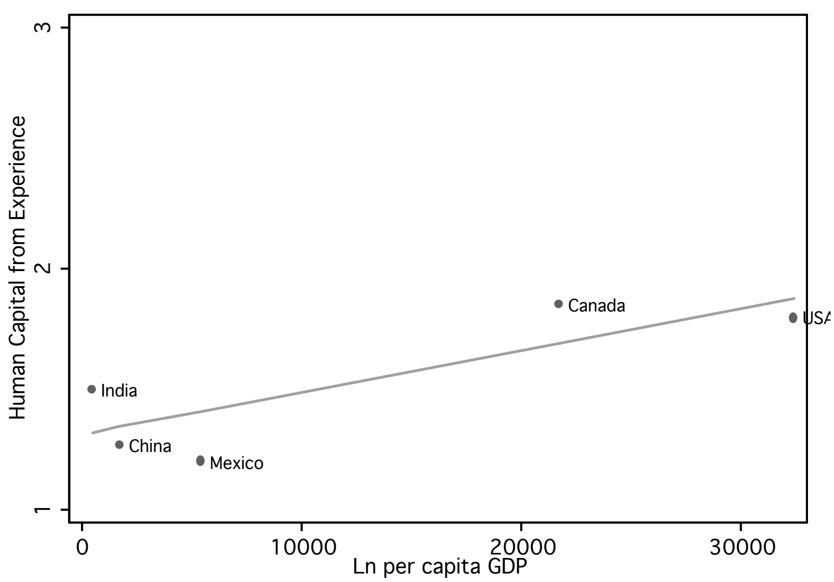


Table A.1: Returns to Experience

Dependent Variable: Ln Wage

	A. Cross-Sectional Estimates									
	USA		Canada		Mexico		India		China	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	coef	se	coef	se	coef	se	coef	se	coef	se
Edu. Years	0.100	(0.001)	0.059	(0.001)	0.088	(0.000)	0.103	(0.000)	0.067	(0.001)
Exp=4	0.283	(0.015)	0.337	(0.022)	0.094	(0.034)	0.154	(0.043)	-0.180	(0.166)
Exp=5	0.432	(0.015)	0.465	(0.021)	0.149	(0.031)	0.078	(0.042)	0.210	(0.129)
Exp=6	0.547	(0.014)	0.548	(0.020)	0.231	(0.030)	0.202	(0.038)	-0.036	(0.111)
Exp=7	0.606	(0.014)	0.615	(0.019)	0.231	(0.029)	0.102	(0.038)	0.173	(0.105)
Exp=8	0.685	(0.013)	0.713	(0.019)	0.284	(0.028)	0.194	(0.035)	0.128	(0.101)
Exp=9	0.734	(0.013)	0.743	(0.018)	0.268	(0.027)	0.214	(0.035)	0.186	(0.098)
Exp=10	0.774	(0.013)	0.797	(0.018)	0.270	(0.027)	0.243	(0.035)	0.181	(0.097)
Exp=11	0.824	(0.013)	0.821	(0.018)	0.310	(0.027)	0.261	(0.033)	0.176	(0.097)
Exp=12	0.850	(0.013)	0.843	(0.018)	0.310	(0.027)	0.330	(0.034)	0.189	(0.096)
Exp=13	0.867	(0.013)	0.888	(0.018)	0.321	(0.027)	0.225	(0.034)	0.168	(0.095)
Exp=14	0.920	(0.013)	0.920	(0.018)	0.353	(0.027)	0.323	(0.033)	0.197	(0.095)
Exp=15	0.938	(0.013)	0.928	(0.018)	0.357	(0.027)	0.358	(0.034)	0.192	(0.095)
Exp=16	0.941	(0.013)	0.959	(0.018)	0.332	(0.027)	0.361	(0.032)	0.193	(0.095)
Exp=17	0.970	(0.013)	0.962	(0.017)	0.383	(0.027)	0.364	(0.034)	0.188	(0.094)
Exp=18	0.992	(0.013)	0.972	(0.017)	0.370	(0.027)	0.338	(0.032)	0.186	(0.094)
Exp=19	0.998	(0.013)	0.988	(0.018)	0.420	(0.027)	0.439	(0.034)	0.204	(0.094)
Exp=20	1.014	(0.013)	1.028	(0.018)	0.400	(0.027)	0.400	(0.034)	0.200	(0.094)
Exp=21	1.022	(0.013)	1.030	(0.017)	0.429	(0.027)	0.447	(0.032)	0.207	(0.094)
Exp=22	1.037	(0.013)	1.037	(0.017)	0.412	(0.027)	0.470	(0.033)	0.195	(0.094)
Exp=23	1.044	(0.013)	1.050	(0.017)	0.447	(0.027)	0.461	(0.034)	0.181	(0.094)
Exp=24	1.057	(0.013)	1.035	(0.018)	0.434	(0.027)	0.493	(0.033)	0.153	(0.094)
Exp=25	1.062	(0.013)	1.059	(0.018)	0.467	(0.028)	0.546	(0.035)	0.158	(0.094)
Exp=26	1.074	(0.013)	1.084	(0.018)	0.452	(0.027)	0.497	(0.032)	0.170	(0.094)
Exp=27	1.078	(0.013)	1.078	(0.018)	0.454	(0.029)	0.592	(0.035)	0.187	(0.094)
Exp=28	1.075	(0.013)	1.078	(0.018)	0.463	(0.028)	0.525	(0.033)	0.197	(0.094)
Exp=29	1.087	(0.013)	1.093	(0.018)	0.469	(0.028)	0.675	(0.035)	0.186	(0.094)
Exp=30	1.088	(0.013)	1.077	(0.018)	0.481	(0.029)	0.592	(0.036)	0.141	(0.094)
Exp=31	1.097	(0.013)	1.115	(0.018)	0.453	(0.028)	0.506	(0.032)	0.138	(0.094)
Exp=32	1.096	(0.013)	1.105	(0.018)	0.513	(0.029)	0.643	(0.035)	0.159	(0.094)
Exp=33	1.081	(0.013)	1.111	(0.019)	0.458	(0.030)	0.667	(0.035)	0.121	(0.094)
Exp=34	1.083	(0.014)	1.088	(0.019)	0.466	(0.029)	0.588	(0.034)	0.181	(0.094)
Exp=35	1.065	(0.014)	1.096	(0.019)	0.465	(0.030)	0.659	(0.037)	0.107	(0.094)
Exp=36	1.067	(0.014)	1.068	(0.019)	0.421	(0.029)	0.536	(0.032)	0.128	(0.094)
Exp=37	1.058	(0.014)	1.045	(0.020)	0.483	(0.032)	0.685	(0.039)	0.147	(0.094)
Exp=38	1.040	(0.015)	1.052	(0.020)	0.474	(0.031)	0.598	(0.035)	0.166	(0.094)
Exp=39	1.039	(0.015)	1.037	(0.020)	0.482	(0.031)	0.733	(0.040)	0.077	(0.094)
Exp=40	0.992	(0.015)	1.040	(0.021)	0.454	(0.032)	0.699	(0.039)	0.044	(0.094)
Exp=41	1.012	(0.015)	1.007	(0.021)	0.432	(0.032)	0.458	(0.033)	0.011	(0.095)
Exp=42	0.969	(0.016)	0.985	(0.022)	0.381	(0.033)	0.560	(0.039)	-0.061	(0.095)
Exp=43	0.986	(0.016)	0.957	(0.023)	0.446	(0.035)	0.702	(0.045)	-0.254	(0.096)
Exp=44	0.929	(0.017)	0.941	(0.023)	0.415	(0.034)	0.497	(0.039)	-0.445	(0.096)
Exp=45	0.917	(0.018)	0.908	(0.024)	0.452	(0.036)	0.813	(0.056)	-0.377	(0.097)
Exp=46	0.850	(0.019)	0.923	(0.026)	0.335	(0.033)	0.312	(0.035)	-0.556	(0.098)
Exp=47	0.782	(0.020)	0.793	(0.027)	0.441	(0.044)	0.159	(0.070)	-0.785	(0.101)
Exp=48	0.631	(0.021)	0.795	(0.029)	0.330	(0.040)	0.245	(0.044)	-1.319	(0.104)
Exp=49	0.514	(0.026)	0.778	(0.032)	0.393	(0.041)	0.292	(0.068)	-1.334	(0.109)
Exp=50	0.601	(0.027)	0.768	(0.036)	0.343	(0.043)	0.277	(0.071)	-1.160	(0.110)
Exp=51	0.391	(0.030)	0.673	(0.044)	0.311	(0.039)	0.243	(0.038)	-1.348	(0.110)
Exp=52	0.386	(0.034)	0.497	(0.057)	0.335	(0.050)	0.272	(0.065)	-1.175	(0.113)
Exp=53	0.536	(0.055)	0.628	(0.066)	0.312	(0.052)	0.217	(0.100)	-1.595	(0.123)
Exp=54	0.537	(0.055)	0.392	(0.072)	0.255	(0.052)	0.209	(0.065)	-1.206	(0.138)
Exp=55	0.622	(0.055)	0.112	(0.077)	0.485	(0.062)	0.147	(0.100)	-1.863	(0.136)
Obs	240930		157615		109756		103887		97651	
R-Sq	0.210		0.111		0.266		0.439		0.150	

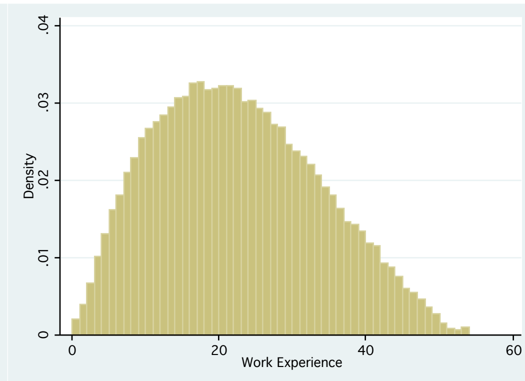
	B. Control for Cohort Effects									
	USA		Canada		Mexico		India		China	
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	coef	se	coef	se	coef	se	coef	se	coef	se
Edu. Years	0.099	(0.001)	0.057	(0.001)	0.085	(0.000)	0.102	(0.000)	0.103	(0.001)
Exp=4	0.282	(0.015)	0.337	(0.022)	0.091	(0.034)	0.152	(0.043)	-0.170	(0.161)
Exp=5	0.431	(0.015)	0.465	(0.021)	0.145	(0.031)	0.077	(0.042)	0.206	(0.125)
Exp=6	0.545	(0.014)	0.547	(0.020)	0.218	(0.030)	0.198	(0.038)	-0.041	(0.108)
Exp=7	0.602	(0.014)	0.607	(0.019)	0.214	(0.029)	0.101	(0.038)	0.167	(0.101)
Exp=8	0.681	(0.013)	0.705	(0.019)	0.264	(0.028)	0.190	(0.035)	0.128	(0.098)
Exp=9	0.730	(0.013)	0.726	(0.019)	0.228	(0.027)	0.210	(0.036)	0.194	(0.095)
Exp=10	0.769	(0.013)	0.779	(0.018)	0.229	(0.027)	0.239	(0.035)	0.195	(0.094)
Exp=11	0.820	(0.013)	0.800	(0.018)	0.263	(0.027)	0.255	(0.033)	0.203	(0.094)
Exp=12	0.845	(0.013)	0.822	(0.018)	0.257	(0.027)	0.319	(0.034)	0.217	(0.093)
Exp=13	0.861	(0.013)	0.864	(0.018)	0.264	(0.027)	0.216	(0.034)	0.204	(0.092)
Exp=14	0.914	(0.013)	0.894	(0.018)	0.265	(0.027)	0.310	(0.033)	0.244	(0.092)
Exp=15	0.932	(0.013)	0.899	(0.018)	0.254	(0.027)	0.344	(0.035)	0.257	(0.092)
Exp=16	0.933	(0.013)	0.930	(0.018)	0.220	(0.027)	0.347	(0.032)	0.277	(0.092)
Exp=17	0.960	(0.013)	0.926	(0.018)	0.265	(0.027)	0.344	(0.035)	0.280	(0.092)
Exp=18	0.981	(0.013)	0.936	(0.018)	0.249	(0.027)	0.313	(0.033)	0.288	(0.091)
Exp=19	0.986	(0.013)	0.941	(0.018)	0.265	(0.028)	0.410	(0.034)	0.315	(0.091)
Exp=20	1.001	(0.013)	0.978	(0.018)	0.227	(0.028)	0.372	(0.035)	0.356	(0.091)
Exp=21	1.007	(0.013)	0.972	(0.018)	0.227	(0.028)	0.419	(0.032)	0.407	(0.091)
Exp=22	1.021	(0.013)	0.980	(0.018)	0.205	(0.028)	0.439	(0.033)	0.454	(0.091)
Exp=23	1.029	(0.013)	0.987	(0.018)	0.237	(0.028)	0.421	(0.035)	0.495	(0.091)
Exp=24	1.040	(0.013)	0.970	(0.019)	0.221	(0.028)	0.440	(0.034)	0.507	(0.091)
Exp=25	1.044	(0.013)	0.991	(0.019)	0.228	(0.029)	0.496	(0.036)	0.544	(0.091)
Exp=26	1.055	(0.013)	1.010	(0.019)	0.180	(0.029)	0.444	(0.033)	0.623	(0.091)
Exp=27	1.057	(0.014)	1.002	(0.019)	0.178	(0.030)	0.535	(0.036)	0.703	(0.091)
Exp=28	1.053	(0.014)	1.002	(0.019)	0.187	(0.029)	0.469	(0.034)	0.748	(0.091)
Exp=29	1.064	(0.014)	1.011	(0.019)	0.158	(0.030)	0.610	(0.036)	0.781	(0.091)
Exp=30	1.064	(0.014)	0.993	(0.020)	0.172	(0.030)	0.521	(0.037)	0.785	(0.091)
Exp=31	1.071	(0.014)	1.024	(0.020)	0.102	(0.030)	0.429	(0.034)	0.822	(0.091)
Exp=32	1.070	(0.014)	1.014	(0.020)	0.159	(0.031)	0.567	(0.036)	0.876	(0.092)
Exp=33	1.055	(0.014)	1.013	(0.020)	0.106	(0.032)	0.589	(0.037)	0.897	(0.092)
Exp=34	1.053	(0.015)	0.989	(0.021)	0.071	(0.031)	0.513	(0.035)	0.991	(0.092)
Exp=35	1.034	(0.015)	0.997	(0.021)	0.075	(0.032)	0.573	(0.039)	0.953	(0.092)
Exp=36	1.035	(0.015)	0.962	(0.021)	0.026	(0.032)	0.447	(0.034)	1.034	(0.092)
Exp=37	1.024	(0.015)	0.939	(0.022)	0.092	(0.034)	0.598	(0.040)	1.070	(0.092)
Exp=38	1.002	(0.016)	0.943	(0.022)	0.085	(0.033)	0.509	(0.037)	1.153	(0.092)
Exp=39	0.998	(0.016)	0.927	(0.023)	0.040	(0.034)	0.644	(0.042)	1.121	(0.092)
Exp=40	0.952	(0.016)	0.928	(0.023)	0.011	(0.035)	0.610	(0.041)	1.137	(0.093)
Exp=41	0.970	(0.017)	0.895	(0.024)	-0.012	(0.035)	0.366	(0.036)	1.172	(0.093)
Exp=42	0.924	(0.017)	0.873	(0.024)	-0.063	(0.036)	0.468	(0.042)	1.122	(0.094)
Exp=43	0.938	(0.018)	0.841	(0.025)	0.004	(0.037)	0.611	(0.047)	1.012	(0.094)
Exp=44	0.881	(0.018)	0.824	(0.026)	-0.031	(0.037)	0.404	(0.042)	0.895	(0.095)
Exp=45	0.869	(0.019)	0.791	(0.027)	0.006	(0.038)	0.722	(0.058)	1.028	(0.096)
Exp=46	0.799	(0.020)	0.805	(0.028)	-0.113	(0.036)	0.218	(0.037)	0.906	(0.097)
Exp=47	0.731	(0.021)	0.675	(0.029)	-0.002	(0.046)	0.067	(0.071)	0.674	(0.099)
Exp=48	0.581	(0.023)	0.676	(0.031)	-0.115	(0.042)	0.151	(0.047)	0.141	(0.102)
Exp=49	0.463	(0.027)	0.658	(0.033)	-0.055	(0.043)	0.200	(0.070)	0.143	(0.107)
Exp=50	0.549	(0.028)	0.647	(0.037)	-0.106	(0.045)	0.183	(0.073)	0.342	(0.108)
Exp=51	0.340	(0.031)	0.553	(0.046)	-0.138	(0.041)	0.149	(0.041)	0.165	(0.108)
Exp=52	0.335	(0.035)	0.377	(0.058)	-0.116	(0.052)	0.178	(0.066)	0.334	(0.111)
Exp=53	0.482	(0.055)	0.506	(0.067)	-0.137	(0.054)	0.124	(0.101)	-0.044	(0.121)
Exp=54	0.484	(0.056)	0.270	(0.072)	-0.195	(0.054)	0.116	(0.067)	0.331	(0.135)
Exp=55	0.569	(0.055)	-0.009	(0.078)	0.037	(0.064)	0.054	(0.101)	-0.306	(0.133)
Obs	240930		157615		109756		103887		97651	
R-Sq	0.210		0.112		0.273		0.439		0.201	

	C. Control for Time Effects									
	USA		Canada		Mexico		India		China	
	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
	coef	se	coef	se	coef	se	coef	se	coef	se
Edu. Years	0.100	(0.001)	0.060	(0.001)	0.090	(0.000)	0.103	(0.000)	0.057	(0.001)
Exp=4	0.283	(0.015)	0.336	(0.022)	0.090	(0.034)	0.152	(0.043)	-0.134	(0.156)
Exp=5	0.432	(0.015)	0.465	(0.021)	0.147	(0.031)	0.075	(0.042)	0.239	(0.122)
Exp=6	0.547	(0.014)	0.547	(0.020)	0.225	(0.030)	0.207	(0.038)	0.044	(0.105)
Exp=7	0.606	(0.014)	0.614	(0.019)	0.228	(0.029)	0.101	(0.038)	0.214	(0.099)
Exp=8	0.685	(0.013)	0.712	(0.019)	0.279	(0.028)	0.192	(0.034)	0.220	(0.095)
Exp=9	0.734	(0.013)	0.742	(0.018)	0.265	(0.027)	0.215	(0.035)	0.240	(0.092)
Exp=10	0.773	(0.013)	0.795	(0.018)	0.266	(0.027)	0.239	(0.035)	0.235	(0.092)
Exp=11	0.824	(0.013)	0.820	(0.018)	0.307	(0.027)	0.260	(0.033)	0.239	(0.091)
Exp=12	0.850	(0.013)	0.841	(0.018)	0.307	(0.027)	0.327	(0.033)	0.245	(0.090)
Exp=13	0.867	(0.013)	0.886	(0.018)	0.319	(0.027)	0.222	(0.034)	0.213	(0.090)
Exp=14	0.920	(0.013)	0.919	(0.018)	0.352	(0.027)	0.321	(0.033)	0.230	(0.090)
Exp=15	0.938	(0.013)	0.927	(0.018)	0.358	(0.027)	0.355	(0.034)	0.221	(0.089)
Exp=16	0.941	(0.013)	0.959	(0.018)	0.332	(0.027)	0.362	(0.032)	0.228	(0.089)
Exp=17	0.970	(0.013)	0.963	(0.017)	0.384	(0.027)	0.362	(0.034)	0.230	(0.089)
Exp=18	0.992	(0.013)	0.973	(0.017)	0.371	(0.027)	0.335	(0.032)	0.232	(0.089)
Exp=19	0.998	(0.013)	0.989	(0.018)	0.424	(0.027)	0.437	(0.034)	0.242	(0.089)
Exp=20	1.014	(0.013)	1.029	(0.017)	0.403	(0.027)	0.397	(0.034)	0.230	(0.089)
Exp=21	1.022	(0.013)	1.031	(0.017)	0.430	(0.027)	0.444	(0.032)	0.236	(0.089)
Exp=22	1.037	(0.013)	1.040	(0.017)	0.415	(0.027)	0.466	(0.033)	0.230	(0.089)
Exp=23	1.044	(0.013)	1.052	(0.017)	0.449	(0.027)	0.459	(0.034)	0.231	(0.089)
Exp=24	1.057	(0.013)	1.038	(0.018)	0.436	(0.027)	0.489	(0.032)	0.197	(0.089)
Exp=25	1.062	(0.013)	1.063	(0.018)	0.471	(0.027)	0.544	(0.035)	0.185	(0.089)
Exp=26	1.074	(0.013)	1.088	(0.018)	0.453	(0.027)	0.492	(0.032)	0.197	(0.089)
Exp=27	1.078	(0.013)	1.082	(0.018)	0.459	(0.029)	0.588	(0.035)	0.206	(0.088)
Exp=28	1.075	(0.013)	1.083	(0.018)	0.469	(0.028)	0.521	(0.033)	0.208	(0.088)
Exp=29	1.087	(0.013)	1.098	(0.018)	0.473	(0.028)	0.672	(0.035)	0.200	(0.088)
Exp=30	1.088	(0.013)	1.084	(0.018)	0.487	(0.029)	0.587	(0.036)	0.157	(0.088)
Exp=31	1.097	(0.013)	1.121	(0.018)	0.459	(0.028)	0.501	(0.032)	0.145	(0.088)
Exp=32	1.096	(0.013)	1.111	(0.018)	0.517	(0.029)	0.641	(0.035)	0.159	(0.089)
Exp=33	1.081	(0.013)	1.118	(0.019)	0.466	(0.030)	0.665	(0.035)	0.129	(0.089)
Exp=34	1.083	(0.014)	1.093	(0.019)	0.468	(0.029)	0.584	(0.034)	0.170	(0.089)
Exp=35	1.065	(0.014)	1.101	(0.019)	0.471	(0.030)	0.656	(0.037)	0.091	(0.089)
Exp=36	1.067	(0.014)	1.074	(0.019)	0.425	(0.029)	0.532	(0.032)	0.115	(0.089)
Exp=37	1.058	(0.014)	1.051	(0.020)	0.493	(0.032)	0.681	(0.039)	0.118	(0.089)
Exp=38	1.040	(0.015)	1.057	(0.020)	0.484	(0.030)	0.592	(0.034)	0.121	(0.089)
Exp=39	1.038	(0.015)	1.041	(0.020)	0.493	(0.031)	0.733	(0.040)	0.026	(0.089)
Exp=40	0.992	(0.015)	1.044	(0.021)	0.463	(0.032)	0.695	(0.039)	-0.016	(0.089)
Exp=41	1.012	(0.015)	1.011	(0.021)	0.440	(0.032)	0.456	(0.033)	-0.051	(0.089)
Exp=42	0.969	(0.016)	0.989	(0.022)	0.388	(0.033)	0.555	(0.039)	-0.094	(0.090)
Exp=43	0.986	(0.016)	0.961	(0.023)	0.452	(0.034)	0.700	(0.045)	-0.286	(0.090)
Exp=44	0.929	(0.017)	0.944	(0.023)	0.419	(0.034)	0.491	(0.039)	-0.445	(0.091)
Exp=45	0.917	(0.018)	0.912	(0.024)	0.462	(0.036)	0.804	(0.056)	-0.364	(0.092)
Exp=46	0.850	(0.019)	0.928	(0.026)	0.340	(0.033)	0.309	(0.035)	-0.546	(0.093)
Exp=47	0.782	(0.020)	0.797	(0.027)	0.443	(0.044)	0.157	(0.070)	-0.767	(0.095)
Exp=48	0.631	(0.021)	0.799	(0.029)	0.336	(0.040)	0.239	(0.044)	-1.224	(0.098)
Exp=49	0.514	(0.026)	0.782	(0.032)	0.405	(0.041)	0.294	(0.068)	-1.240	(0.103)
Exp=50	0.600	(0.027)	0.771	(0.036)	0.357	(0.043)	0.263	(0.071)	-1.068	(0.103)
Exp=51	0.391	(0.030)	0.679	(0.044)	0.314	(0.039)	0.237	(0.038)	-1.278	(0.103)
Exp=52	0.386	(0.034)	0.501	(0.057)	0.357	(0.050)	0.259	(0.065)	-1.082	(0.107)
Exp=53	0.536	(0.055)	0.637	(0.066)	0.320	(0.052)	0.226	(0.100)	-1.518	(0.116)
Exp=54	0.537	(0.055)	0.398	(0.072)	0.267	(0.052)	0.193	(0.065)	-1.052	(0.130)
Exp=55	0.622	(0.055)	0.126	(0.077)	0.490	(0.062)	0.141	(0.100)	-1.832	(0.128)
Obs	240930		157615		109756		103887		97651	
R-Sq	0.210		0.112		0.272		0.441		0.243	

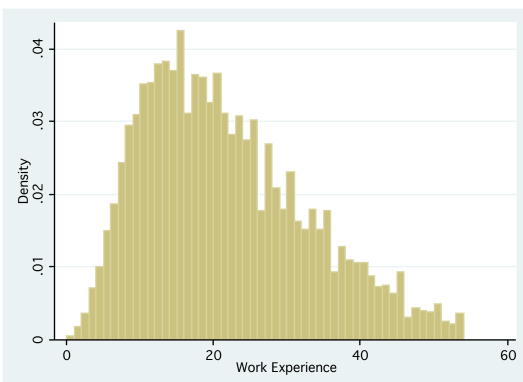
Note: The reference group for each estimate comprises of workers with 0-3 years of experience. In panel B, we include categorical controls for birth cohorts (e.g., dummy variables indicating ten-year intervals for birth year). In panel C, we include controls for calendar year dummy variables.

Figure 10: Experience Histograms

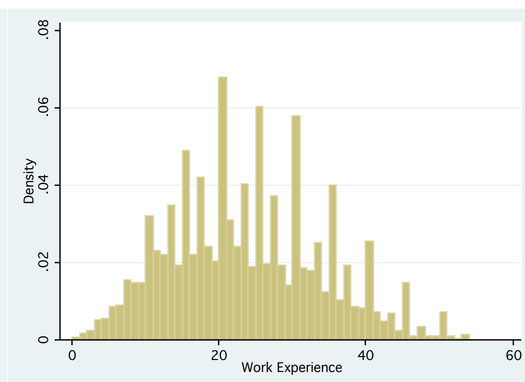
(a) USA



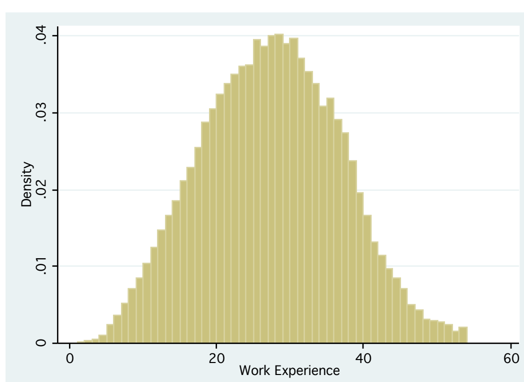
(b) Canada



(c) Mexico



(d) India



(e) China