# Experience Matters:

## Human Capital and Development Accounting*

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**Abstract**

A large literature on development accounting has concluded that differences in aggregate human and physical capital stocks across countries account for less than half of cross-country income differences. This same literature has argued that taking into account human capital from experience does not change the explanatory power of human and physical capital. Using recently available large-sample micro data, this paper documents a new fact that suggests a very different conclusion. The fact is that experience-earnings profiles are flatter in poor countries than rich countries. This suggests that poor countries have substantially smaller stocks of human capital from experience than rich countries, and taking this into account increases the contribution of human and physical capital to the variation in cross-country income differences from around forty to around sixty percent.

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## 1 Introduction

Understanding the determinants of cross-country income differences is one of the central aims of development and growth economics. An important first step in addressing this difficult question is to assess what fraction of these income differences are due to observable factors of production, namely physical and human capital. The clear consensus in the literature is that human and physical capital together account for less than half of cross-country income differences (Klenow and Rodriguez-Clare, 1997, Hall and Jones, 1999, Caselli, 2005, Hsieh and Klenow, 2010). In other words, more than half of world income inequality is accounted for by residual total factor productivity (TFP).

To measure aggregate human capital stocks, most of the literature has focused on human capital that is acquired through schooling. The rationale for ignoring human capital accumulation occuring *after* schooling comes primarily from the Mincerian wage regressions of Psacharopoulos (1994) and collaborators, which suggest that returns to potential experience are roughly constant across countries (see Bils and Klenow, 2000). Since the average *level* of potential experience is roughly constant across countries as well, the argument goes, then the stock of human capital arising through experience must be similar in magnitude in rich and poor countries.[1]

In this paper we document a new fact which suggests a very different conclusion. The fact is that experience-earnings profiles are flatter in poor countries than in rich countries. What the fact suggests is that human capital stocks arising from experience are in fact substantially smaller in poor countries than in rich countries. Moreover, we show that using the same "development accounting" as the previous literature – but allowing the returns to experience to vary across countries – the conclusion is that human and physical capital differences account for around sixty percent of cross-country income differences, as compared to around forty percent in previous studies.

To document our fact, we rely on recently available large-sample micro data for 36 countries. These data, which comprise over 200 household surveys, provide several important benefits relative to previous studies, and in particular the work of Psacharopoulos (1994) and those researchers relying on his estimates (e.g. Klenow and Rodriguez-Clare (1997), Hall and Jones (1999) and Caselli (2005)). First, the large sample sizes – at least five thousand individuals per survey – allow

[1] Studies that take a broader view of human capital include the work of Weil (2007) and Shastry and Weil (2003), who include the role of health, and Barro and Lee (2001), Hanushek and Kimko (2000), Hendricks (2002) and Schoellman (2012), who focus on quality differences in schooling.

us to estimate the returns to experience with minimal restrictions on functional form. Second, the comparable sampling frames across countries provide substantial scope for making international comparisons. Finally, the availability of multiple cross sections spanning relatively long time periods in a number of countries allow us to control for cohort effects or time effects in our estimates. Hence, we can gauge the extent to which our cross-sectional estimates of the experience-earnings profiles are driven by factors correlated with time, such as aggregate TFP growth, or those correlated with birth cohort, such as improvements in health.[2]

One important limitation of our study is that our data cover only 36 countries and represent much but not all of the world's population. The countries in our sample represent 68% of the world's population and range between the 1st (United States) and 83rd percentile (Bangladesh) of the world income distribution. Notably, we exclude most of the very poorest countries in the world, such as those in Sub-Saharan Africa. Another limitation is that our results cover wage earners but not the self-employed, whom we exclude (in our main analysis) because of measurement concerns.

Throughout the paper we focus on the returns to *potential experience*, defined as the number of years an individual could have been working, and refer to it simply as *experience*. In our benchmark empirical analysis we allow the returns to experience to vary fully flexibly for each additional year of experience. These fully flexible estimates show that experience-earnings profiles in poor countries typically lie below those of rich countries, i.e., the profiles are "flatter" in poor countries. We then demonstrate that this finding is robust to a number of sample restrictions and controls, and several alterative definitions of potential experience.

A well-known challenge in estimating returns to potential experience is that, due to co-linearity, one cannot separately identify the effects of potential experience (age), birth cohort and time. To address this challenge we follow the approach proposed by Hall (1968) and Deaton (1997), and employed by e.g. Aguiar and Hurst (2013), for estimating returns to experience using repeated cross sections. We draw on data for the fourteen countries for which our data cover at least fifteen years from the earliest to most recent surveys. Fortunately this subset includes all of the largest countries in our data, and specifically comprises Bangladesh, Brazil, Canada, Chile, China, Germany, India,

[2]Many of the surveys available to Psacharopoulos (1994) and his collaborators were based on small sample sizes and/or non-representative samples. For example, his estimates for China and India are based on 145 and 507 observations, respectively. He also did not attempt to control for cohort or year effects in his estimates, presumably because his data did not span a long enough time period.

Indonesia, Italy, Jamaica, Mexico, Puerto Rico, the United Kingdom and the United States.

We consider three different versions of the Deaton-Hall approach, which calls for one additional linear restriction on the time or cohort effects. The first version we consider assumes that time effects sum to zero, so that time effects capture cyclical conditions. The second version assumes that time effects sum to the TFP growth rate in the economy, so that time effects capture secural trends in growth plus cyclical conditions. The third variant assumes that cohort effects sum to zero, which allow the least restrictions on time effects. What we find is that while some countries, such as China, have estimated returns to experience that vary a lot under the different versions, the overall finding of steeper experience-earnings profiles in rich countries is present in all three.

To the extent that the data allow, we also examine the drivers of the cross-country differences in profiles. We find that the flatter experience-earnings profiles in poorer countries are due to flatter experience-*hours* profiles and experience-*wage* profiles and roughly in equal measure. We also find that the flatter profiles are present for both men and women and by schooling level and broad sector of the economy, suggesting that our main results are not due to simple composition effects.

To illustrate the economic significance of our empirical findings, we show what they imply for development accounting. The one thing we change relative to the seminal work of Klenow and Rodriguez-Clare (1997), Hall and Jones (1999) and Caselli (2005) is that we allow the returns to experience to vary across countries. Making use of our estimated experience-wage profiles, we show that the implied human capital due to experience is positively correlated with income, and furthermore that its cross-country dispersion is similar in magnitude to the dispersion of human capital due to schooling. Putting these together, we find that the contribution of physical and human capital in accounting for cross-country income differences increases from around forty percent to around sixty percent.

We conclude by looking at our facts through the lens of several theories relating earnings to experience. We argue that while cross-country differences in human capital is one plausible interpretation of experience-earnings profiles, there are other theories which are consistent with our facts. Moreover, even among theories of human capital accumulation, the quantitative implications for development accounting depend on the specifics of the theories, in particular whether human capital is actively accumulated (such as Ben-Porath type models) or passively accumulated. We conclude that understanding better the determinants of experience-earnings profiles across countries

is a fruitful avenue for future research, and discuss some of our own work along these lines (Lagakos, Moll, Porzio, Qian, and Schoellman, 2013).

Our paper closely relates to the literature dating back to the work of Mankiw, Romer, and Weil (1992), who argue that human capital (though only through schooling) explains the majority of cross-country income differences. Two recent examples which complement our work are those of Manuelli and Seshadri (2010) and Erosa, Koreshkova, and Restuccia (2010), who use Ben-Porath style models to argue that differences in the quality of education across countries are large. Schoellman (2012) reaches a similar conclusion by estimating returns to schooling by country among U.S. immigrants, and finding much lower returns among immigrants from poor countries than immigrants from rich countries. Jones (2011) argues that relaxing the assumption that different skill types are perfect substitutes in production leads to a much larger role of human capital in an otherwise standard developing accounting exercise. Gennaioli, La Porta, Lopez-de-Silanes, and Shleifer (forthcoming) conduct a development accounting exercise for sub-national regions from countries around the world, and find that human capital is the most important determinant of regional development.[3]

This paper is organized as follows. Section 2 describes the data. Section 3 presents our main result, namely that experience-earnings profiles are flatter in poor countries than rich countries. Section 4 applies the empirical estimates to a development accounting exercise and compares the results to existing accounting exercises. Section 5 discusses alternative interpretations of our empirical findings, including both theories of human capital accumulation and other explanations. Section 6 offers concluding remarks.

## 2 Data

Our analysis uses large-sample household survey data from 36 countries. The surveys we employ satisfy two basic criteria: (i) they are nationally representative or representative of urban areas; and (ii) they contain data on labor income for at least five thousand individuals. We make use of multiple surveys for each country whenever data are available. The final sample is comprised of 242 surveys

[3]Our empirical analysis also adds to recent studies that attempt to understand cross-country productivity differences with micro data, which have this far mostly focused on firm-level data. For example, Hsieh and Klenow (2009) document that there is more dispersion in marginal revenue products across firms in China and India than the United States. Hsieh and Klenow (2012) refine the analysis by documenting that firms grow less with age in Mexico and India than the United States. Similarly, Bloom and Van Reenen (2007) and Bloom, Mahajan, McKenzie, and Roberts (2010) document that managerial practices are systematically worse in poor countries than in rich countries.

spanning the years 1960 to 2011. The complete list of countries and data sources are listed in Appendix A.1.

The countries in our sample comprise a wide range of income levels, with the United States, Canada and Switzerland at the high end and Bangladesh, Vietnam and Indonesia at the low end. The combined population of the countries for which we have at least one survey amounts to 68% of the world population. Thus, while we lack data from many countries, our sample does represent a sizeable fraction of the world's total population. The biggest limitation of our sample in terms of coverage is that we have no data for the very poorest countries in the world, particularly those in Sub-Saharan Africa.

Our main outcome variable is labor earnings, which we measure, in the majority of our surveys, as monthly wage payments or salaries from both primary and secondary jobs. For all but five countries we observe hours worked as well, most often over the week prior to the survey date. For these countries we define an individual's wage to be her labor earnings divided by her hours worked. In the countries without hours data, we impute an individual's number of hours worked as the average number of hours across all other countries for that individual's experience level. Following Lemieux (2006) and others, we restrict attention to individuals with zero to 40 years of experience who have positive labor income and non-missing age and schooling information. In all surveys, we impute the years of schooling using educational attainment data. See Appendix A.1 for more specifics on the data employed in each country.

In our main analysis we restrict attention to workers that are wage earners, and exclude any workers with self-employed income. We do so for several reasons. First, it is widely believed that self-employed individuals tend to mis-report their income when asked directly (Deaton, 1997). Second, the income of the self-employed conceptually consists of payments to both labor and to capital, which are difficult to distinguish in practice (Gollin, 2002). Third, self-employed income often accrues to the household rather than the individual, which makes it difficult to interpret self-employed income reported at the individual level. In Section A.2 we show that when we nonetheless include the self employed where our data allow, taking their income data at face value, our main finding is still present.

In our main analysis we define potential experience such that $experience = age - schooling - 6$ for all individuals with eight or more years of schooling and $experience = age - 14$ for individuals

with fewer than eight years of schooling. This definition implies that individuals begin to work at age fourteen or after they finish school, whichever comes later. The cutoff at age fourteen is motivated by the fact that we observe very few individuals with positive wage income before the age of fourteen in our countries (see Figure A.5). Later, in Section 3.6 we show that our results are robust to several alternative definitions of potential experience and using age rather than experience.

## 3 Estimating Experience-Earnings Profiles

Most of our empirical results are estimated using flexible versions of Mincerian regressions of individuals' earnings on their years of schooling and potential experience. That is, we estimate equations of the form

$$\log y_{ict} = \alpha + g(s_{ict}) + f(x_{ict}) + \gamma_t + \psi_c + \varepsilon_{ict}, \tag{1}$$

where $y_{ict}$ are the earnings of individual $i$, who is a member of birth cohort $c$ observed at time $t$, $s_{ict}$ and $x_{ict}$ are her years of schooling and experience, $\gamma_t$ is a vector of time-period dummy variables, $\psi_c$ is a vector of cohort dummy variables and $\varepsilon_{ict}$ is a mean-zero error term.[4] In what follows we estimate the function $f(\cdot)$ and assess how it varies across countries. Our first empirical exercise is to estimate equation (1) for each country under the assumption that there are no cohort or time effects, $\gamma_t = \psi_c = 0$. Afterwards we turn to richer specifications that consider cohort and time effects.

### 3.1 Benchmark Results

We begin our empirical analysis by allowing the relationship between experience and earnings to vary for each year of experience. This flexible functional form fully accounts for changes in the slope of the experience-earnings profile. We estimate

$$\log y_{ict} = \alpha + \theta s_{ict} + \sum_{x=1}^{45} \phi_x D_{ict}^x + \varepsilon_{ict}, \tag{2}$$

where $D_{ict}^x$ is a dummy variable that takes the value of one if a worker has $x$ years of experience. The coefficient $\phi_x$ estimates the average earnings of workers with $x$ years of experience relative to

[4] The choice of an additively separable specification in schooling and experience has the benefit that the returns to schooling and experience are independent of each other. It is chosen solely for simplicity and most of our results can be generalized to the case where there is earnings depend on schooling and experience in a non-separable way.

the average earnings of workers with zero years of experience. In terms of our notation from the previous section, $\phi_x = f(x)$ such that the coefficient estimate corresponding to each experience level, $x$, identifies the experience-earnings profile evaluated at point $x$.

Figure 1 presents the main finding of the paper: experience-earnings profiles are flatter in poor countries than rich countries. Panel (a) displays the experience-earnings profiles for six large and representative countries in our sample (see Figure A.1 for the estimated profiles for our entire set of countries). For brevity, we will use "steepness" to refer to the average slope of the profiles over all experience levels (as opposed to the pointwise slope at a given level of experience.) The steepest profile among these six countries is in the United States, which is also the richest country. Germany has the next steepest profile, followed by China, Brazil, Mexico and finally, India.

Figure 1a also shows that the cross-country differences in the profiles are mostly realized by twenty years of experience, which is also approximately the average experience level of most countries in our sample. Therefore, to illustrate the relationship between the steepness of the profiles and income for all of the countries in our sample, we plot the height of the estimated profiles evaluated at twenty years potential experience against the log of GDP per capita at PPP in Figure 1b. The figure clearly shows that the experience-earnings profiles in poor countries are systematically flatter than those in rich countries. The correlation between the height of the profiles at 20 years and log GDP per capita is 0.68 and is significant at well below the 1% level. The slope coefficient from a regression of the height at 20 years potential experience and log GDP per capita is 0.32, and also significant at the 1% level**.** The correlations and slopes are reported in Table 1.[5]

### 3.2 Cohort and Time Effects

A well-known challenge to estimating returns to potential experience (or age, more precisely) using cross-sectional data is that one cannot separately identify the effects of experience, birth cohort and time due to co-linearity. Thus, our finding of lower returns to experience in poor countries than rich countries in cross-sectional data may in fact be driven by either cohort or time effects that operate differently across countries. In particular, one may worry that in countries with rapid economic growth, such as China, or significant improvements in health over time, such as India, the omission of such controls could be important.

[5]We find that the results are similar if we plot the heights at 10 or 15 years potential experience; results are available upon request.

In this section we consider the effects of cohort and time controls following the approach proposed by Hall (1968) and Deaton (1997) for estimating returns to experience using repeated cross sections. We draw on data for the fourteen countries for which our data cover at least fifteen years from the earliest to most recent surveys. Fortunately this subset includes all of the largest countries in our data, and specifically comprises Bangladesh, Brazil, Canada, Chile, China, Germany, India, Indonesia, Italy, Jamaica, Mexico, Puerto Rico, the United Kingdom and the United States. The data, which cover 142 surveys and span an average of 26 years per country, are listed in Table A.1.

We consider three versions of the approach proposed by Hall (1968) and Deaton (1997) for estimating returns to experience using repeated cross sections. Their insight is that if one imposes one additional linear restriction on the three effects, then one can use the time dimension of the repeated cross sections to draw inferences about the three effects. The first version we consider assumes that time effects sum to zero, following e.g. Aguiar and Hurst (2013), so that time effects capture cyclical conditions. The second version makes the "opposite" assumption that cohort effects sum to zero, so that time effects (in addition to experience effects) are unrestricted. The third version assumes that time effects sum to the TFP growth rate in the economy in question, so that time effects capture secural trends in growth in addition to cyclical conditions.[6] One motivation for this third version is that in standard neoclassical theory the log wage is a linear function of log TFP. As such time effects should capture TFP growth. In all three versions time effects take the form of calendar-year dummy variables, and cohort effects are yearly birth-cohort dummies.

In Figure 2 we plot the predicted profiles based on the estimates of equation (2) when we restrict time effects to sum to zero. As the figure shows, adding cohort controls and time controls that sum to zero does not affect estimates for most countries, but for some the profiles change considerably. The profile for China in particular becomes very steep. This is not altogether surprising: China grew dramatically during the time-period of our study and therefore following a given cohort over time while restricting time effects to only capture cyclical fluctuations, profiles are necessarily steep. Despite this, our overall cross-country pattern does not change much. Figure 2b shows that the

[6]We calculate TFP growth as $1 + g_{TFP} = (TFP_L/TFP_F)^{1/(L-F)}$, where $F$ and $L$ are the first and last years for wich we have available micro data, and restrict the time effects to cycle around a linear trend with slope $\log(1 + g_{TFP})$: the linear restriction is $\sum_{t=F}^{L} \gamma_t = \sum_{t=F}^{L} (t - F) \log(1 + g_{TFP})$ . TFP is computed using data on investment, GDP, and number of workers from the Penn World Table version 7.0., and data on years of schooling from the Barro-Lee dataset. More precisely, TFP is $Y/(K^{\alpha}H^{1-\alpha})$ where $\alpha = \frac{1}{3}$, $K$ is calculated with a perpetual inventory method, and $H$ is calculated as in Hall and Jones (1999).

correlation between the height of the profiles at twenty years and income is still 0.54 and significant at the 5% level.

Figure 3 plots the predicted profiles for the returns to experience when we instead restrict cohort effects to sum to zero. As the figure shows, results are very similar to the cross-sectional profiles in Figure 1. Figure 3b shows that the correlation between the height of the profiles at twenty years and income is 0.68 and is statistically significant at the 1% level.

Finally, we estimated equation (2) restricting the time effects to sum to each country's growth rate of aggregate TFP for the period for which we have data. Results are shown in Figure 4. For most countries, the experience-earnings profiles lie somewhere between those in the previous two variants of the Deaton-Hall method and the correlation between log GDP per capita and the profile heights at twenty years of experience is 0.70, approximately the same number as for the cross-sectional profiles.

Finally, we have also estimated profiles with either only time effects and no cohort effects, or only cohort effects and no time effects. This approach has been taken by a number of papers in the literature, including Guvenen (2007) and Huggett, Ventura, and Yaron (forthcoming). We find that results here look very similar to our first and second variants of the Deaton-Hall method. Results are not presented but are available upon request.

The estimates in this section show that for particular countries, in particular China, our estimated profiles are quite sensitive to the inclusion of cohort and time effects, depending on the exact way in which this is done. Nevertheless our overall cross-country finding that experience-earnings profiles are flatter in poor countries is robust to their inclusion. Thus, in much of the remainder of the paper we will focus on the cross-sectional estimates of the experience-earnings profile.

### 3.3 Parsimonious Functional Form for Experience-Earnings Profiles

While the fully flexible estimates are necessary for revealing the true functional form of the experience-earnings relationship, a parsimonious approximation of the relationship is more convenient for several exercises that we will conduct in this paper (e.g., examining compositional effects) and for comparing our results to the existing development accounting literature. Figures 1a to 4a show that experience-earnings profiles are highly non-linear, particularly in rich countries. A quadratic specification therefore provides a poor approximation of the true profiles, and we found

that the lowest-order polynomial that well approximates the true profiles is a quintic. This is not surprising given the finding of Murphy and Welch (1990) that the U.S. experience-earnings profile cannot be captured with a quadratic specification, but instead requires at least a quartic.

The parsimonious quintic specification is

$$\log y_{ict} = \alpha + \theta s_{ict} + \sum_{k=1}^{5} \phi_k x_{ict}^k + \varepsilon_{ict}, \tag{3}$$

where the log wage of individual $i$ of cohort $c$ during year $t$ is a function of her years of schooling, $s_{ict}$, and her years of experience, $x_{ict}$. This is the special case of equation 1 with $g(s) = \theta s$ and $f(x) = \sum_{k=1}^{5} \phi_k x^k$. Figure 5a plots the predicted experience-earnings profiles based on our quintic estimates. It shows that the quintic estimates closely resemble the fully flexible estimates in Figure 1a. Thus, for parsimony we will use the quintic specification for the remainder of the paper.[7]

### 3.4 Experience-Wage Profiles

A worker's earnings are the product of her hours worked and her hourly wages. A natural question is therefore whether flat experience-earnings profiles in poor countries reflect flat wage or hours profiles. In this section, we show that both wage and hours profiles are flatter in poor countries**.** We estimate equations of the form

$$\log w_{ict} = \alpha + g(s_{ict}) + f(x_{ict}) + \gamma_t + \psi_c + \varepsilon_{ict}, \tag{4}$$

where $w_{ict}$ is an individual's hourly wage (earnings divided by hours worked). Figure 6a plots the height of the experience-wage profiles at twenty years of experience against GDP per capita. Similarly to Figure 1, there is a strong positive relationship between the two, with a correlation of 0.51. Therefore, our finding that experience-earnings profiles are flatter in poor countries is also a finding about wage profiles. Figure 6b plots the height of the experience-hours profiles at twenty years of experience against income. It can be seen that also hours profiles are flatter in poor countries (the correlation with income is 0.49). While these cross-country differences in hours profiles are striking, we will not explore them further in the present paper and will instead focus

[7]The correlation between the height of the profiles at 20 years of experience from the quintic specification and log GDP per capita equals 0.68, which is identical to the correlation when using the fully flexible specification. Also all of our results are robust to using the fully flexible specification in (2). They are not reported for brevity but are available upon request.

on differences in earnings and wage profiles. Finally, we have estimated experience-wage profiles controlling for cohort and time effects using the three variants of the Deaton-Hall method described in (3.2). We again find that controlling for cohort and time effects can make a big difference for particular countries, but that the overall cross-country pattern is robust to their inclusion. These results are available upon request. Finally, note that our experience-wage profiles for the United States are quite similar to others in the literature. See e.g. Figures 11.6 and 11.7 of Lemieux, who also finds a height of the experience-wage profile at 20 years potential experience of around 0.8.

### 3.5 Composition Effects

In this section, we attempt to shed light on the underlying forces of our cross-country findings by examining the extent to which the estimated cross-country differences in experience-earnings profiles are due to differences in worker compositions across workers.

**Agriculture** A key difference between rich and poor countries is that poor countries tend to have a much larger share of workers in agriculture than rich countries. This could affect our estimates of average experience-earnings profiles for each country as Herrendorf and Schoellman (2011, Figure 4b) document that profiles are generally flatter among agricultural workers than non-agricultural workers in the United States.

To consider the role that this composition difference may play, we estimate equation (1) separately for the agricultural and non-agricultural sectors. The experience-earnings profile of country $j$ is then simply a weighted average of the sectoral profiles

$$f_j(x) = \ell_{A,j} f_{A,j}(x) + (1 - \ell_{A,j}) f_{N,j}(x), \tag{5}$$

where $\ell_{A,j}$ is the employment share in agriculture in country $j$ and $A$ stands for agriculture and $N$ for non-agriculture.[8] Figure 7a shows the height of the experience-earnings profile at twenty years of experience in agriculture plotted against that in non-agriculture. It can be seen that all but a few countries lie below the 45 degree line. In other words, for all but a few countries the experience-earnings profiles in agriculture are flatter than those in non-agriculture, though only modestly so.

[8]To see this, note that by the law of iterated expectations, the projection of earnings on experience, schooling, cohort and time can be decomposed by sector $s$ as $E[y|x,s,c,t] = \Pr(s = A)E[y|x,s,c,t,s = A] + \Pr(s = N)E[y|x,s,c,t,s = N]$.

To assess the quantitative importance of the cross-country differences in the proportions of workers engaged in agriculture for the differences in experience-earnings profiles, we conduct the following counterfactual exercise: we ask what would a country's experience-earnings profile look like if that country had the United States' employment share in agriculture. We compute the following counterfactual experience earnings profiles for each country $j$

$$\tilde{f}_j(x) = \ell_{A,US} f_{A,j}(x) + (1 - \ell_{A,US}) f_{N,j}(x), \tag{6}$$

If all of the cross-country differences in experience-earnings profiles were due to sectoral differences, then this counterfactual would eliminate all such differences. Figure 7b graphs the height of both the actual and counterfactual profiles at twenty years of experience against per capita GDP (using the countries for which data allow us to identify a worker's sector). If composition effects explained all of cross-country differences in returns to experience, the counterfactual heights for all countries would lie on a straight horizontal line at the level of the U.S. But instead, the counterfactual profiles are very similar to the actual ones. We calculate a correlation coefficient of 0.73 in the data, and 0.69 in the counterfactual, or just six percent lower. Put differently, differences in employment shares between agriculture and non-agriculture explain a very small part of our cross-country pattern.

**Schooling** Another important compositional difference between rich and poor countries is that workers in poor countries attain fewer years of schooling, which could drive our cross-country results since several studies have shown that college graduates have steeper *age*-earnings profiles than high school graduates (Carroll and Summers, 1991, Figures 10.7a and 10.8a; Guvenen, 2007, Figure 2; Kambourov and Manovskii, 2009, Figures 3,6,8 and 10; Elsby and Shapiro, 2012, Figure 3).

We explore the extent to which this difference drives our results by allowing the returns to experience to vary by the different levels of schooling in the human capital production function in equation (1). We work with a simple cutoff specification that allows for different returns to experience according to whether a worker has "high" ($H$) or "low" ($L$) educational attainment, i.e. whether his years of schooling are larger or smaller than some cutoff $\bar{s}$ that is common across countries. We define the threshold to be at ten years of schooling, $\bar{s} = 10$, which approximately the average years of schooling in our set of countries, and also a cutoff for which we have sufficient observations above and below in all countries. When we plot the height of the experience-earnings

profile for workers with low schooling (less than ten years) plotted against the height for those with high schooling (more than ten years). We find that in some countries, experience profiles are roughly similar by educational attainment, with some countries having modestly flatter profiles for less-skilled workers, and others having the opposite.[9]

Next, we conduct a similar counterfactual exercise as earlier and compute the implied experience-earnings profile if all countries had the same share of highly educated individuals as the United States. What we find is that the relation between the height of the counterfactual profiles and GDP is slightly steeper than that between the height of the actual profiles and GDP, with an actual correlation of 0.67 compared to a counterfactual one of 0.73. Thus, our results do not appear to be driven by differences in the composition of workers across countries by educational attainment.

**Other Composition Effects** Using the same basic approach as above, we have explored composition effects along other dimensions that may differ systematically between rich and poor countries: services versus non-services, manufacturing versus non-manufacturing, public- versus private-sector employment, male versus female, urban versus rural, and full- versus part-time employment. We also explored compositional effects for different combinations of these categories. We found none of these decompositions are important for explaining cross-country differences in the returns to experience. These results are not reported, for brevity, and are available upon request.

### 3.6 Robustness

This section demonstrates that our finding of flatter experience profiles in poor countries is robust to a variety of sample restrictions and alternative measures of potential experience, some of which can be important for interpreting the estimates. We also show that our main results are unlikely to be driven by measurement error in age or schooling in the data.

**Sample Restrictions** Our results so far include all individuals earning a wage, regardless of sex, sector of work, or part-time/full-time status. In addition, we do not restriction the age of individuals in our sample other than through the restriction that potential experience is positive. One potential concern is that our results are driven by cross-country differences in extent of female work, or timing of female entry into or exit out of the labor force. Another concern is that workers in the public

[9]Our findings are consistent with those of Heckman, Lochner, and Todd (2006) for the United States, who show that experience-earnings profiles are not substantially different by schooling level for white males, while *age*-earnings profiles are steeper for more educated workers. They also show that this is consistent with a simple model of lifecycle earnings dynamics ("Mincer's accounting identity model").

sector may earn wages that are not tied closely to market forces. Similarly, one may worry that wages for agricultural workers in poor countries are mis-measured. Finally, one may worry that our findings are driven by the inclusion of very young workers, or cross-country differences in the fraction of workers that are below a certain age.

To address these concerns, we repeat our estimates of the experience-earnings profiles on samples that are restricted to male workers, private-sector workers, non-agricultural workers, and different combinations thereof. We then do the same when restricting the sample by dropping all workers below a certain age threshold. Panel (a) Table 2 presents the correlation between the height of the experience-earnings profile and GDP per capita, as well as the slope coefficient from a regression of the former on the latter, under these alternative sample restricitons. The correlation in the benchmark estimates from Section 3.1 is 0.68 and significant at the 1% level. Under the alternative sample restrictions, the correlations range from 0.53 to 0.72 and are all significant at the 1% level. The slope coefficients in the benchmark is 0.32 and significant at the 1% level, while the slope coefficients range from 0.26 to 0.43 under the alternative restrictions and all significant. We conclude that none of these restrictions makes an appreciable difference to our main result.

**Experience Definition** Our main exercise assumes that individuals start work when they finish schooling or reach fourteen years of age, whichever comes sooner. Panel (b) of Table 2 reports the correlation for alternative definitions of potential experience.

The first of these makes the more standard assumption, as in Caselli (2005), that all workers begin work at age six or whenever they finish schooling and hence sets *experience = age - schooling – 6.* The next three take the same definition of potential experience but restrict the sample to males, private-sector males and full-time private-sector males. The last assumes that all workers begin work at age fifteen or whenever they finish schooling, which is another plausible assumption given our observations in Figure A.5 and hence sets *experience = age – schooling – 6* for all individuals with nine or more years of schooling, and *experience = age – 15* for other workers. The correlations range from 0.61 to 0.67 when experience is assumed to start accruing at age six and is 0.71 when experience begins only at age fifteen. The slopes show a similar pattern. In all cases, the correlations are statistically significant at below the 1% level. Thus, our main result is not an artifact of our choice of definition for experience.

**Age-Earnings Profiles** An alternative to experience-earnings profiles are *age*-earnings profiles. The age-earnings profiles for our six large and representative countries are plotted in Figure A.7a, and the height of the profiles at age 40 for all countries is plotted in Figure A.7b. The correlation between the height of the profile at age 40 and GDP is 0.69. Thus, we conclude that when looking at age-earnings profiles, we still find that profiles are flatter in poor countries than rich countries.

**Returns to Schooling** One concern is that our estimated returns to experience lead to implausible returns to schooling, or returns to schooling that differ from the literature in a substantial way. In fact neither is the case. Figure A.3 shows the estimated returns to schooling for the countries in our sample. As in the previous literature they range from 3% to 17% with a mean return of 9%. The Figure also shows the regression line of returns to schooling on GDP per capita, and shows that the correlation is weak at best. This is very much in line with previous estimates, in particular those surveyed by Banerjee and Duflo (2005), who find a mean return of 9% and a range of 3% to 15% across countries in their sample.

A second concern is that our returns to our experience decrease the importance of schooling in development accounting, while raising the importance of experience. To check that this is not the case, we first estimate the returns to experience under the restriction that returns to schooling satisfy the non-linear function used by Hall and Jones (1999).[10] Then, we follow Hsieh and Klenow (2010) and estimate the returns to experience by restricting the returns to schooling to be a constant 10%. The correlations between the profile heights and the log of GDP per capita in the two exercises range between 0.69 and 0.71, and are both statistically significant. Thus, our main result is not an artifact of our choice for estimating the returns to schooling.

**Measurement Error in Age** In Bangladesh and India, two of the poorer countries in our sample, we observe age-heaping in the data, where individuals seem to be rounding their ages to the nearest five years. This is presumably due to survey respondents not knowing their true ages. Since random measurement error in age will attenuate our estimates for the returns to experience and this is more likely to be a problem in poor countries than rich countries, one may be concerned that a significant part of the cross country differences in profiles is due to differences in measurement error.

To investigate the potential quantitative effect of bias caused by heaping, we construct a new

[10] They impose diminishing returns by assuming that $g(s)$ is a piecewise linear function with slope 0.13 for $s \leqslant 4$ , 0.10 for $4 < s \leqslant 8$ and 0.07 for $8 < s$.

auxiliary dataset for the United States where we replace the age of a certain percentage of workers with their age rounded to the nearest five years. We then re-estimate the returns to experience with this auxiliary dataset. Figure 8a shows that increasing the fraction of the sample to which we introduce measurement error does bias downward the profiles, but the effect is not quantitatively large. Even in the extreme case when we allow 90% of the U.S. population to mis-report their age, the profile is still far above that of India. Thus, our main cross-country results are not driven by biases induced through age-heaping.

**Measurement Error in Education Years** For most countries, direct measures of the years that individuals spent in school are not available. We therefore had to rely on educational attainment data (e.g., "secondary school degree" or "college degree") in order to construct the "years of schooling" variable. Moreover, the precision of the educational attainment data differs across countries. For example, for the U.S. we obtained *Current Population Survey* (CPS) data (in addition to the data we use in our main exercise) and in this dataset we have fifteen education groups from zero to 21 years of schooling. In contrast, for China we only have six education groups, with respectively six, nine, twelve, fifteen, sixteen or nineteen years of education. In the data, there is no correlation between the precision of education years estimates and the level of a country's GDP. Nevertheless, we here show that measurement error in education years is not able to generate quantitatively large differences in experience profiles.

To investigate the potential quantitative effect of bias caused by mismeasuring education years, we use the United States CPS data with its very precise educational attainment variable to construct a new auxiliary dataset in which we replace the education years of individuals with a fictitious educational attainment variable with wider year intervals. More specifically, we assume that we only have data on completed degrees and thus substitute zero years of education for all individuals with education less than five (no degree), five years of education for all individuals with education above or equal to five and below eight (primary school degree) and so on. After having constructed this new educational attainment variable, we recalculate potential experience for all individuals and re-estimate the experience-earnings profiles. Figure 8b shows that the experience-earnings profiles using the modified schooling measures are different, but the differences are not quantitatively large compared with the differences between the profiles of India and the United States.[11] This is also

[11]The profile with artificial measurement error is steeper than that in our benchmark exercise. This is because

true if we recode years of education assuming to have information only on attained degrees ("degrees only") and if we recode it using the coarser categorization used in IPUMS ("IPUMS categories"). Thus, our main cross-country results are not driven by biases induced through measurement error in education.

**Additional Sensitivity Tests** Given the large labor economics literature that studies the returns to experience using the *Current Population Survey* (CPS), we replicate our estimates with these data to check that our results for the U.S. experience-earnings profiles are not driven by our choice of data. In fact the profiles from the CPS and Census are virtually identical. For brevity, we do not motivate or present the results for a large number of other robustness checks that we performed, which include showing that our results are robust to: different functional forms for estimating the returns to schooling, in particular higher order polynomials and fully flexible returns to education; alternative imputation methods for hours worked in countries with no hours data; restricting the sample to only include household heads; and restricting the maximum years of experience at 40, 45 or 50 years. These results are available upon request.

## 4 Development Accounting

In this section we ilustrate the economic significance of our findings by applying them to a development accounting exercise. Our accounting exercise follows the previous literature, in particular the work of Klenow and Rodriguez-Clare, 1997, Hall and Jones, 1999, Caselli, 2005**,** in constructing measures of the aggregate physical and human capital stocks across countries using data on the average quanitites and returns to schooling and potential experience. Unlike in the previous literature, however, we allow the return to experience to differ across countries. What we show is that this change implies large variation in human capital stocks from experience across countries, not little or no varation, as concluded by the previous literature. In addition, we show that this one change increases the importance of physical and human capital in accounting for income differences from around forty percent to around sixty percent.

To meaure human capital, we assume that the human capital of individual $i$ at time $t$ with schooling $s_{it}$ and experience $x_{it}$ is

measurement error in education affects profile steepness through two mechanisms: (i) it results in measurement error in potential experience and hence induces classical attenuation bias, (ii) it results in attenuation bias of the coefficient on *schooling* which in turn increases the steepness of the experience profile.

$$h_{it} = \exp(g(s_{it}) + f(x_{it})). \tag{7}$$

which is the specification assumed by Bils and Klenow (2000). Studies such as those of Hall and Jones (1999) and Caselli (2005) posit the same equation but ignore the $f(x_{it})$ term and focus just on schooling. Given country-specific estimates of the returns to schooling and experience $g$ and $f$, it is then easy to compute individual human capital stocks and to aggregate them. This is what we do next.

### 4.1 Aggregate Experience Human Capital

We begin by decomposing individual human capital stocks into the components due to experience and schooling $h_{it} = h_{it}^S h_{it}^X$, where

$$h_{it}^X = \exp(f(x_{it})), \qquad h_{it}^S = \exp(g(s_{it})).$$

Analogously, define the aggregate experience human capital stock per worker as the average of the individual stocks across individuals and over time

$$H^X = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t} h_{it}^X. \tag{8}$$

Our estimates for aggregate experience human capital stocks are simply the integral of the estimated experience-*wage* profiles from the previous section (i.e., the area beneath the wage profiles) using the distribution of work experience from the data.[12]

Figures 9a-9d plot the implied experience human capital against per capita GDP for each country during this period. For these figures, the experience human capital stocks are calculated using the quintic specification in equation (3) and each figure corresponds to a different restriction on cohort and year effects, analogous to Figures 1-4. These figures display a strong and significant relationship

[12] Figure A.4 plots the average potential experience for all countries in our sample against GDP per capita. Our data show positive correlation between average potential experience and GDP per capita. However, as we show in Appendix A.3, differences in average potential experience account for little cross-country variation in experience human capital stocks. As concluded by Caselli (2005) and Bils and Klenow (2000), cross-country differences in average potential experience are of modest from a development accounting perspective.

between human capital from experience and income levels. In Figure 9b the correlation becomes strongly positive and significant if we exclude China, which is an outlier due to its very fast GDP growth. The cross-sectional estimates of experience human capital stocks for each country that are used in the figures are reported in Table A.3 in the appendix. The Deaton-Hall methods estimates country-by-country are available upon request.

### 4.2 Aggregate Human Capital from Both Schooling and Experience

We define the total human capital stock per worker (due to both schooling and experience) in a country to be the average of individual human capital stocks, $h_{it} = \exp(g(s_{it}) + f(x_{it}))$,

$$H = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t} h_{it}. \tag{9}$$

The estimates of these human capital stocks are based on our estimated returns to schooling and experience from the quintic specification. Comparing (8) and (9), note that we are *not* decomposing the aggregate human capital stocks into a part due to schooling and a part due to experience. In particular, $H \neq H^S H^X$ (even though at the individual level $h_{it} = h_{it}^S h_{it}^X$). Instead we are simply asking what human capital stocks would be if one were to *only* take into account schooling or *only* experience.

Table 2 Panel (a) summarizes our country-specific estimates of aggregate human capital stocks and presents two measures of the cross-country distribution of total human capital stocks. The first measure we use is the log variation in human capital stocks, the second measure is the slope of a linear regression of log human capital stocks on log GDP per capita. The second measure is reported in column (2) and shows that a 1% increase in log GDP per capita corresponds to a 0.17% increase in human capital stock from experience. For the sake of comparison, we also present the increase in the human capital stock from schooling, which equals also 0.17% . These results show that experience and schooling contributes equally to generate the differences in human capital stocks between rich and poor countries[13]. The first measure is reported in column (1) and shows

[13]Note that while cross-country differences in human capital due to schooling and experience are similar in magnitude, there is an important asymmetry in how those differences arise. In the case of schooling, it is well known that returns to a year of school completed are roughly similar across countries, while average years of schooling completed are higher in richer countries. For experience, as we document, returns to a year of experience are higher in rich countries, while the average level of experience does not vary substantially between countries. We further discuss this insight in the appendix.

that simple dispersion of human capital stocks, as measured by the log variation, is somewhat larger for schooling than for experience, but both are of the same order of magnitude.

Finally, the third row of Panel (a) in Table 2 reports the dispersion of total human capital stocks, where we take into account both schooling and experience. It shows that taking into account cross-country differences in returns to experience (going from row one to three) roughly doubles both the dispersion in human capital stocks across countries and the slope of the relationship between human capital stocks and GDP per capita. Panels (b), (c) and (d) of Table 2 shows that these numbers change somewhat when we use our three versions of the Deaton-Hall method, but that our main finding – that allowing returns to experience to vary across countries increases cross-country human capital gaps – is robust to the inclusions of cohort and year effects. The results reported in Panel (a) of Table 2 are constructed from the country-specific estimates which are reported in Appendix Table A.3. The country-specific estimates of the Deaton-Hall methods are available upon request.

### 4.3 Development Accounting

To make the development accounting exercise comparable to the existing development accounting literature, we use the same accounting method as in the survey by Caselli (2005). Our accounting procedure uses a Cobb-Douglas aggregate production function $Y = K^{\alpha}(AH)^{1-\alpha}$, where $Y$ is a country's real GDP per worker, $K$ is its physical capital stock per worker, $A$ is total factor productivity, and $H$ is our measure of the aggregate human capital stock per worker. The capital share is assumed to equal one-third, $\alpha = 1/3$, following the work of Gollin (2002).

As in Caselli (2005) we calculate the measure:

$$success_1 = \frac{\text{var}(\ln Y_{KH})}{\text{var}(\ln Y)}$$

where $Y_{KH} = K^{\alpha}H^{1-\alpha}$ is the component of output explained by factors of production. Intuitively, $success_1$ is the fraction of the variance of log GDP per worker that is explained by human and physical capital. One limitation of this measure is that it does not take into accont the correlation between $Y_{KH}$ and $Y$, and as such could be inflated by noisy estimates. For example, high measurement error in $Y_{KH}$ could be confounded with high explanatory power, since it increases artificially $\text{var}(\ln Y_{KH})$. In order to overcome this limitation, we report also the slope of a linear regression of $\ln Y_{KH}$ on $\ln Y$. Measurement error in $Y_{KH}$ would increase the measure of success, but decrease the

linear coefficient between $\ln Y_{KH}$ and $\ln Y$, as such if we report both an increase in $success1$ and in the slope measure, we can be confident that the raise in explanatory power derives from valuable information and not from confounding noise.

Table 3 presents these measures when we calculate aggregate human capital stocks either only from schooling, only from experience or from both schooling and experience. When human capital is identified by only schooling as in most of the literature, $success1$ is equal to forty percent. Recall that in Table 2, we showed that cross-country differences in experience human capital are roughly as big as those in schooling human capital. This is reflected in Table 3: comparing the first and the second rows reveals that schooling and experience human capital are roughly equally important determinants of cross-country income differences. Finally, when both schooling and experience are taken into account as in the third row, both measures of success increase dramatically. Physical and human capital taken together now account for sixty percent of the variation in cross-country income differences as compared to forty percent when experience is not taken into account. From the slope of the regression of $\ln Y_{KH}$ on $\ln Y$, reported in column (2), we can notice that our concerns on $success1$ were unfounded: calculating human capital from both education and experience we increase not only the total variability of $\ln Y_{KH}$ across countries, but also its correlation with $\ln Y$.

We can also conduct our development accounting exercise "country-by-country". To do this, we report a different measure:

$$success_2^j = \frac{Y_{KH}^{US}/Y_{KH}^{j}}{Y^{US}/Y^{j}}. \tag{10}$$

This is the fraction of the income gap between the United States and a poorer country $j$ that can be explained by factors of production only.[14] Table A.3 first reports Caselli's numbers for output and physical capital in columns (1) and (2). The estimates for $success_2^j$ are presented in columns (3)-(7). The results indicate that 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

[14] Caselli (2005) calculates also $success_2 = \frac{Y_{KH}^{90}/Y_{KH}^{10}}{Y^{90}/Y^{10}}$ as an overall measure (across all countries) of the importance of human and physical capital in accounting for income differences. However, as previously noticed, our data are not representative of the bottom quarter of the world income distribution, and as such we do not focus on this measure. The poorest country in our sample, in terms of output per worker, is Nicaragua, which corresponds to the 30th percentile of the income distribution in the data of Caselli (2005). Nonetheless we have calculated the measure of $success_2$ for our data we get 0.73 when both schooling and experience are counted as part of human capital, 0.45 when just schooling is included, and 0.45 when just experience is included.

of cross-country income differences than does the existing literature. Most countries still have large TFP gaps with the United States, though adding experience does help close the gaps.

### 4.4 Comparison to Existing Accounting Exercises

We now summarize our development accounting results with a series of accounting exercises that precisely illustrate the effects of each departure that we take from existing accounting exercises and their influences on our final result. All exercises use our data and are shown in Table 4. We begin with a specification that is similar to the one used in Klenow and Rodriguez-Clare (1997) (Panel (a)) and proceed step-by-step to the specification in our benchmark exercise (Panel (e)), adding one element at a time.

The specification in Panel (a) computes human capital stocks using a linear-quadratic Mincer specification and the average returns to schooling and experience as in Klenow and Rodriguez-Clare (1997).[15] $Success_1$, when taking into account human capital due to both schooling and experience, is only 0.44 (Panel (a), third row, third column), which is remarkably similar to 0.39, as reported in Caselli (2005).

Panel (b) uses the same specification, but imposes diminishing returns to schooling as in Hall and Jones (1999). This is also similar to Bils and Klenow (2000). $Success_1$ is essentially unchanged at 0.42. Panel (c) allows returns to experience to vary across countries, but retains the quadratic specification for estimating the returns to experience. This induces an increase in $success_1$ from 0.42 to 0.49. Panel (d) allows the returns to experience to vary across countries *and* uses our main quintic functional form for estimating the returns to experience. This causes $success_1$ to further increase from 0.49 to 0.59. Panel (e) additionally allows returns to schooling to vary across countries (estimated using a linear control for the years of schooling). This produces our main results shown in Tables 2 and 3: $success_1$ is 0.60.

The results in Table 4 show that our finding that human and physical capital contribute to sixty percent instead of forty percent of cross-country income differences is due to our allowing the returns to experience to vary across countries *and* the more accurate approximation of the experience-earnings profile from using a quintic functional form. To illustrate the importance of the flexible functional form more clearly, Figure A.6 repeats our empirical exercises from Section 3, but

[15] In our sample of 36 countries, the average coefficients on *schooling*, *experience* and $experience^2$ are 0.09211, 0.04775 and -0.000758, which are similar to those in Klenow and Rodriguez Clare (1997).

uses a linear-quadratic specification for estimating the experience-earnings profiles. Panel (a) shows that the quadratic experience-earnings profiles provide a poor approximation of the fully flexible ones whereas a quintic specification is much more accurate. Moreover, Panel (b) plots the height of both the quadratic and quintic experience-earnings profiles at twenty years of experience against countries' income levels and shows only a weak relationship for the quadratic profiles (black line) whereas it is much stronger for the quintic ones (light grey line).

## 5 Discussion: Interpretation of Experience-Earnings Profiles

Thus far, we document that experience-earnings profiles in poor countries are flatter than in rich countries and show that if one amends standard development accounting to allow for different returns to experience across countries (guided by our empirical estimates), then the importance of human and physical capital in explaining international income differences is greatly increased. In this section, we discuss the cross-country experience-earnings profiles in the context of the theoretical literature on human capital accumulation. This discussion serves two purposes. First, it suggests that there is a natural set of models for future research to consider when attempting to understand cross-country income differences. Second, it provides a framework for understanding the implications of the assumptions that we have made throughout the paper for interpreting the empirical results.

Specifically, we categorize the theories of human capital accumulation into two groups, according to whether human capital is accumulated passively as in learning-by-doing models, or actively, as in Ben-Porath type models. Then, we discuss the implications and interpretations of our empirical findings within the framework of each category. Finally, we briefly discuss alternative theories which postulate that factors other than human capital accumulation can affect experience-earnings profiles.

### 5.1 Theories of Human Capital Accumulation

First, we consider models where human capital is passively accumulated. The simplest possible interpretation of flat experience-earnings profiles in poor countries is that workers in developing countries may simply have less opportunity to improve their skills over their lifetimes than their counterparts in rich countries. This can, in turn, be due to reasons such as worse training opportunities, simpler technologies, fewer and weaker social interactions (Lucas, 2009; Lucas and Moll 2012; Perla and Tonetti 2012), or worse management practices in developing countries (Bloom and

Van Reenen, 2007; Bloom, Mahajan, McKenzie, and Roberts, 2010).[16]

To formalize this idea, consider individuals who live from time $t = 0$ to $t = T$. They go to school from year zero to year $s$ and work thereafter so that their work experience is $x(t) = t - s$. An individual's human capital accumulates passively according to

$$\dot{h}(t) = F(h(t), t), \tag{11}$$

where $h(0) = 1$ and $F$ is a smooth function. Note the absence of any investment in human capital. Workers earn their marginal products, supply their entire human capital to the labor market and human capital is valued in efficiency units up to a mean-zero error term. Hence, an individual's hourly wage is equal to the product of her human capital, a skill price $\bar{\omega}$, and an error term $\varepsilon$:

$$w(t) = \bar{\omega} h(t) \exp(\varepsilon), \quad t > s. \tag{12}$$

The following special case is instructive because it maps back to our empirical model in section (3) exactly:

$$\dot{h}(t) = F(h(t), t) = \begin{cases} \theta(t)h(t), & t \in [0, s] \\ \phi(x(t))h(t), & t \in (s, T] \end{cases} \tag{13}$$

Here, $\theta$ is the marginal return in terms of human capital per additional year of schooling and $\phi$ is the return per additional year of work experience. It is easy to show that

$$\log h(t) = g(s) + f(x(t)), \tag{14}$$

where $g(s)$ and $f(x)$ are the cumulative returns to schooling and experience.[17] Substituting into (12) yields an equation linking wages, schooling and potential experience that has the same form as

[16]The theories of social interactions just discussed posit that human capital is accumulated through social interactions with others such that an individual learns more when interacting with someone more knowledgeable than herself and more or better interactions lead to steeper age-earnings profiles. Within this framework, all determinants of the frequency or quality of such social interactions, such as the quality of communication technology, are therefore also potential determinants of cross-country differences in returns to experience.

[17]These cumulative returns are defined as $g(s) \equiv \int_0^s \theta(\tilde{s})d\tilde{s}$ and $f(x) \equiv \int_0^x \phi(\tilde{x})d\tilde{x}$. Further note that (14) is the same functional form as the "human capital production function" used by Bils and Klenow (2000).

our main estimating equation (1)

$$\log w(t) = \log \bar{\omega} + g(s) + f(x(t)) + \varepsilon. \tag{15}$$

Viewed through the lens of this simple model, flat experience-earnings profiles, $f(x)$, in poor countries are then simply due to the fact that human capital mechanically grows less for each extra year of experience: $\phi_{\text{poor}}(x) < \phi_{\text{rich}}(x)$. This could, in turn, be due to any of a number of reasons such as those mentioned in the first paragraph of this section (e.g., worse training, simpler technologies or fewer and weaker social interactions).

Second, we consider models where workers actively accumulate human capital. For example, workers in poor countries may *choose* to invest less into human capital. This could, in turn, be due to various reasons, such as low aggregate total factor productivity, credit constraints, high taxation and other allocative distortions which we discuss in more detail below. To formalize this, consider an extension of the simple model in the previous section, but where individuals can now invest into human capital accumulation as in Ben-Porath (1967):

$$\dot{h} = F(h, \ell, i).$$

Here, $\ell$ are time inputs and $i$ are non-time inputs (e.g., goods inputs such as books, computers or buildings). Assuming that an individual has a time endowment of one, her wage is given by $w(t) = \bar{\omega}(1-\ell(t))h(t)\exp(\varepsilon)$. The individual is considered to be in school if $\ell(t) = 1$. In Ben-Porath type models, the time paths for $\ell(t)$ and $i(t)$ are obtained from individuals' optimizing behavior. Before discussing the determinants of these choices, we begin with a simple case that takes these time paths as given. In a special case analogous to (13), we can again obtain an equation for the wage that has the same form as our estimating equation (1)

$$\log w = \log \bar{\omega} + g(s) + \underbrace{\log(1-\ell(x)) + \tilde{f}(x)}_{f(x)} + \varepsilon,$$

where $\tilde{f}(x)$ is the cumulative human capital return to experience.[18] In Ben-Porath type models,

[18]The special case analogous to equation (13) is $\dot{h} = F(h, \ell, i) = \theta(\ell, i)h$ if $\ell = 1$ and $\dot{h} = F(h, \ell, i) = \phi(\ell, i)h$ if $\ell < 1$. The cumulative return to experience is again defined as $\tilde{f}(x) = \int_0^x \phi(\ell(\tilde{x}), i(\tilde{x}))d\tilde{x}$.

there are two reasons for upward-sloping experience-earnings profiles. The first, as before, is human capital accumulation ($\tilde{f}(x)$ increases with each year of experience). Additionally there is a second reason: workers may decrease the amount of time allocated towards human capital accumulation ($\ell(x)$ is decreasing with each year of experience). Empirically, one cannot separately identify these two channels and our estimated experience earnings profiles, $f(x)$, would reflect both. We will return to this point in section (4).

From the perspective of theories of active human capital accumulation, flat experience-earnings profiles in poor countries reflect low investment in either time or non-time inputs. One possible reason for this is that low TFP in poor countries can depress the returns to the accumulation of experience human capital. A recent study that emphasizes this channel is by Manuelli and Seshadri (2010). Their framework is based on a Ben-Porath (1967) model similar to the one above, in which human capital accumulation requires both time and non-time inputs. Low TFP thus implies that the price of non-time inputs is high relative to the wage per unit of human capital. This, in turn, implies that individuals purchase fewer non-time inputs and accumulate less human capital, both in school and on the job. This results in flat experience-earnings profiles. This class of theories also makes clear that the main result of our development accounting exercise – that TFP explains a smaller fraction of cross-country income differences than previously thought – is only true in an accounting sense and does not imply that TFP is less important than human capital as the root cause of cross-country income difference. A similar argument is made by Erosa, Koreshkova, and Restuccia (2010), which shows how the accumulation of schooling human capital can amplify TFP differences across countries.

Flat experience-earnings profiles may also be due to the prevalence of credit constraints. If workers cannot borrow to smooth consumption, they may not take jobs that offer good training opportunities. This could be formalized in a framework in the spirit of Galor and Zeira (1993), but with on-the-job investment in human capital. Another potential cause of lower returns to experience in poor countries is that the higher prevalence of extractive institutions in poorer countries (emphasized by Acemoglu, Johnson, and Robinson (2001) among others) discourages workers from accumulating human capital for which the returns could be confiscated in one way or another. This logic is consistent with recent evidence that higher taxation of labor income in Europe can explain a substantial fraction of European-U.S. differences in wage inequality and lifecycle wage growth

(Guvenen, Kuruscu, and Ozkan, 2011). Similarly, it could be allocative distortions in poor countries that reduce human capital accumulation over the lifecycle (Bhattacharya, Guner, and Ventura, 2012).

More generally, the same factors which cause firms to grow less quickly over the lifecycle in poor countries (Hsieh and Klenow, 2012) may explain why workers' earnings grow less quickly. In this spirit, Seshadri and Roys (2012) propose a theory that can potentially explain both facts simultaneously: workers and managers accumulate human capital and a firm is a match of a manager and some workers. Human capital accumulation and matching interact and jointly determine the lifecycle of both firm size and workers' earnings.

### 5.2 Alternative Explanations

We note that there are several theories besides those that we discuss above which postulate that factors other than human capital accumulation affect the shape of experience-earnings profiles. For example, if workers and firms form long-term contracts (e.g.,Lazear (1979)), wages may not equal workers' marginal product of labor, and this may lead to cross-country differences in returns to experience.[19] In theories with moral hazard or limited commitment on the part of workers, long-term contracting will allow firms to "backload" wages such that earnings-experience profile will be steeper than the true relationship between the marginal product of labor and experience. If these frictions are likely to be more pronounced in poor countries, these theories would predict more backloading in poor countries, which imply that our estimates understate the difference in the steepness of profiles between rich and poor countries.[20] Some studies also show that there is front-loading in wage-contracts because of limited commitment on the side of firms, or if firms lend to financially constrained workers. Front-loading would cause experience-earnings profiles to

[19] To formalize this, assume that human capital is accumulated passively as in (13), but depart from the assumption that individuals are paid their marginal products and instead $w(t) = \bar{\omega}(1+\tau(t))h(t)\exp(\varepsilon)$, where $\tau(t)$ captures deviations from the wage equals marginal product assumption. Then

$$\log w = \log \bar{\omega} + g(s) + \underbrace{\log(1+\tau(x)) + \tilde{f}(x)}_{f(x)} + \varepsilon. \tag{16}$$

Long-term contracting may result in wages being "back-loaded" ($\tau(x)$ is increasing) in which case experience-earnings profiles $f(x)$ are steeper than human capital profiles $\tilde{f}(x)$; and vice versa if wages are "front-loaded" ($\tau(x)$ is decreasing).

[20] In a related study, Michelacci and Quadrini (2009) postulates that financially constrained firms that sign optimal long-term contracts with workers may implicitly borrow from their workers, thereby offering steeper wage profiles than in the frictionless case. If firms in poor countries are more financially constrained, then our empirical estimates will again under-state the steepness of the relationship between the marginal product of labor and experience of rich countries relative to poor ones.

appear flatter than in the frictionless case (Azariadis, 1988; Bernhardt and Timmis, 1990). Another potential determinant of earnings dynamics over the lifecycle is matching frictions. If the labor market features search frictions and match-specific productivity (Burdett, 1978; Jovanovic, 1979), flat experience-earnings profiles in poor countries may partly reflect low labor market turnover. Related to this, they may be due to lower rents from search (Burdett and Mortensen, 1998).

There is little available evidence on the relative influence of long-term contracts, search frictions or other factors on life-time earnings dynamics across countries.[21] However, several pieces of evidence suggest that our results are unlikely to over-state cross-country differences in human capital because of these alternative mechanisms. For example, in a recent empirical study comparing different provinces within Italy, Guiso, Pistaferri, and Schivardi (2010) finds that firms operating in less financially developed provinces offer steeper wage-tenure profiles. If the same relationship between the steepness of wage-tenure profiles and economic development is true across countries, then our results will understate the true difference between human capital and income across countries.[22] More generally, there is a large number of studies that attempt to understand the importance of human capital and other factors, such as job mobility, in determining experience-earnings profiles in the United States (e.g., Altonji, Smith, and Vidangos (2009), Topel and Ward (1992) and Bagger, Fontaine, Postel-Vinay, and Robin (2011)). While these studies vary in their assessment of the exact contribution of each mechanism, they agree that human capital accumulation is the most important source of wage growth, especially during the early phase of workers' careers, which is also the phase in which the cross-country differences in returns to experience that we document are most pronounced.

## 6 Conclusion

The large existing literature on development accounting estimates that human and physical capital account for less than half of cross-country income differences (Klenow and Rodriguez-Clare,

[21] For example, to assess the contribution of long-term contracts in driving the cross-country differences, we would need to the degree to which they are used in countries of different income levels, and the strength of the forces that would cause back-loading relative to the strength of the forces that would cause front-loading and how the relative forces varied with income levels. This is not possible with the existing data.

[22] Also, it is important to note that theories of long-term contracting all refer to the returns to tenure (experience at a specific firm) rather than the return to life-time potential experience. Thus, long-term contracts are *a priori* unlikely to have large quantitative effects on the average experience-earnings profiles of workers for any given country unless if average worker tenure is reasonably long. The limited data on worker tenure does not support this. For example, in the United States, the median tenure is 4.6 years (Bureau of Labor Statistics, 2012).

1997, Hall and Jones, 1999, and Caselli, 2005). To measure human capital stocks, most of this literature focused on human capital acquired through schooling, and due to data limitations, have ignored human capital accumulated through experience. This paper conducts a development accounting exercise that allows returns to experience to vary across countries. We estimate the returns to experience with newly available data and show that experience-earnings profiles are steeper in rich countries. Taking this into account in development accounting significantly increases the contribution of the observable factors of production to cross-country income.

We demonstrate that our empirical findings and preferred interpretation are consistent with the large body of theories which postulate that workers accumulate human capital, actively or passively, over the life-cycle. We cannot conclusively rule out alternative interpretations that life-time earnings dynamics can be an outcome of factors other than human capital accumulation. Distinguishing between the different theories and understanding the determinants of cross-country experience-earnings profiles is an important avenue of future research. For example, in a work-in-progress, Lagakos, Moll, Porzio, Qian, and Schoellman (2013) document that amongst new U.S. immigrants, returns to foreign experience are higher for immigrants from rich countries than immigrants from poor poor countries. Since all wages are paid in the United States, this goes against the alternative that cross-country differences are driven by the different wage-setting structures across countries. In any case, the results in this paper are consistent with the view that exploring the determinants of human capital accumulation and how they vary across countries is likely to be a fruitful endeavor for understanding cross-country income differences.

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Table 1: Returns to Experience and GDP per Capita

| | Corr(Height at 20, log GDP p.c.) | Slope(Height at 20, log GDP p.c.) |
|---|---|---|
| | (a) Experience-Earnings Profiles | |
| Cross-Section (No Cohort or Year Effects) | 0.68*** | 0.32*** |
| Time Effects Sum to Zero | 0.54** | 0.23** |
| Cohort Effects Sum to Zero | 0.68*** | 0.28*** |
| Time Effects Sum to TFP Growth | 0.70*** | 0.26*** |
| Time Effects Only | 0.67*** | 0.32*** |
| Cohort Effects Only | 0.52** | 0.24** |
| | (b) Wage and Hours Profiles | |
| Experience-Wage Profile | 0.51*** | 0.13*** |
| Experience-Hours Profile | 0.49*** | 0.16*** |

Notes: Panel (a) refers to experience-earnings profiles, and Panel (b) refers to experience-wage profiles and experience-hours profiles, respectively. "Height at 20" is the height of the profile at 20 years of potential experience. Corr(Height at 20, log GDP p.c.) is the correlation coefficient between "Height at 20" and log GDP per capita calculated from the Penn World Tables. Slope(Height at 20, log GDP p.c.) is the slope coefficient from a regression of Height at 20 on log GDP per capita and a constant. *** means significant at the 1% level; ** means significant at the 5% level, and * means significant at the 10% level.

Table 2: Returns to Experience and GDP per Capita: Alternate Specifications

| | Corr(Height at 20, log GDP p.c.) | Slope(Height at 20, log GDP p.c.) |
|---|---|---|
| | (a) Sample Restrictions | |
| Male Workers | 0.72*** | 0.43*** |
| Male Private Workers | 0.68*** | 0.43*** |
| Male Private Full-Time Workers | 0.63*** | 0.37*** |
| Non-Agricultural Workers | 0.66*** | 0.33*** |
| Older than 18 Years Workers | 0.67*** | 0.32*** |
| Older than 22 Years Workers | 0.53*** | 0.26*** |
| | (b) Definition of Potential Experience | |
| Start Work at Age 6 | 0.61*** | 0.31*** |
| Start Work at Age 6 (Age 16-64) | 0.67*** | 0.33*** |
| Start Work at Age 15 | 0.71*** | 0.38*** |

Notes: "Height at 20" is the height of the profile at 20 years of potential experience. Corr(Height at 20, log GDP p.c.) is the correlation coefficient between "Height at 20" and log GDP per capita calculated from the Penn World Tables. Slope(Height at 20, log GDP p.c.) is the slope coefficient from a regression of Height at 20 on log GDP per capita and a constant. Each row represents the results under one particular sample restriction, set of controls, or definition of potential experience. *** means significant at the 1% level; ** means significant at the 5% level, and * means significant at the 10% level.

Table 3: Variance of Human Capital Stocks Across Countries

| Human Capital Measure | Var(log(H)) | Slope(log(H),log(GDP)) |
|---|---|---|
| | (a) Cross-sectional Results | |
| Schooling | 0.12 | 0.17 |
| Experience | 0.07 | 0.17 |
| Schooling + Experience | 0.23 | 0.35 |
| | (b) Year Effects Sum to Zero | |
| Schooling | 0.11 | 0.13 |
| Experience | 0.14 | 0.02 |
| Schooling + Experience | 0.39 | 0.15 |
| | (c) Cohort Effects Sum to Zero | |
| Schooling | 0.07 | 0.19 |
| Experience | 0.08 | 0.18 |
| Schooling + Experience | 0.18 | 0.37 |
| | (d) Year Effects Sum to TFP Growth | |
| Schooling | 0.07 | 0.18 |
| Experience | 0.12 | 0.17 |
| Schooling + Experience | 0.26 | 0.36 |

Table 4: Development Accounting

| Human Capital Measure | $\text{Success}_1$ | Slope($\log(Y_{KH})$,log(GDP)) |
|---|---|---|
| | (a) Cross-sectional Results | |
| Schooling | 0.40 | 0.53 |
| Experience | 0.37 | 0.54 |
| Schooling + Experience | 0.60 | 0.64 |
| | (b) Year Effects Sum to Zero | |
| Schooling | 0.35 | 0.52 |
| Experience | 0.29 | 0.43 |
| Schooling + Experience | 0.54 | 0.53 |
| | (c) Cohort Effects Sum to Zero | |
| Schooling | 0.36 | 0.57 |
| Experience | 0.32 | 0.53 |
| Schooling + Experience | 0.51 | 0.67 |
| | (d) Year Effects Sum to TFP Growth | |
| Schooling | 0.35 | 0.56 |
| Experience | 0.33 | 0.52 |
| Schooling + Experience | 0.52 | 0.65 |

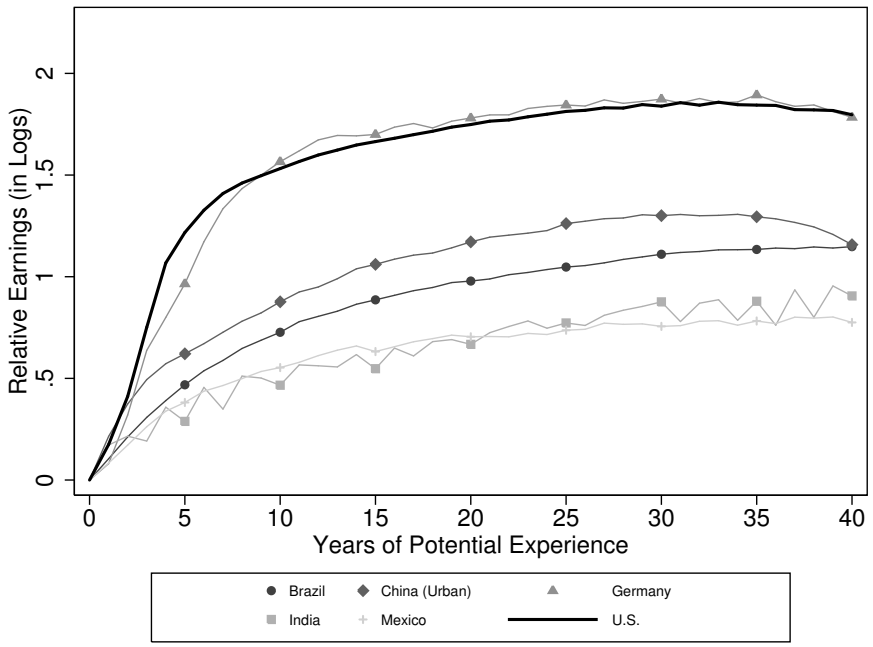
Table 5: Relation to Literature

| Human Capital Measure | Var(log(H)) | Success1 |
|---|---|---|
| | (a) Klenow and Rodriguez-Clare | |
| Schooling | 0.06 | 0.39 |
| Experience | 0.01 | 0.25 |
| Schooling + Experience | 0.08 | 0.44 |
| | (b) Hall-Jones Schooling + Klenow and Rodriguez-Clare Experience | |
| Schooling | 0.05 | 0.37 |
| Experience | 0.01 | 0.25 |
| Schooling + Experience | 0.07 | 0.42 |
| | (c) Hall-Jones Schooling + Country-Specific Quadratic Returns to Exp | |
| Schooling | 0.05 | 0.37 |
| Experience | 0.03 | 0.31 |
| Schooling + Experience | 0.12 | 0.49 |
| | (d) Hall-Jones Schooling + Country-Specific Quintic Returns to Exp | |
| Schooling | 0.05 | 0.37 |
| Experience | 0.08 | 0.38 |
| Schooling + Experience | 0.18 | 0.59 |
| | (e) Country-Specific Returns to Schooling (Linear) and Exp (Quintic) | |
| Schooling | 0.12 | 0.40 |
| Experience | 0.07 | 0.37 |
| Schooling + Experience | 0.23 | 0.60 |

Notes: panel (a) computes human capital stocks using a linear-quadratic Mincer specification and using the *average* returns to schooling and experience as in Klenow and Rodriguez-Clare (1997). In our sample of 36 countries the average coefficients on schooling, experience and experience$^2$ are 0.09211, 0.04775 and -0.000758 which is similar to those in Klenow and Rodriguez Clare (1997). Panel (b) uses the same specification except for imposing *diminishing returns to schooling* using the methodology of Hall and Jones (1999), namely assuming that g(s) is piecewise linear with slope 0.13 for s<=4, 0.10 for 4<s<=8 and 0.07 for 8<s. This is also similar to Bils and Klenow (2000). Panel (c) allows returns to experience to vary across countries, but retains a quadratic specification whereas panel (d) uses a quintic specification. Panel (e) additionally allows returns to *schooling* to vary (linearly) across countries.

Figure 1: Fully Flexible Experience-Earnings Profiles, Cross-Sectional Estimates

(a) Experience-Earnings Profiles for Select Countries




(b) Height of Profiles at 20 Years of Experience versus Income

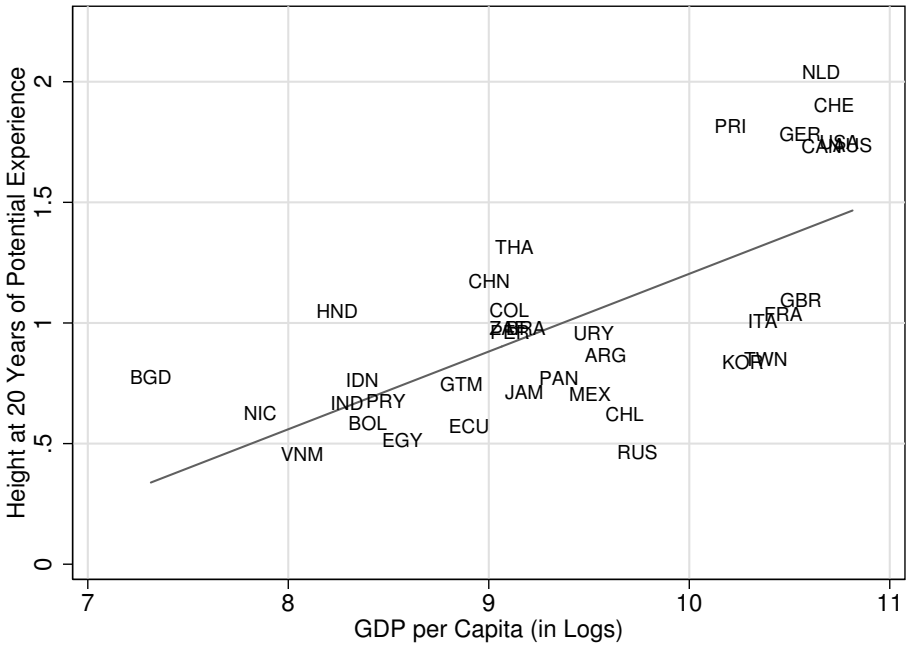
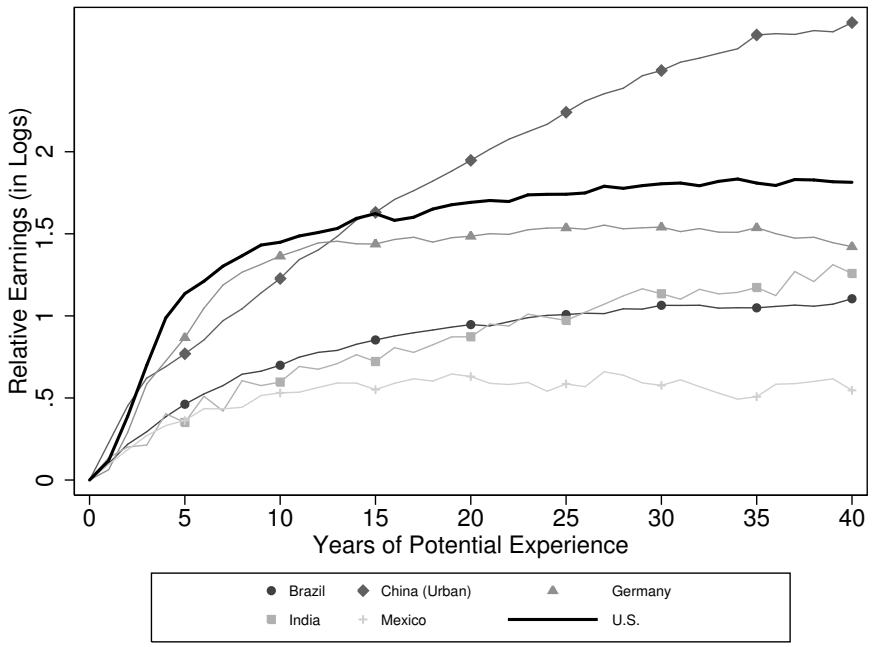


Figure 2: Fully Flexible Experience-Earnings Profiles, Time Effects Sum to Zero

(a) Experience-Earnings Profiles for Select Countries




(b) Height of Profiles at 20 Years of Experience versus Income

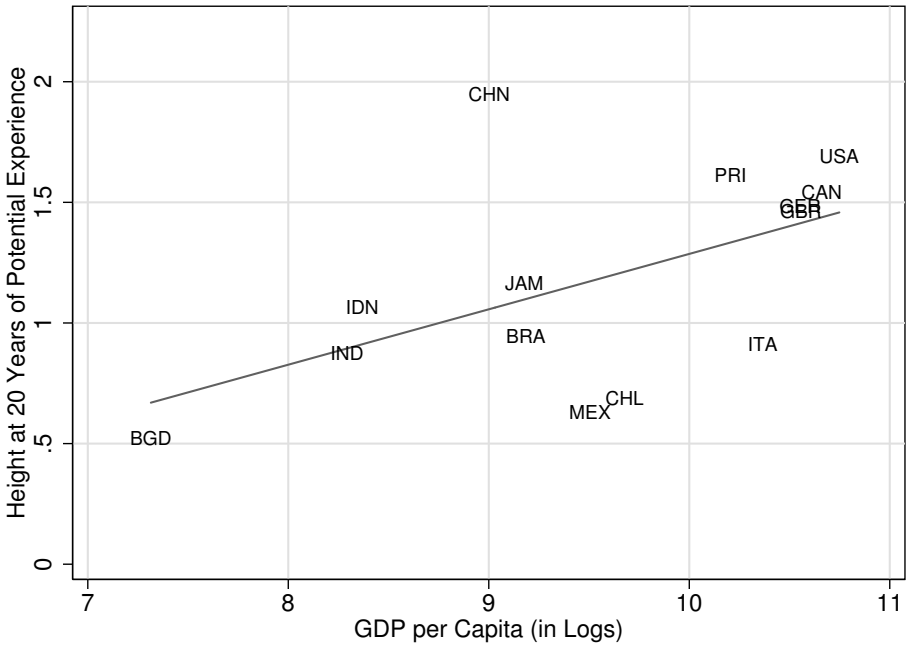
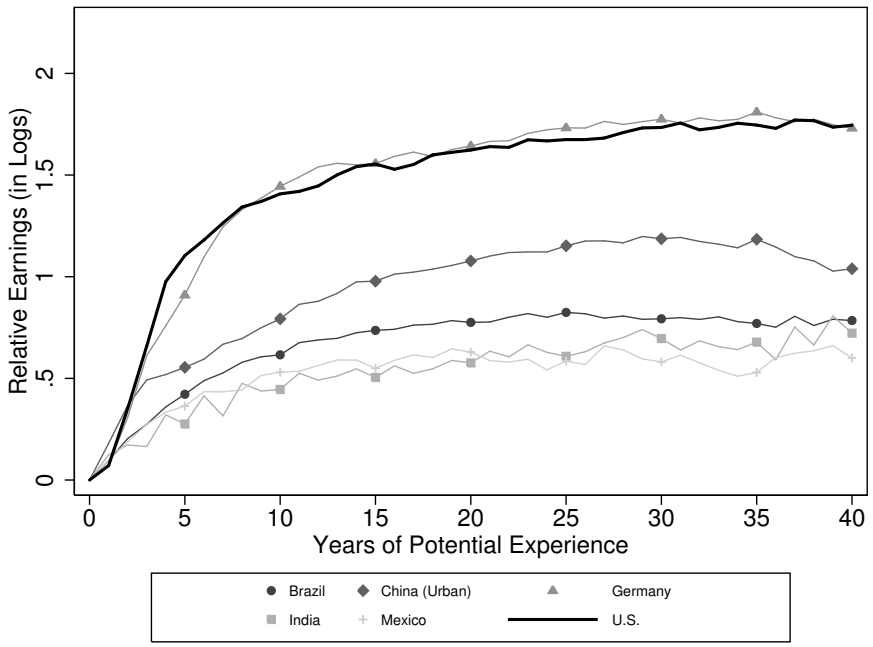


Figure 3: Fully Flexible Experience-Earnings Profiles, Cohort Effects Sum to Zero

(a) Experience-Earnings Profiles for Select Countries




(b) Height of Profiles at 20 Years of Experience versus Income

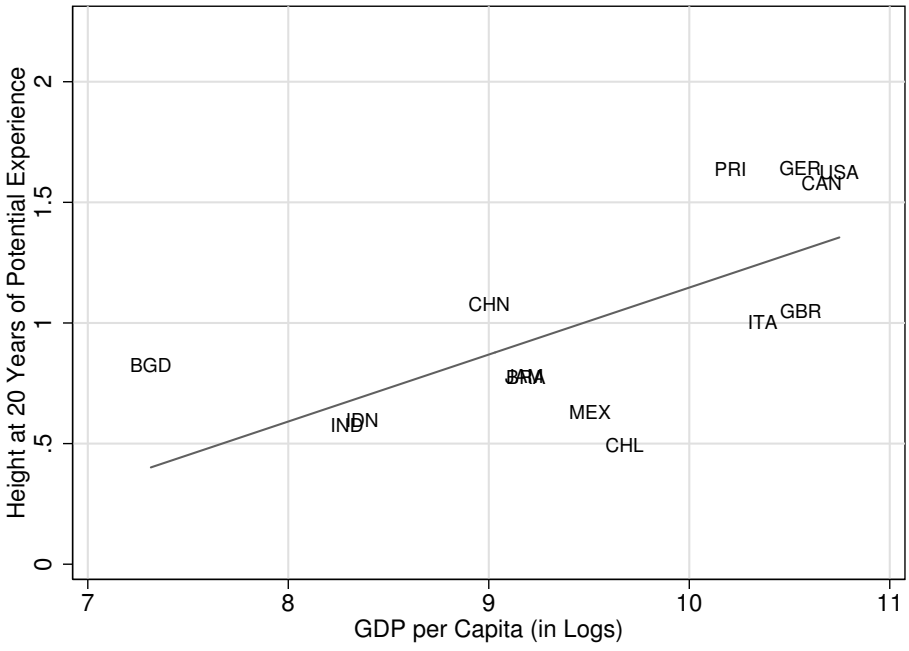
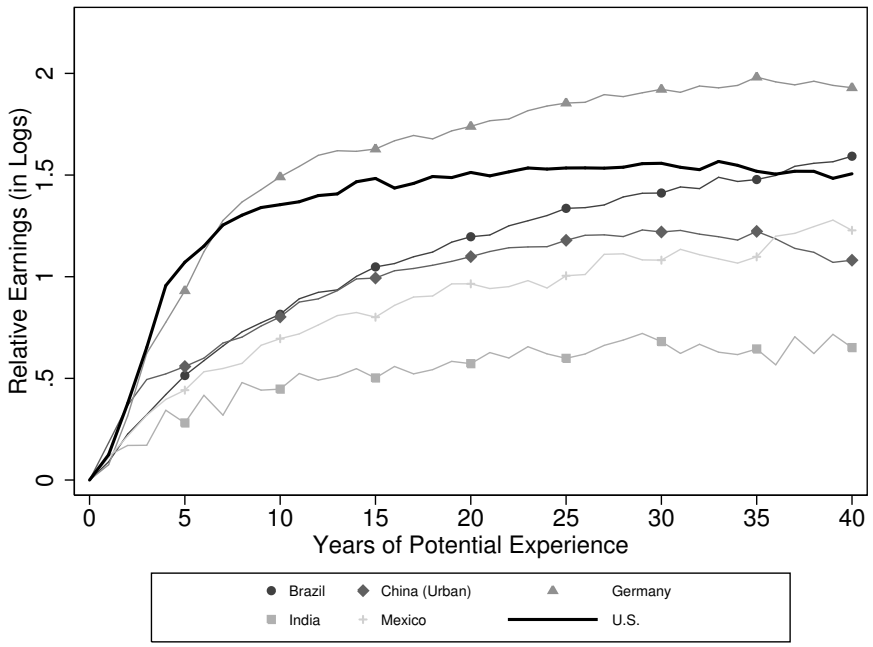


Figure 4: Fully Flexible Experience-Earnings Profiles, Time Effects Sum to TFP Growth

(a) Experience-Earnings Profiles for Select Countries




(b) Height of Profiles at 20 Years of Experience versus Income

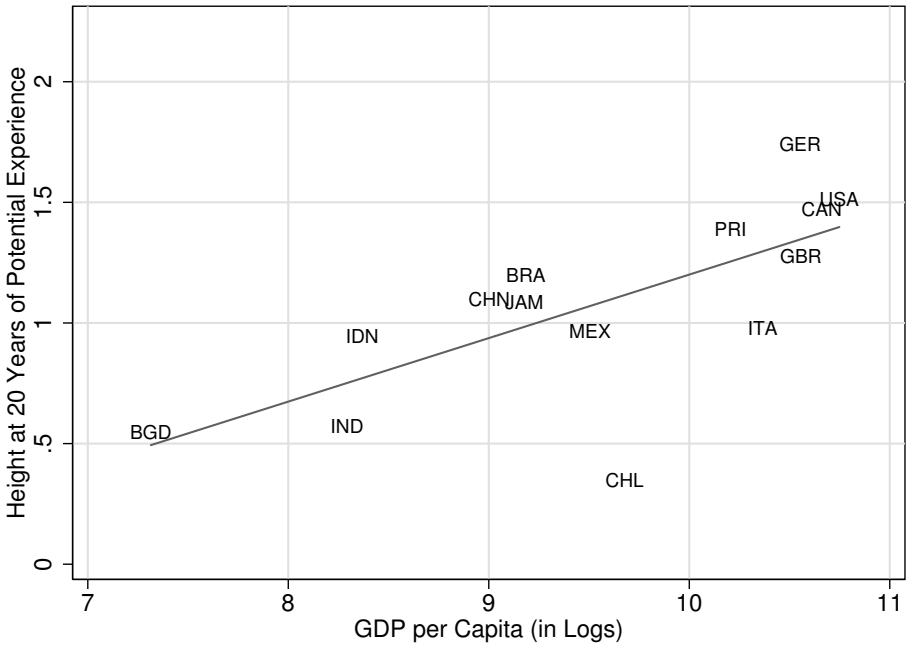
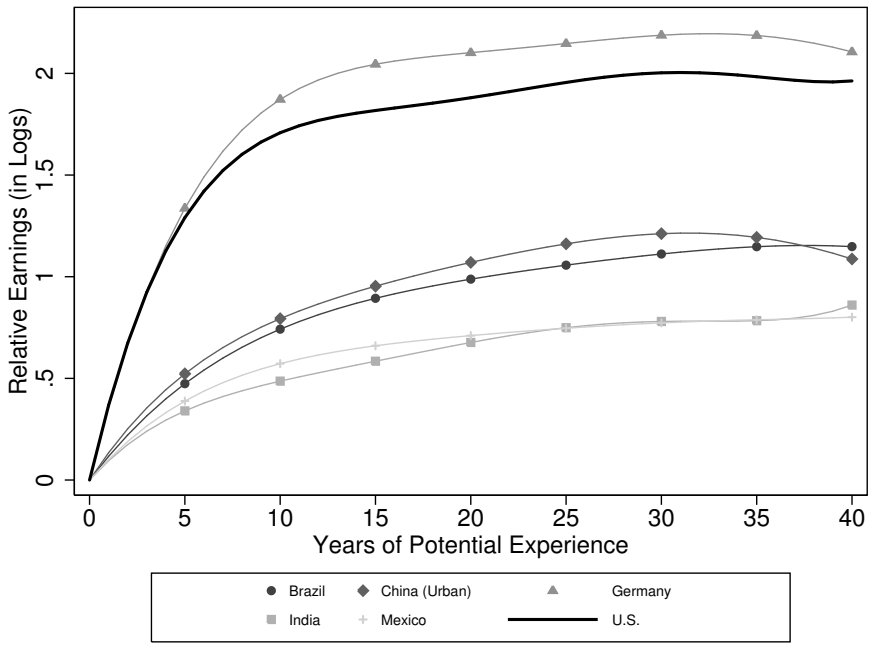


Figure 5: Quintic Experience-Earnings Profiles, Cross-Sectional Estimates

(a) Experience-Earnings Profiles for Select Countries




(b) Height of Profiles at 20 Years of Experience versus Income

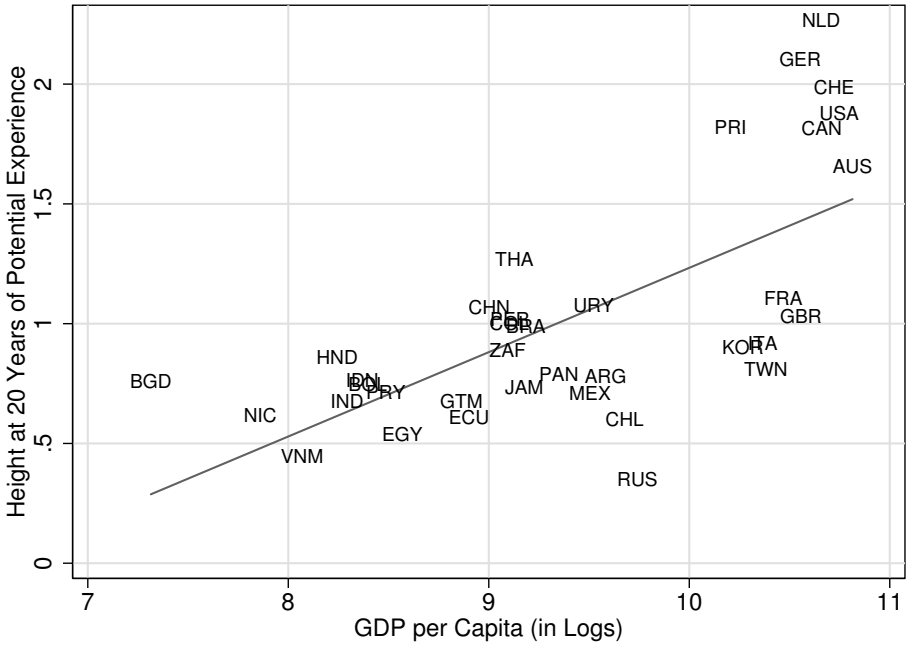
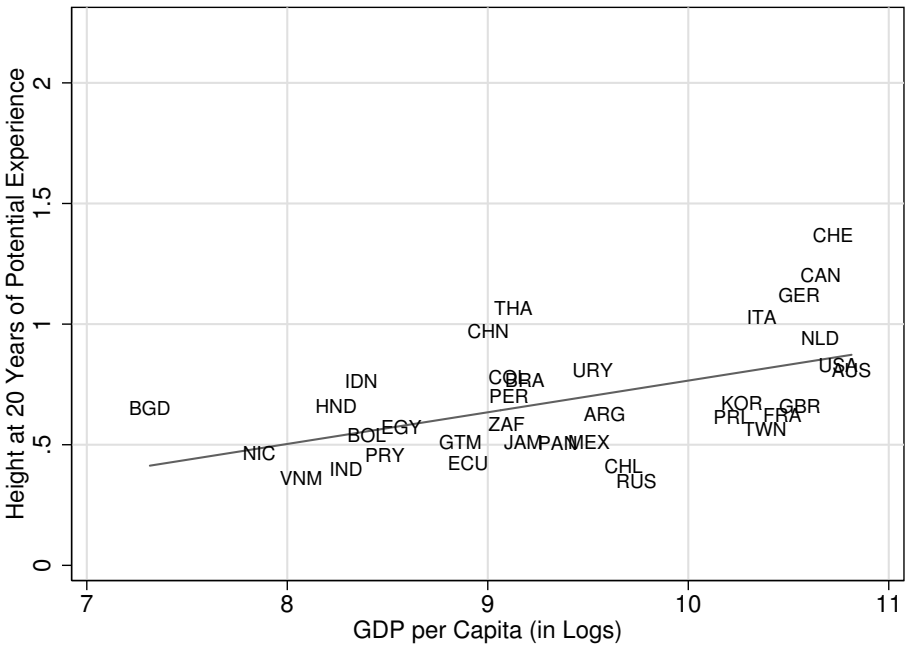


Figure 6: Experience-Wage and Experience-Hours Profiles, Cross-sectional Estimates

(a) Height of Wage Profiles at 20 Years of Experience versus Income




(b) Height of Hours Profiles at 20 Years of Experience versus Income

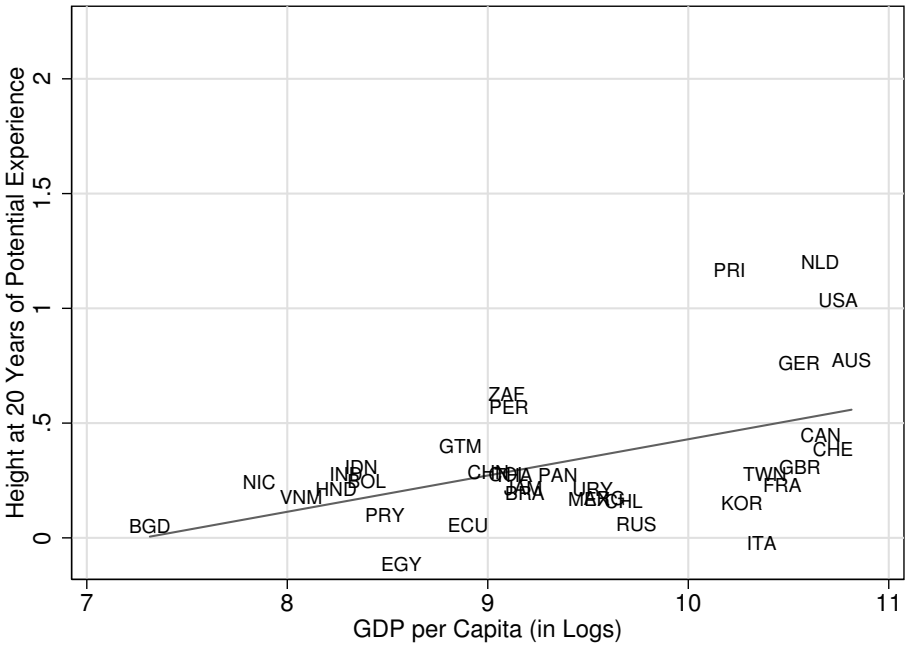
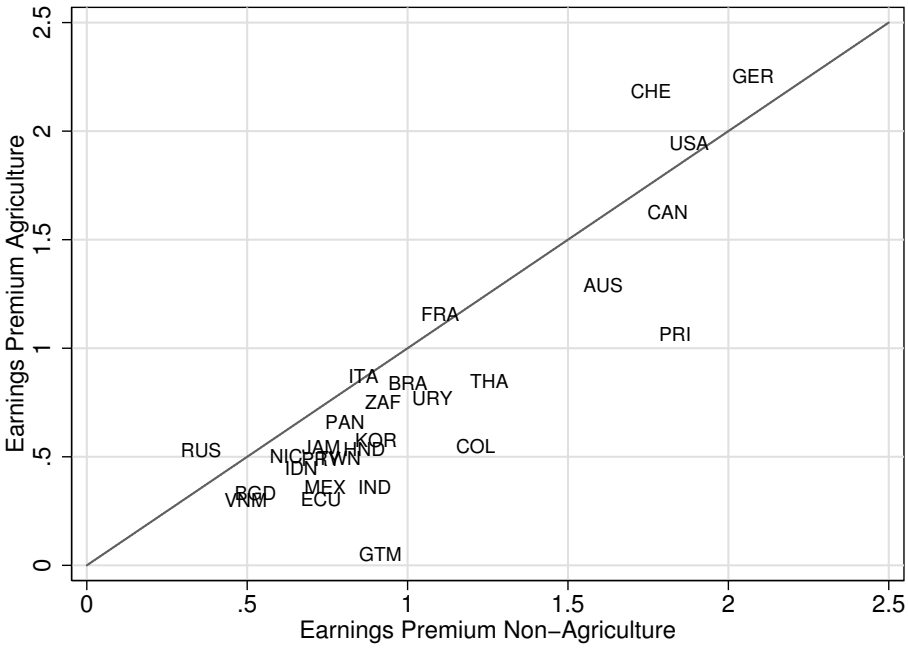


Figure 7: Returns to Experience in Agriculture and Non-Agriculture

(a) Height of Profiles at 20 Years of Experience by Sector




(b) Counterfactual: U.S. Employment Share in Agriculture

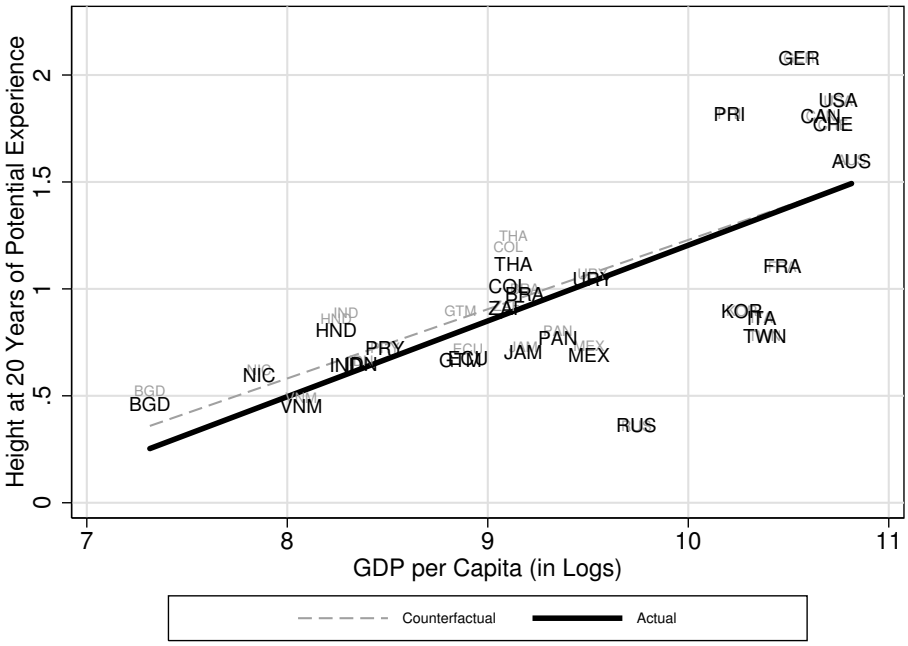
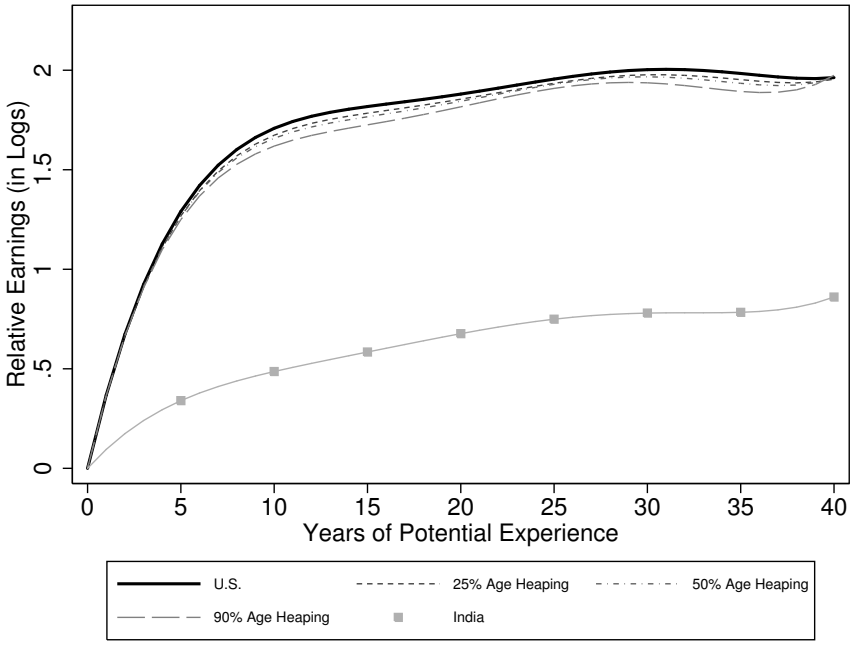


Figure 8: Returns to Experience – Robustness to Measurement Issues

(a) Adjusted for Age Heaping




(b) Adjusted for Differences in Education Reporting

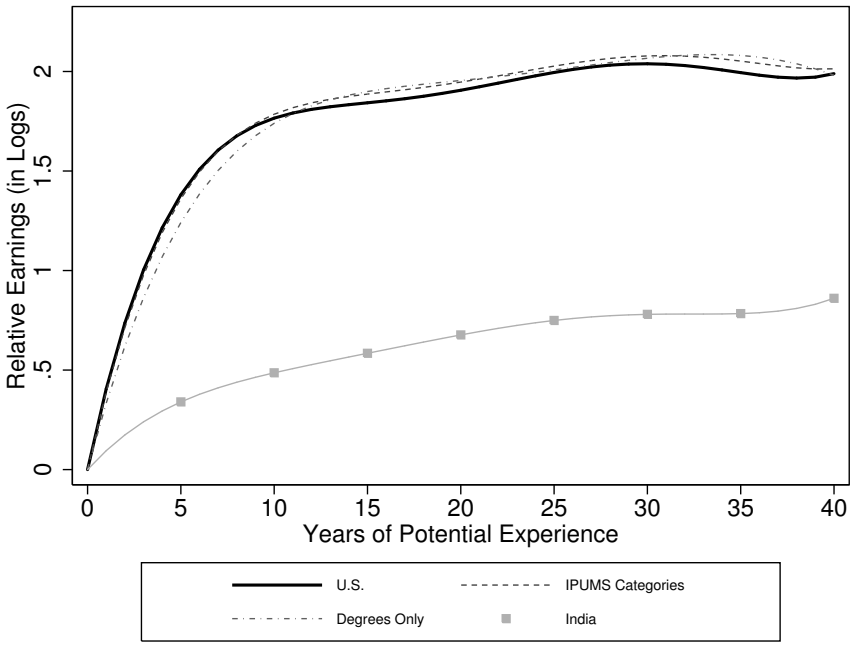
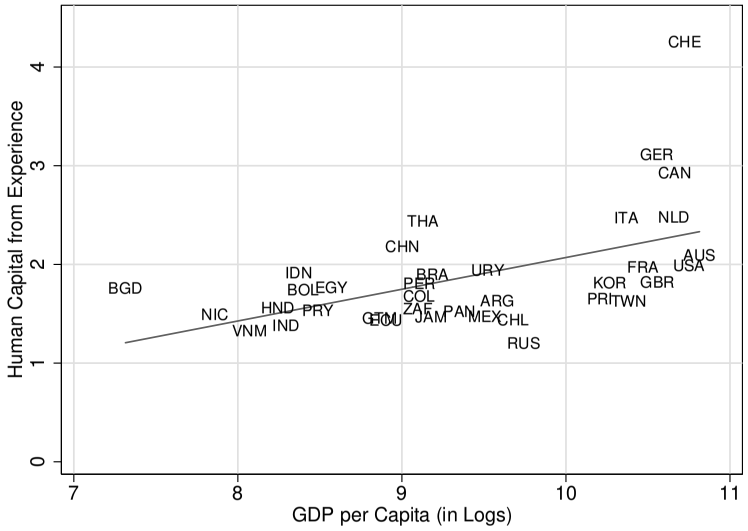
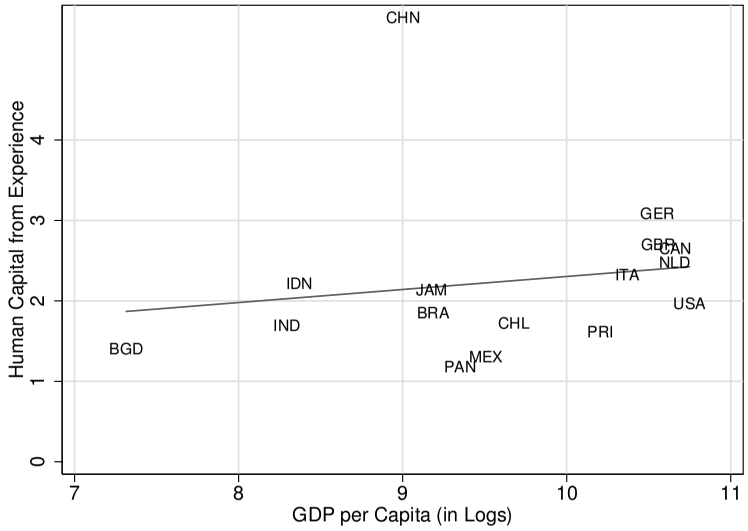


Figure 9: Implied Human Capital from Experience versus Income

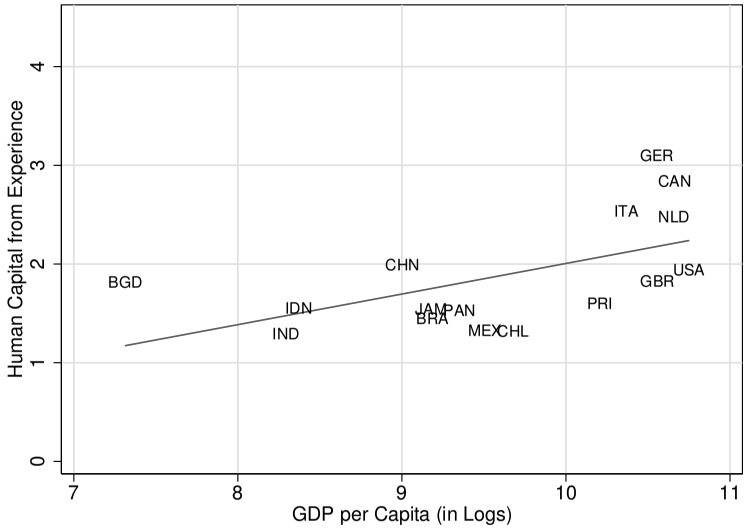
(a) From Quintic Estimates, Cross-Section



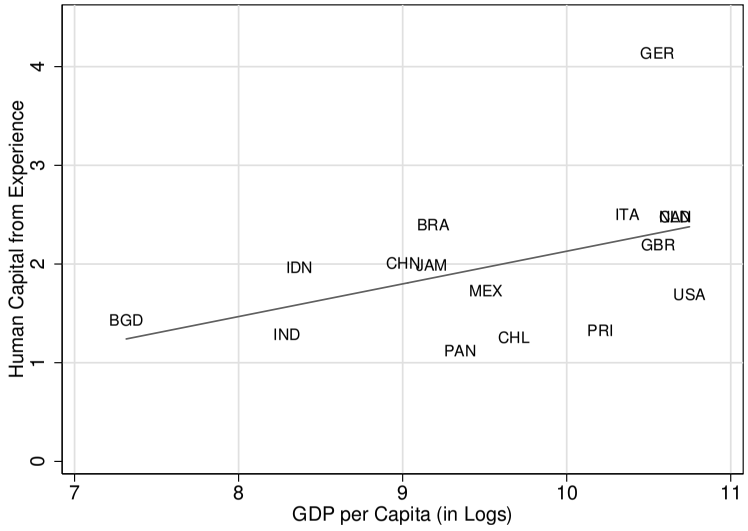

(b) From Quintic Estimates, Time Effects Sum to Zero




(c) From Quintic Estimates, Cohort Effects Sum to Zero




(d) From Quintic Estimates, Time Effects Sum to TFP Growth



# A Appendix (For Online Publication)

## A.1 Data Sources

The surveys we employ in our analysis are listed below for each country. All surveys are nationally representative unless noted. We attempted to obtain data for every country in the world with a population greater than one million people. We obtained a number of surveys from the Food and Agriculture Organization's (FAO) Rural Income Generating Activity (RIGA) database; these surveys are available here: www.fao.org/economic/riga/riga-database/en/. We obtained a number of other surveys through the Integrated Public Use Microdata Series (IPUMS) (Minnesota Population Center, 2011; King, Ruggles, Alexander, Flood, Genadek, Schroeder, Trampe, and Vick, 2010), which can be found here: www.ipums.org. The remaining surveys were made available to us by the statistical agencies of the countries in question or other sources, as listed below.

- Argentina: *Encuesta Permanente de Hogares,* 2003, 2007 and 2010, from the Instituto Nacional de Estadística y Censos; *representative of urban areas.*
- Australia: *Household Income and Labour Dynamics in Australia,* yearly from 2001 to 2009, from the Australian Department of Families, Housing, Community Services and Indigenous Affairs, available from the Cornell Department of Policy Analysis and Management.
- Bangladesh: *Household Income and Expenditure Survey,* 1990, 1995, 2000, and 2005 from the Bangladesh Bureau of Statistics, available from the FAO RIGA database.
- Bolivia: *Encuesta de Hogares,* 2005, from the Bolivian Instituto Nacional de Estadística.
- Brazil: *Recenseamento Geral do Brasil, Censo Demográfico,* 1970 (5% sample), 1980 (5% sample), 1991 (5.8% sample), and 2000 (6% sample), from the Instituto Brasileiro de Geografia e Estatística (IBGE), available from IPUMS, and *Pesquisa Nacional por Amostra de Domicilios,* yearly from 2001 to 2010, from IBGE.
- Canada: *Census of Canada,* 1971 (1% Sample), 1981 (2% Sample), 1991 (3% Sample) and 2001 (2.7% Sample), available from IPUMS.
- Chile: *National Socioeconomic Characterization Survey (CASEN),* 2000 and 2009, from the Chilean Ministry of Planning and Cooperation.
- China: *Urban Household Surveys* (0.01% of urban households, 27 cities), year from 1989 to 2005; *representative of urban areas.*
- Colombia: *XIV National Population and III Housing Census* by Departmento Administrativo Nacional de Estadística (DANE), 1973 (10% of households), available from IPUMS.
- Ecuador: *Estudio de Condiciones de Vida,* 1995, from the Instituto Nacional de Estadística y Censos, available from the FAO RIGA database.
- Egypt: *Labor Market Panel Survey, 2006* from the Egyptian Central Agency for Public Mobilization and Statistics.

- France: *Enquete Emploi*, yearly from 1993 to 2001, from the Ministre de l'Économie de l'Industrie et de l'Emploi.
- Germany: *German Socioeconomic Panel (SOEP),* yearly from 1991 to 2009, from the German Institute for Economic Research (DIW Berlin).
- Guatemala: *Encuesta Nacional de Condiciones de Vida,* 2000 and 2006*,* from the Instituto Nacional de Estadistica.
- Honduras: *Encuesta Permanente de Hogares de Propósitos Multiples,* 2005, from the Secretaria de Trabajo y Seguridad Social.
- India: *Socio Economic Survey* by National Sample Survey Organization, 1993 (0.07% of households), 1999 (0.07% of households), 2004 (0.06% of households), available from IPUMS.
- Indonesia: *Family Life Survey,* 2000, from RAND, available from the FAO RIGA database; National Labour Force Survey (SAKERNAS), 2007, 2008, 2009, 2010, 2011, from the Indonesia Badan Pusat Statistik
- Italy: *Survey on Household Income and Wealth*, 1991, 1993, 1995, 1998, 2000, 2002, 2004, 2006, 2008, 2010, from the Bank of Italy.
- Jamaica: *Population Census*, 1982, 1991 and 2001, (10.0% samples) from the Statistical Institute of Jamaica, available from IPUMS.
- 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), available from IPUMS.
- Netherlands: *DNB Household Survey,* yearly from 1994 to 2010, available from centERdata.
- Nicaragua: *Encuesta Nacional de Hogares sobre Medición de Nivel de Vida,* 1998 and 2001, from the Instituto Nacional de Estadística y Censos, available from the FAO RIGA database.
- Panama: *Censo Nacional de Población y de Vivienda de Panamá*, 1990 (10% sample), available from IPUMS, and the *Encuesta de Condiciones de Vida,* 2003, from the Dirección de Estadística y Censos de Panamá, available from the FAO RIGA database.
- Paraguay: *Encuesta Permanente de Hogares*, 2011, from the Direccion General de Estadistica.
- Peru: *Encuesta Nacional de Hogares,* 2004 and 2010, from the from the Instituto Nacional de Estadística y Informática.
- Puerto Rico: *Census of Population and Housing,* 1970 (1% Sample), 1980 (5% Sample), 1990 (5% Sample) , 2000 (5% Sample) ; *American Community Survey*, 2005 (1% Sample), available from IPUMS.
- Russia: *Russia Longitudinal Monitoring Survey,* yearly from 2000 to 2010, available from the Carolina Population Center at the University of North Carolina, Chapel Hill.
- South Africa: *Labor Force Survey,* 2000, 2001 and 2002 from Statistics South Africa.
- South Korea: *Korea Labor and Income Panel Study,* yearly from 1999 to 2008, from the Korea Labor Institute, available from the Cornell Department of Policy Analysis and Management.

- Switzerland: *Swiss Household Panel*, yearly from 1999 to 2009, from the Swiss Foundation for Research in Social Sciences, available from the Cornell Department of Policy Analysis and Management.
- Taiwan: *Survey of Family Income and Expenditure*, yearly from 1995 to 2003, available from the Research Program in Development Studies at Princeton University.
- Thailand: *Thailand Socioeconomic Survey,* 1990, 1992, 1994, 1996, 1998 and 1999, available from the Research Program in Development Studies at Princeton University.
- United Kingdom: *British Household Panel Survey,* yearly from 1992 to 2009, from the Institute for Social & Economic Research at the University of Essex.
- United States: *Census of Population and Housing,* 1960 (1% Sample), 1970 (1% Sample), 1980 (5% Sample), 1990 (5% Sample) , 2000 (5% Sample); *American Community Survey*, 2005 (1% Sample); *Current Population Survey,* yearly from 1980 to 2010; all available from IPUMS.
- Uruguay: *Extended National Survey of Households*, 2006, from the Uruguay National Institute of Statistics, available from IPUMS.
- Vietnam: *Living Standards Survey*, 1998 and *Household Living Standards Survey,* 2002, both from the General Statistics Office of Vietnam, available from the FAO RIGA.

All calculations in our analysis are weighted using the applicable sample weights for each survey. We express all earnings and wage data in local currency units of the most recent year in the data using the consumer price index of the country in question, taken from the IMF's International Financial Statistics database. In each survey we drop the top and bottom 1% of earners to remove potential outliers, and to minimize the impact of potential cross-country differences in top-coding procedures.

For most countries, we measure hours as the actual hours worked in the past week (or in some recent reference week.) For the United States, Brazil (the census data), Italy and Puerto Rico, we measure hours as the *usual* weekly hours worked (which is what is available). For China, India, Panama (the census data), Taiwan and Thailand, we have no hours data available, and impute hours as the average hours worked in all other countries for the individual's level of experience.

For most countries, labor earnings and hours worked are for both primary and secondary jobs. In Argentina, Chile, France, South Korea and Uruguay, labor earnings and hours worked are for just the primary job. For Brazil (the census data) and Switzerland, we measure labor income as the total income earned of individuals reporting to be primarily wage earners (as opposed to self employed.) In most countries, earnings are reported at the monthly frequency. The exceptions are Australia, Canada, Germany, Jamaica, South Korea, and the United States, in which earnings are measured at the annual frequency, and India, in which earnings are measured at the weekly frequency. In all surveys, earnings are before taxes. The numbers for per capita GDP at PPP that we use in some of our calculations and figures are taken from the Penn World Tables (Heston, Summers, and Aten, 2011).

## A.2 Inclusion of the Self-Employed

In the main analysis of the paper, we kept only wage earners, and excluded any workers with self employment income. We did this due to the measurement concerns raised in Section 2. In this section we relax this restriction, and include all workers with either wage income or self employed income (or both.) In Figure A.2 we plot the height of the experience-earnings profile at 20 years of

potential experience against log GDP per capita when we include the self employed in our sample. We find that the correlation is still positive, as in our main analysis, with the steepest profiles by far being in the richest countries: the United States, Canada and Puerto Rico. We also find (but do not report, for brevity) that the positive correlation between the height at 20 and log GDP per capita is present when we consider *only* the self employed. The main limitation of these two calculations is, of course, that we have fewer countries here than in our main analysis. Still, the countries for which we do have data do not give us reason to believe that our main results are all overturned once we add the self-employed.

As an additional robustness check that includes all of our countries, we regress the height of our profiles on GDP per capita and the fraction of workers that are self employed (from the World Bank's World Development Indicators.) It is well known that the self-employed fraction is strongly negatively correlated with GDP per capita. What we are interested in is whether countries that have particularly high self employment rates given their level of GDP per capita systemtically have lower returns to experience. If this were the case, one might be worried that a high prevalence of self employment is associated with profiles that are biased downward. We do not find this is the case, however. The coefficient on the fraction self employed is small (0.007) and statistically insignificant (standard error 0.006). This gives us one more reason to doubt that our results are an artifact of our ommitting the self employed from our main analysis.

### A.3 Origins of Human Capital Variation: Returns vs Levels

As noted in the text, the cross-country differences in human capital stocks are generated in similar magnitude by differences in experience and schooling. We also noted that the origins of the variation is different: rich countries have more human capital due to higher *levels* of schooling and higher *returns* to experience. In contrast the *returns* to school and the *levels* of experience are similar across countries. We here formalize this insight through two counterfactual exercises. We compute two counterfactual human capital stocks, both for human capital generated only through schooling and only through experience: (i) the first one computes the human capital stocks of an hypothetical world in which all countries have the United States distributions of either experience or schooling (hence the same *levels*), but keep the country-specific *returns*; (ii) the second one computes the human capital stocks of an hypothetical world in which all countries have the United States *returns*, but keep the country-specific distributions. We then regress the log of those counterfactual human capital stocks on log GDP per worker. The results are reported in Table A.2 and clearly show how most of the correlation between experience human capital stocks and output per worker is generated by differences in returns, while all the correlation between schooling human capital stocks and output per worker is generated by differences in levels.

Table A.1: Countries with Fifteen or More Years of Repeated Cross Sections

| Country | Years of Surveys | Span (Years) |
|---|---|---|
| Bangladesh | 1995, 2000, 2005, 2010 | 15 |
| Brazil | 1970, 1980, 1991, 2000-2009 | 40 |
| Canada | 1971, 1981, 1991, 2001 | 31 |
| Chile | 1990, 1992, 1994, 1996, 1998, 2000, 2003, 2006, 2009 | 20 |
| China | 1988-2005 | 18 |
| Germany | 1991-2009 | 19 |
| India | 1983, 1987, 1993, 1999, 2004 | 22 |
| Indonesia | 1988-1994, 1996-2011 | 24 |
| Italy | 1991, 1993, 1995, 1998, 2000, 2002, 2004, 2006, 2008, 2010 | 20 |
| Jamaica | 1982, 1991, 2001 | 20 |
| Mexico | 1970, 1990, 1995, 2000, 2005 | 41 |
| Puerto Rico | 1970, 1980, 1995, 2000, 2005 | 36 |
| United Kingdom | 1992-2009 | 18 |
| United States | 1980, 1990, 2000, 2005 | 46 |

Table A.2: Counterfacturals: Returns to Experience versus Average Experience Level

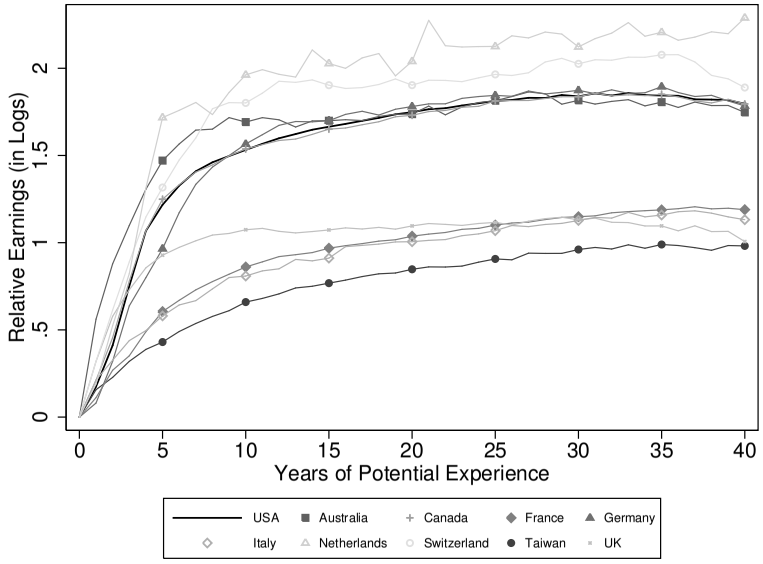
| | Human Capital Stocks from Experience | | |
|---|---|---|---|
| | Benchmark | Country-specific Returns | Country-specific Levels |
| Slope(log(H),log(GDP)) | 0.17*** | 0.14*** | 0.03*** |
| | (0.048) | (0.044) | (0.008) |
| | Human Capital Stocks from Education | | |
| | Benchmark | Country-specific Returns | Country-specific Levels |
| Slope(log(H),log(GDP)) | 0.17** | -0.01 | 0.20*** |
| | (0.068) | (0.089) | (0.039) |

Notes: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1;

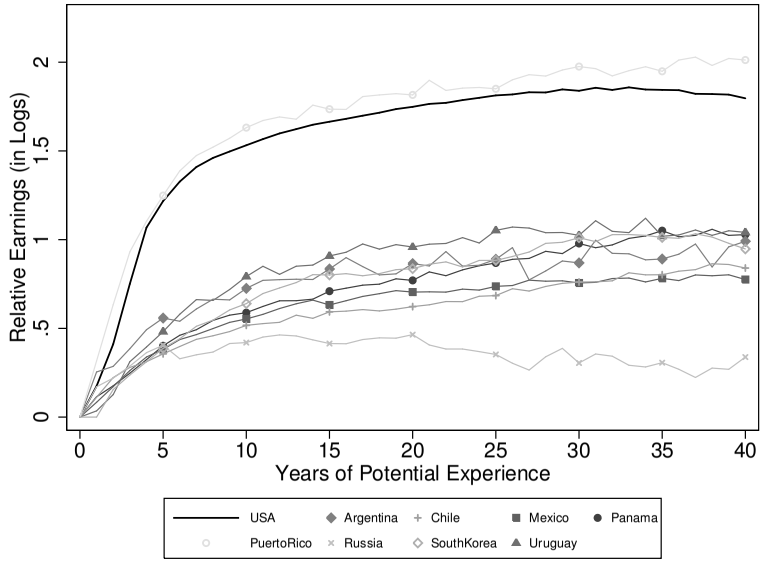
Table A.3: Aggregate Human Capital from Experience

| | Human Capital Stocks Relative to the U.S. | | | Development Accounting | | | |
|---|---|---|---|---|---|---|---|
| | | | | Data from Caselli (2005) | | Country-specific *success* $_2{}^j$ | |
| | Schooling | Experience | Both | Y | K | Schooling | Schooling and Experience |
| Argentina | 0.82 | 0.82 | 0.66 | 0.45 | 0.39 | 0.70 | 0.81 |
| Australia | 0.85 | 1.05 | 0.89 | 0.81 | 0.95 | 0.92 | 0.89 |
| Bangladesh | 0.42 | 0.88 | 0.36 | 0.11 | 0.05 | 0.54 | 0.59 |
| Bolivia | 0.99 | 0.87 | 0.83 | 0.12 | 0.06 | 0.31 | 0.35 |
| Brazil | 0.83 | 0.95 | 0.77 | 0.33 | 0.31 | 0.55 | 0.58 |
| Canada | 0.86 | 1.47 | 1.25 | 0.79 | 0.98 | 0.88 | 0.69 |
| Chile | 1.19 | 0.72 | 0.83 | 0.41 | 0.29 | 0.54 | 0.69 |
| China | 1.05 | 1.10 | 1.13 | 0.09 | 0.06 | 0.21 | 0.20 |
| Colombia | 0.65 | 0.84 | 0.53 | 0.21 | 0.12 | 0.57 | 0.66 |
| Ecuador | 0.50 | 0.72 | 0.35 | 0.22 | 0.20 | 0.60 | 0.76 |
| Egypt | 0.51 | 0.89 | 0.44 | 0.22 | 0.06 | 0.87 | 0.96 |
| France | 0.66 | 0.99 | 0.64 | 0.79 | 1.08 | 1.02 | 1.04 |
| Germany | 0.80 | 1.56 | 1.23 | 0.75 | | | |
| Guatemala | 0.71 | 0.73 | 0.50 | 0.23 | 0.09 | 0.66 | 0.83 |
| Honduras | 0.81 | 0.78 | 0.62 | 0.12 | 0.08 | 0.32 | 0.38 |
| India | 0.59 | 0.69 | 0.40 | 0.09 | 0.04 | 0.38 | 0.49 |
| Indonesia | 0.69 | 0.96 | 0.64 | 0.17 | 0.11 | 0.46 | 0.48 |
| Italy | 0.67 | 1.24 | 0.81 | 0.89 | 1.11 | 1.12 | 0.99 |
| Jamaica | 0.87 | 0.74 | 0.63 | 0.13 | 0.14 | 0.28 | 0.35 |
| Korea, Rep. | 0.99 | 0.91 | 0.87 | 0.60 | 0.78 | 0.65 | 0.71 |
| Mexico | 0.67 | 0.74 | 0.48 | 0.37 | 0.35 | 0.69 | 0.86 |
| Netherlands | 1.03 | 1.25 | 1.26 | 0.80 | 0.98 | 0.79 | 0.69 |
| Nicaragua | 0.45 | 0.75 | 0.33 | 0.10 | 0.08 | 0.40 | 0.49 |
| Panama | 0.64 | 0.77 | 0.48 | 0.27 | 0.25 | 0.57 | 0.70 |
| Paraguay | 0.91 | 0.77 | 0.68 | 0.21 | 0.11 | 0.47 | 0.57 |
| Peru | 1.13 | 0.91 | 1.00 | 0.18 | 0.18 | 0.29 | 0.31 |
| Puerto Rico | 0.79 | 0.83 | 0.65 | 0.49 | | | |
| Russia | 0.83 | 0.60 | 0.50 | 0.25 | | | |
| SouthAfrica | 1.57 | 0.78 | 1.17 | 0.38 | 0.22 | 0.47 | 0.57 |
| Switzerland | 1.04 | 2.14 | 2.24 | 0.77 | 1.27 | 0.70 | 0.42 |
| Taiwan | 0.93 | 0.82 | 0.74 | 0.62 | 0.44 | 0.86 | 1.00 |
| Thailand | 1.59 | 1.23 | 1.76 | 0.23 | 0.30 | 0.26 | 0.24 |
| United Kingdom | 1.34 | 0.91 | 1.21 | 0.71 | 0.70 | 0.66 | 0.70 |
| United States | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Uruguay | 0.53 | 0.98 | 0.51 | 0.36 | 0.24 | 0.89 | 0.92 |
| Vietnam | 0.40 | 0.67 | 0.26 | 0.06 | | | |

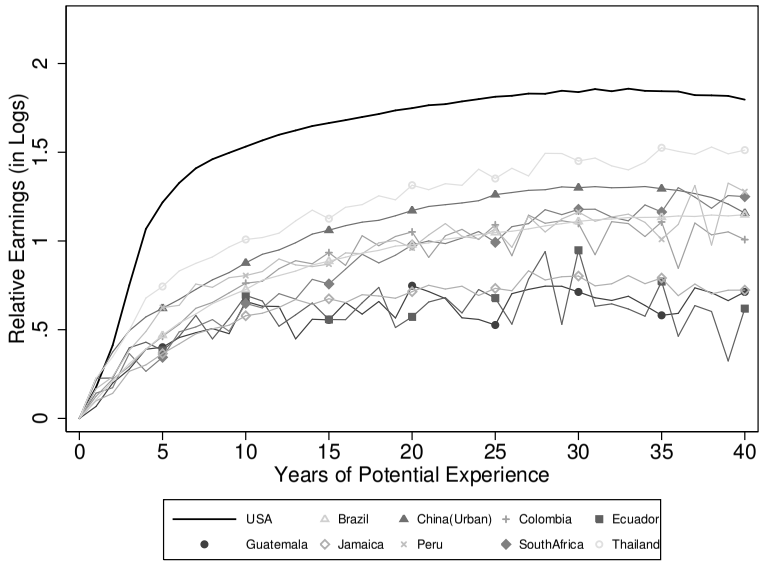
Figure A.1: Fully Flexible Experience-Earnings Profiles by Income Quartile



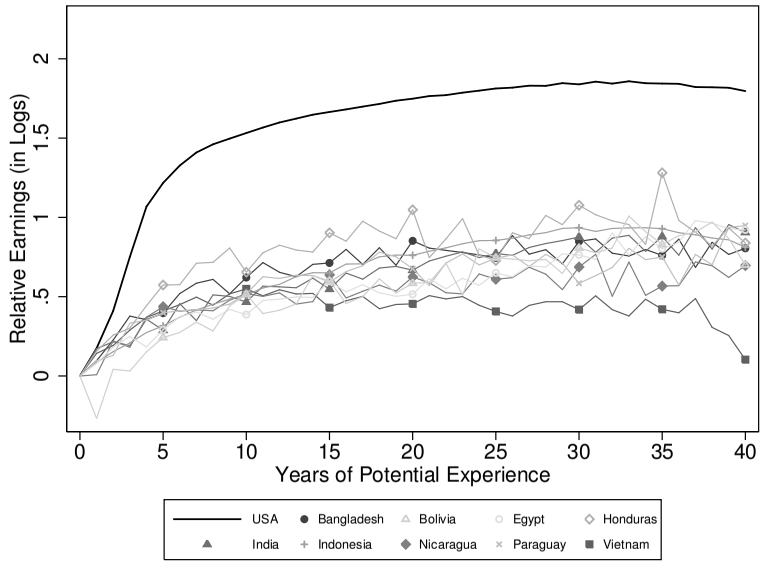

(a) Top Quartile




(b) Second Quartile




(c) Third Quartile




(d) Poorest Quartile

Figure A.2: Returns to Experience Including the Self Employed

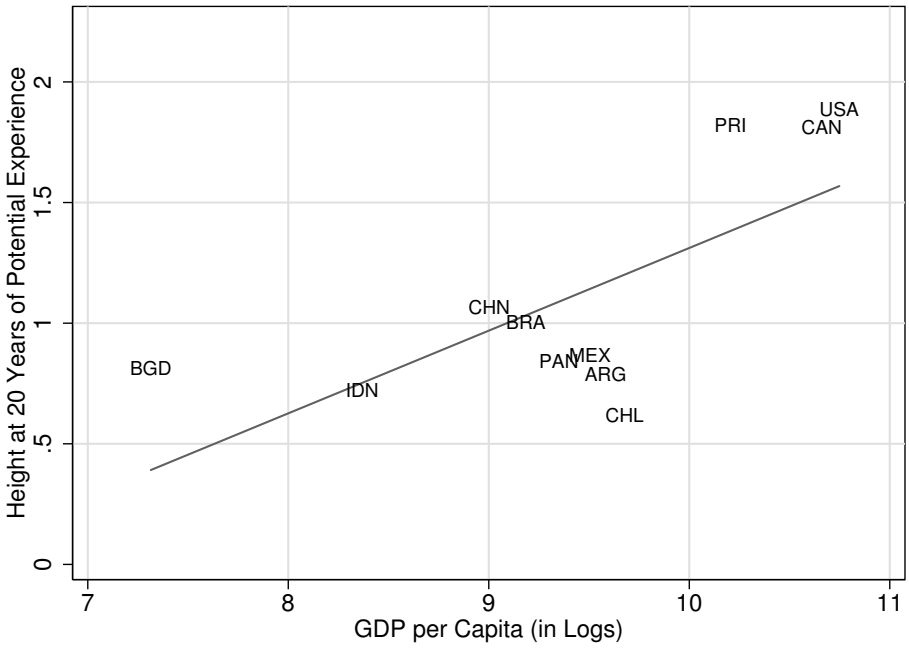



Figure A.3: Estimated Returns to Schooling versus Income

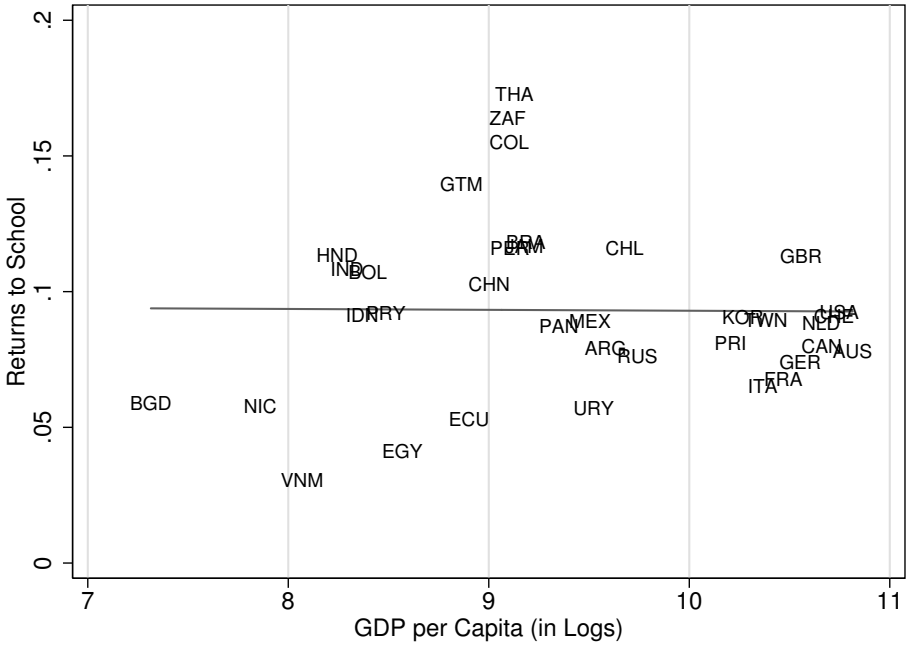


Figure A.4: Average Experience versus Income

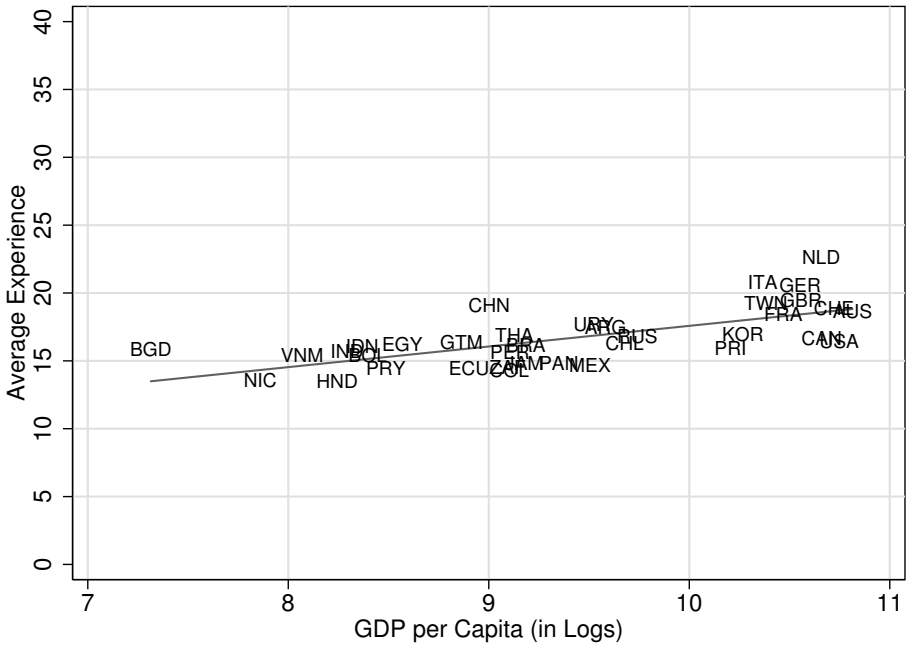



Figure A.5: Fraction of Individuals with Positive Wage Earnings by Age

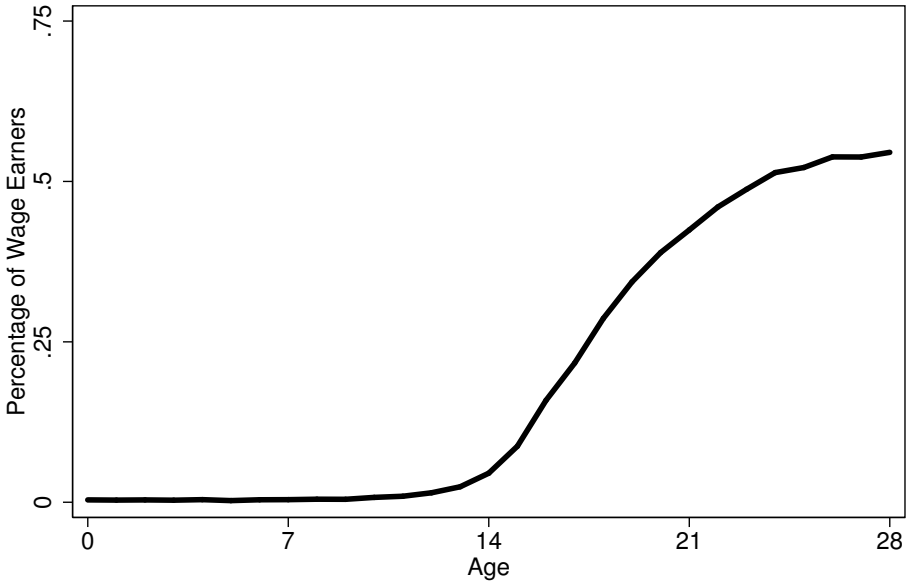
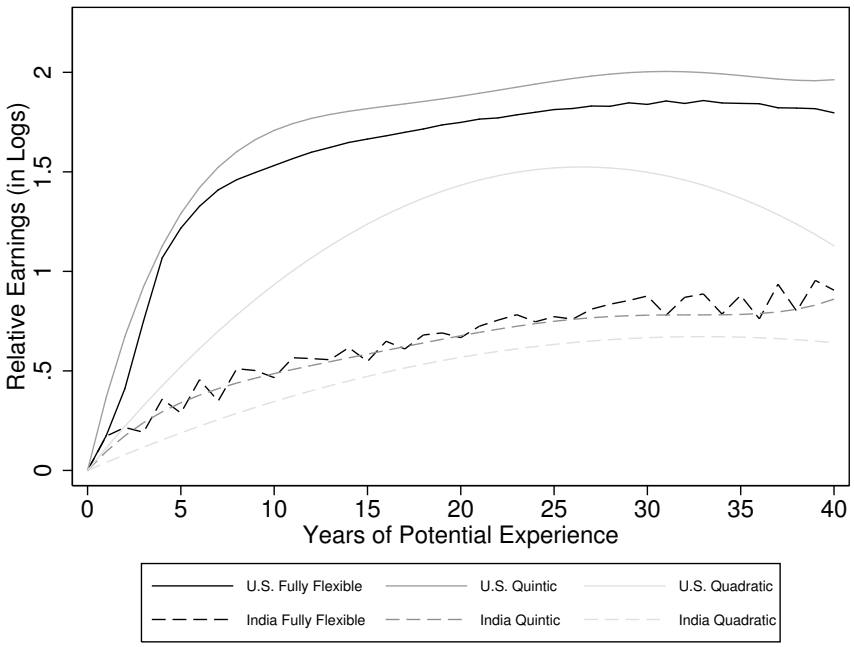


Figure A.6: Quadratic Experience-Earnings Profiles, Cross-Sectional Estimates

(a) Experience-Earnings Profiles for Select Countries




(b) Height of Profiles at 20 Years of Experience versus Income

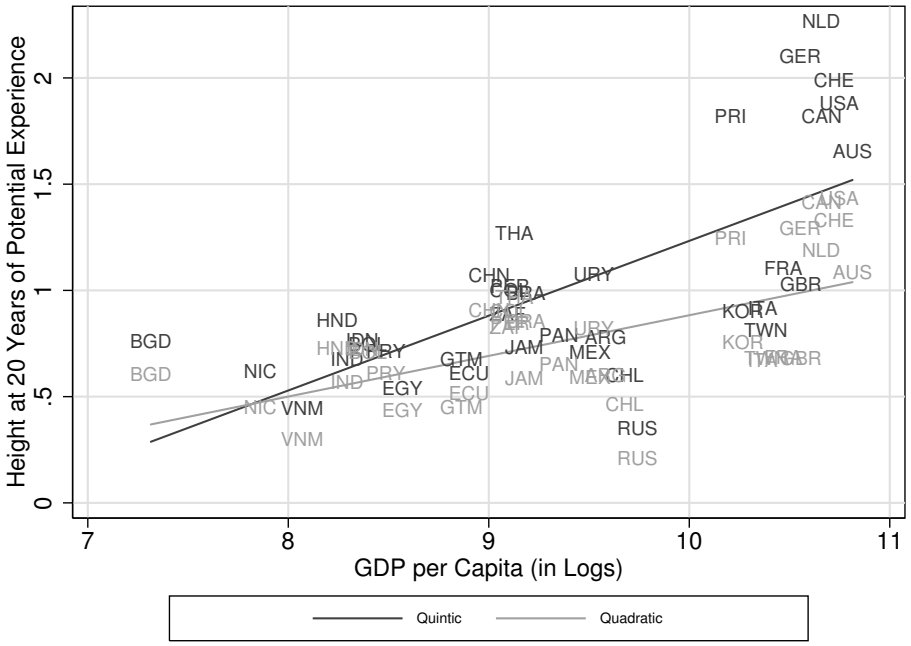
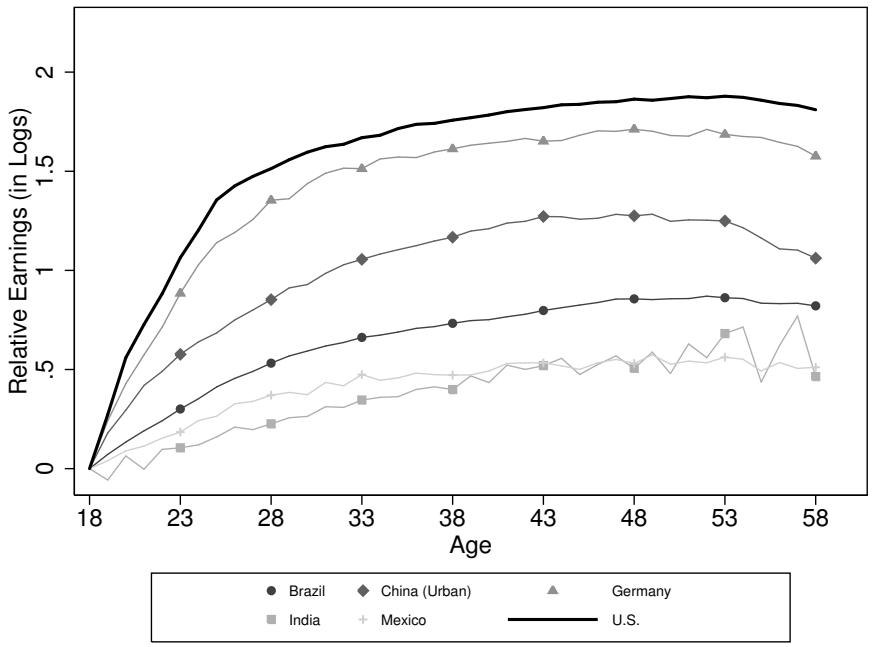


Figure A.7: Age-Earnings Profiles, Cross-Sectional Estimates

(a) Age-Earnings Profiles for Select Countries




(b) Height of Profiles at 40 Years of Age versus Income

