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EXPERIENCE MATTERS: HUMAN CAPITAL AND DEVELOPMENT ACCOUNTING

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ABSTRACT

The current consensus in the development accounting literature is that differences in aggregate human and physical capital stocks across countries account for less than half of cross-country income differences. This literature has found that taking human capital from experience into account does not change the explanatory power of human capital. In this paper, we document a new fact that suggests a different conclusion. We find that experience-wage profiles are flatter in poorer countries than in richer countries. Taking this into account substantially increases the contribution of human and physical capital in development accounting.

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1 Introduction

Understanding the determinants of cross-country income differences is one of the central aims of growth and development economics. An important first step in addressing this difficult question is development accounting, which assesses how much of these income differences is due to observable factors of production, namely physical and human capital. The consensus in this 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 past studies have focused on human capital that is acquired through schooling. A few studies have taken into account human capital accumulation occurring after schooling but have found that this does not improve the explanatory power of human and physical capital (Klenow and Rodriguez-Clare, 1997; Bils and Klenow, 2000, 2002; Caselli, 2005). Given the data limitations at the time, these studies obtained secondary measures of country-specific returns to worker experience mainly from estimates provided by Psacharopoulos (1994), which show no systematic relationship between returns and income across countries (Bils and Klenow, 2000, 2002). Past accounting exercises therefore assumed that the return to experience is the same across countries. Since the average level of potential experience is roughly constant across countries as well, these studies concluded that the stock of human capital arising through experience must be similar in magnitude in rich and poor countries.

In this paper we document a new fact that suggests a very different conclusion. Specifically, we document that experience-wage profiles are flatter in poor countries than in rich countries. Within a development accounting framework, this means that human capital stocks arising from experience are substantially smaller in poor countries than in rich countries. We find that when we conduct a textbook development accounting exercise, with the exception that we allow the returns to experience to vary across countries, human and physical capital account for around sixty percent of cross-country income differences, as compared to around forty percent in previous studies.

To document our finding, we harmonize recently available large-sample micro data for 35 countries. These data, which comprise over 200 household surveys, provide several important benefits relative to previous studies, and in particular to 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 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-wage profiles are driven by factors correlated with time, such as aggregate TFP growth, or those correlated with birth cohort, such as improvements in health.[1]

The countries in our sample represent 68 percent of the world's population and range between the 1st (United States) and 83rd percentile (Bangladesh) of the world income distribution. One limitation of our data is that it excludes the very poorest countries in the world, such as those in Sub-Saharan Africa. Another limitation is that our results pertain to wage earners but not the self-employed, whom we exclude from our main analysis because of measurement concerns. We discuss the latter in detail in the paper, and provide evidence that including self-employed workers is unlikely to overturn our results.

Throughout the paper, we follow the development accounting literature and focus on the returns to *potential experience*, defined as the number of years that have elapsed since an individual finished schooling. In the paper, we will interchangeably refer to it 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-wage 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

[1] 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 he often only had one cross section of data.

to a number of sample restrictions and controls, and alternative definitions of experience.

A well-known challenge in estimating returns to potential experience is that, due to collinearity, one cannot separately identify the effects of potential experience (or 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 thirteen countries for which the data cover at least fifteen years from the earliest to most recent surveys: Bangladesh, Brazil, Canada, Chile, China, Germany, India, Indonesia, Italy, Jamaica, Mexico, 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 assumes that all growth over time is driven by cohort effects, while time effects reflect cyclical conditions. The second version assumes, in contrast, that all growth is due to time effects. The third version assumes that growth is due equally to cohort and time effects. We find that for some countries, such as China, the estimated returns to experience vary significantly under the different specifications. However, more importantly, we find that our main finding of steeper experience-wage profiles in rich countries is present under all three versions.

Next, we show what our finding implies for development accounting. Relative to the seminal work of Klenow and Rodriguez-Clare (1997), Hall and Jones (1999) and Caselli (2005), the only difference is that we allow 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 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 to accounting for income differences increases from around forty percent to around sixty percent.

The paper concludes by considering some explanations of why experience-wage profiles would be flatter in poor countries. Although it is not our goal to distinguish between theories, we show that our development accounting results are exactly consistent with theories of "passive" human capital accumulation, such as those in which cross-country differences in the scope for on-the-job learning drive the differences in experience-wage profiles. In contrast, interpreted through theories of "active" human capital accumulation, such as the Ben-Porath model, our development accounting results provide an upper bound on the importance of lifecycle human capital differences across countries. Nevertheless, a simple calibrated Ben-Porath model shows that our empirical findings still substantially increase the importance of human capital to development accounting relative to previous studies. We acknowledge that there are alternative theories that postulate that factors other than human capital accumulation can affect experience-wage profiles. While it is beyond the scope of our paper to rule out these alternatives, we provide suggestive evidence against them.

In addition to the development accounting studies discussed at the beginning of the introduction, our study is related to the recent literature that measures aggregate human capital stocks using a broader definition than years of schooling. In particular, Weil (2007) and Shastry and Weil (2003) include the role of health, and Barro and Lee (2001), Hanushek and Kimko (2000) and Hendricks (2002), among others, include schooling quality. Two studies that we complement are by Manuelli and Seshadri (2010) and Erosa et al. (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 much lower returns to schooling among U.S. immigrants from poor countries than U.S. immigrants from rich countries. Jones (2011) argues that relaxing the assumption of perfect substitutability across skill types leads to a much larger role of human capital in development accounting. Gennaioli et al. (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. None of these studies, however, focus on the importance of human capital from experience, as we do.

This paper is organized as follows. Section 2 describes the data. Section 3 presents the estimated experience-wage profiles across countries and documents that the profiles are flatter in poor countries than in rich countries. Section 4 applies the empirical estimates to a development accounting exercise. Section 5 relates the empirical findings to theories of human capital accumulation. Section 6 offers concluding remarks.

2 Data

Our analysis uses large-sample household survey data from 35 countries. The surveys we use satisfy two 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 comprises 242 surveys spanning the years 1970 to 2011 and covering 62,000 observations in the median country. The complete list of countries and data sources is listed in Section A.1 of the Online Appendix.

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 percent of the world population. Thus, while we lack data from many countries, our sample does represent a sizable fraction of the world's total population. The main limitation in terms of data 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 an individual's wage, which we define to be her labor earnings divided by her hours worked. In most countries, we observe earnings over the month prior to the survey and hours worked over the week prior to the survey. In the few 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. We restrict attention to individuals with zero to forty 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. For all countries, we express earnings and wages in local currency units of the most recent year for which we have a survey, using the price deflators provided by the International Monetary Fund's International Financial Statistics. See Section A.1 of the Online Appendix for details on the data construction.

In our main analysis, we restrict attention to workers that are full-time wage earners, and exclude any workers with self-employed income. We exclude the self-employed for several reasons. First, evidence suggests self-employed individuals tend to mis-report their income in surveys when asked directly (Deaton, 1997; Hurst et al., Forthcoming). 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 3.6, we show that when we nonetheless include the self-employed in countries where our data allow, returns to experience are similar with and without the self-employed.

In our main analysis, we define potential experience as *experience = age – schooling – 6* for all individuals with eight or more years of schooling and as *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.2 of the Online Appendix). Later, in Section 3.6, we show that our results are robust to several alternative definitions of potential experience, and are similar when we estimate age-wage profiles or experience-earnings profiles rather than experience-wage profiles.

3 Returns to Experience Across Countries

3.1 Conceptual Framework

We use a simple model of human capital, similar to the one proposed by Bils and Klenow (1998), to motivate our empirical estimation. Human capital of individual i, who is born in year c and surveyed in time t, h_{ict}, depends on schooling, s_{ict} and experience, x_{ict}:

$$h_{ict} = \exp(g(s_{ict}) + f(x_{ict})). \tag{1}$$

We further impose $f(0) = g(0) = 0$, meaning that we normalize the human capital of a worker with zero years of both schooling and experience to be one. Thus, we focus on the part of human capital due to schooling or experience.[2]

[2]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. We find similar results to those presented below when we allow interactions between schooling and experience; details are available upon

Following standard development accounting exercises, we assume that workers earn their marginal products, supply their entire human capital to the labor market and that human capital is valued in efficiency units up to a mean-zero error term. These assumptions will allow us to identify individual human capital stocks directly from individual wages.[3]

Hence, an individual's hourly wage is equal to the product of her human capital, a skill price ω_{ct}, and an error term ε_{ict}:

$$w_{ict} = \omega_{ct} h_{ict} \exp(\varepsilon_{ict}). \tag{2}$$

We allow the skill price, ω_{ct}, to differ across cohorts and time periods:

$$\omega_{ct} = \bar{\omega} \exp(\gamma_t + \chi_c). \tag{3}$$

Time and cohort effects, γ_t and χ_c, represent time- and cohort-specific determinants of labor productivity that are not captured by human capital due to schooling or experience. Thus, time effects represent things like cohort-neutral technical change and capital accumulation, and cohort effects capture cohort-specific technical change and accumulation of cohort-specific capital.[4] Substituting (1) and (3) into (2) and taking logs, we obtain

$$\log w_{ict} = \log \bar{\omega} + g(s_{ict}) + f(x_{ict}) + \gamma_t + \chi_c + \varepsilon_{ict}. \tag{4}$$

Thus, a worker's wage is a function of: her years of schooling and experience, s_{ict} and x_{ict}; a vector of time-period dummy variables, γ_t; a vector of cohort dummy variables, ψ_c; and a mean-zero error term, ε_{ict}. In this section, we estimate the function $f(\cdot)$ and assess how it varies across countries. Our first empirical exercise is to estimate equation (4) for each country under the assumption that there are no cohort or time effects, $\gamma_t = \chi_c = 0$.

request. We also show later in the paper that separability between schooling and experience is not necessary for identifying total human capital stocks.

[3] In Section 5, we discuss the interpretation of experience-wage profiles when some of these assumptions are relaxed.

[4] Cohort effects can also capture things like cohort-specific changes in health status, i.e. determinants of labor productivity that, as a matter of semantics, one may call "human capital." As already noted, however, the focus of our paper is on human capital due to schooling or experience. We therefore do not include cohort effects in our definition of human capital in (1).

Afterwards, we turn to richer specifications that consider cohort and time effects.

3.2 Benchmark Results

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

$$\log w_{ict} = \alpha + \theta s_{ict} + \sum_{x=1}^{45} \phi_x D_{ict}^x + \varepsilon_{ict}, \tag{5}$$

where D_{ict}^x is a dummy variable that takes the value of one if a worker has x years of experience. The coefficient ϕ_x estimates the average wage of workers with x years of experience relative to the average wage of workers with zero years of experience. In terms of our notation from the previous section, the ϕ_x terms represent $f(x)$ such that the coefficient estimate corresponding to each experience level, x, identifies the experience-wage profile evaluated at point x.

Figure 1 displays the experience-wage profiles for three large countries in our sample: the United States, Mexico and India (see Figure A.1 for the estimated profiles for all countries). For brevity, we will use "steepness" to refer to the average slope of the profiles over all experience levels (as opposed to the point-wise slope at a given level of experience). The steepest profile among these three countries is in the United States, which is also the richest country of the three. Mexico has the next steepest profile, followed by India.[5]

Figure 1 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 2010 in Figure 2. The figure shows the main empirical finding of our paper, which is that the experience-wage profiles in poor countries are systematically flatter than those in rich countries. The correlation between the height of

[5]The confidence intervals tend to be tight for most countries, so we omit them for brevity; see Figure A.2 for the confidence intervals for India, Mexico and the United States. Note that our experience-wage profiles for the United States are quite similar to others in the literature (e.g., Lemieux, 2006).

the profiles at twenty years on log GDP per capita is 0.60. The slope coefficient from a regression of the height at twenty years potential experience and log GDP per capita is 0.20 and is statistically significant at the one percent level. In terms of economic significance, the slope tells us that one log point higher GDP per capita – such as the United States relative to Mexico – is associated with twenty percent higher returns to the first twenty years of potential experience.[6]

3.3 Cohort and Time Effects

The main challenge to estimating returns to experience (or age) is that one cannot separately identify the effects of experience, birth cohort and time, due to collinearity. 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 use data from thirteen countries for which our data cover at least fifteen years. This includes the most populous countries in our data: Bangladesh, Brazil, Canada, Chile, China, Germany, India, Indonesia, Italy, Jamaica, Mexico, the United Kingdom and the United States. The data, which cover 142 surveys and span an average of 26 years per country. The years of coverage for each country are listed in Table A.1 of the Online Appendix.

We consider three different versions of the *Deaton-Hall* approach. The key insight of this approach is that the time dimension of the repeated cross sections can be used to make inferences about the three effects (age, time and cohort) if one additional linear restriction is made on the three effects. To derive meaningful restrictions on cohort and time effects, we slightly generalize the approach used in Deaton's (1997) original analysis. In our conceptual framework, aggregate labor productivity can improve over time for two reasons: first, due to time effects, i.e. economy-wide changes affecting everyone; and second, due to cohort effects, i.e. improvements specific to individual cohorts. The three versions differ in the weight they put on cohort and time effects in driving growth over time. Section A.2 of the Online Appendix provides a more detailed discussion. In all three

[6]We find a positive correlation between log GDP per capita and the heights of the profiles at ten, fifteen and thirty years potential experience as well. We also find similar results when using log of per capita GDP for the year which is the midpoint of the sample for each individual country, rather than 2010. These results are available upon request.

versions, time effects take the form of calendar-year dummy variables, and cohort effects are yearly birth-cohort dummies.

The first version of the Deaton-Hall approach attributes all labor productivity growth to cohort effects, and uses year dummies to capture only cyclical fluctuations. This is the assumption that is made in Deaton's (1997) original analysis and others, such as Aguiar and Hurst (2013). The second version takes the "opposite" extreme and attributes all labor productivity growth to time effects. The third version takes the intermediate view that productivity growth is attributed in equal parts to cohort and time effects. While we are agnostic on the most natural split between time and cohort effects, the case of an equal split is nonetheless useful for illustrating how estimated returns to experience across countries depend on the relative importance of the two effects.

In Figure 3, we plot the predicted profiles based on the estimates of equation (5) when all labor productivity growth is attributed to cohort effects. As the figure shows, the correlation between income and steepness is still present. Table 1 shows that the correlation between the height of the profiles at twenty years of experience and log GDP per capita is still 0.42 (second row), compared to 0.60 in the benchmark cross-sectional estimates (first row). The slope coefficient is 0.14 under this version compared to 0.20 in the benchmark.

Figure 3 also shows that the profiles for most countries are steeper in this version than in the cross-sectional estimates (Figure 2). China, which becomes particularly steep, is a useful case for understanding the mechanics of the controls. Under this version, all of China's dramatic growth is attributed to newer cohorts being more productive than older ones. Thus, cohort effects are strongly upward sloping, while time effects have no positive trend. Since wages in the cross section are still higher for individuals from older cohorts (who also have more experience), returns to experience must be higher than they appear by looking at the cross section.[7] The same logic applies to other countries that experienced economic growth. But since China grew much more than the other countries in our sample, the effects are most pronounced for China.

[7]See Figure A.6 in the Online Appendix, which plots the estimated effects of experience, cohort and time for China in this version.

Figure 4 plots the predicted profiles for the returns to experience when we instead attribute all labor productivity growth to time effects. As the figure shows, the results are very similar to the cross-sectional profiles in Figure 1. Table 1 (third row) shows that the correlation between the height of the profiles at twenty years and income is 0.58, just below the benchmark, and the slope coefficient is 0.13. To see why the profiles in this version appear more like the benchmark, again consider the case of China. In this version, China's growth is attributed to factors that affect all individuals in the economy, and hence the time effect is strongly upward sloping. Cohort effects, by contrast, have no positive trend. Thus, the experience-wage profile is similar to the one estimated using cross-sectional data.[8]

Figure 5 plots the profiles when we attribute half of labor productivity growth to time effects and the remaining one half to cohort effects. For most countries, the experience-wage profiles lie somewhere between those in the previous two versions of the Deaton-Hall method. The correlation between log GDP per capita and the profile heights at twenty years of experience is 0.52, and the slope coefficient is again 0.13. In growing economies, the cohort and time effects are both upward sloping in this version, though less so than in the first and second variants, respectively.[9]

The estimates in this section show that while experience profiles differ for some countries depending on the exact specification, our overall cross-country finding that experience-wage profiles are flatter in poor countries is present when controlling for cohort or time effects in all three methods we consider. Thus, our finding is unlikely to be over-turned by the inclusion of controls for cohort and time effects.

3.4 Parsimonious Functional Form for Experience-Wage Profiles

While the fully flexible estimates are useful for revealing the true functional form of the experience-wage relationship, a parsimonious approximation of the relationship is more convenient for several exercises that we will conduct in this paper (e.g., examining com-

[8]See Online Appendix Figure A.7 for the estimated effects from China under this version.

[9]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 et al. (2011). The results here look quite similar to the first and second variants of the Deaton-Hall method, respectively, and are available upon request.

positional effects) and for comparing our results to the existing development accounting literature. As can be seen in Figure 1, experience-wage profiles are highly non-linear, particularly in rich countries. A quadratic specification, such as used by Psacharopoulos (1994), therefore provides a poor approximation of the true profiles.[10]

Thus, for parsimony, we will measure experience using a quintic polynomial:

$$\log w_{ict} = \alpha + \theta s_{ict} + \sum_{k=1}^{5} \phi_k x_{ict}^k + \varepsilon_{ict}, \tag{6}$$

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 (4) with $g(s) = \theta s$ and $f(x) = \sum_{k=1}^{5} \phi_k x^k$.

The estimated returns to experience appear very similar using the quintic specification as under the fully flexible specification (see Figure A.10 of the Online Appendix.) Furthermore, the cross-country relationship between returns to experience and log GDP per capita is almost the same using the quintic and fully flexible specifications, with a correlation of 0.56 in the former and 0.60 in the latter. Thus, we will mostly focus on the quintic specification henceforth.

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-wage 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 that engage in agriculture than rich countries. This could affect our estimates of average experience-wage profiles for each country if profiles are flatter for agricultural workers, which has been found to be true in the United States (Herrendorf and Schoellman, 2011).

To consider the role of this compositional difference, we estimate equation (4) separately for the agricultural and non-agricultural sectors. The experience-wage profile of country j

[10]The observation that a higher order polynomial is necessary for capturing the true profiles for rich countries such as the United States was made by Murphy and Welch (1990).

is then simply a weighted average of the sectoral profiles

$$f_j(x) = \ell_{A,j}(x) f_{A,j}(x) + (1 - \ell_{A,j}(x)) f_{N,j}(x), \tag{7}$$

where $\ell_{A,j}(x)$ is the employment share in agriculture in country j and A stands for agrsculture and N for non-agriculture.[11] Figure 7a shows the height of the experience-wage 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-wage profiles in agriculture are flatter than those in non-agriculture, though only modestly so.

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

$$\tilde{f}_j(x) = \ell_{A,US}(x) f_{A,j}(x) + (1 - \ell_{A,US}(x)) f_{N,j}(x). \tag{8}$$

If all of the cross-country differences in experience-wage 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 cross-country differences in the returns to experience, the counterfactual heights for all countries would lie on a straight horizontal line at the level of the United States. Instead, the counterfactual profiles are very similar to the actual ones. We calculate a slope coefficient of 0.19 in the counterfactual, compared to 0.22 in the actual data. In other words, differences in employment shares between agriculture and non-agriculture explain a very small part of the cross-country differences in

[11]To see this, note that by the law of iterated expectations, the projection of wages on experience, x, and schooling, s, can be decomposed by sector, z, as $E[\log(w)|x, s] = \Pr(z = A|s, x)E[\log(w)|x, s, z = A] + \Pr(z = N|s, x)E[\log(w)|x, s, z = N]$.

experience-wage profiles.

Schooling Another important compositional difference between rich and poor countries is that workers in poor countries attain fewer years of schooling on average, which could drive our cross-country results if more educated workers have steeper experience-wage profiles than less educated ones. Several studies have pointed out that more educated workers have steeper *age*-wage profiles.[12]

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 (4). For simplicity, we use 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 is 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-wage profile for workers with low schooling (less than ten years) against the height for those with high schooling (more than ten years), we find no systematic pattern between the steepness of profiles and educational attainment across countries.

Next, we conduct a similar counterfactual exercise as earlier and compute the implied experience-wage profile if all countries had the same share of highly educated individuals as the United States. We find that the relationship between the height of the counterfactual profiles and log GDP per capita is identical in the counterfactual and actual exercise, with a slope coefficient of 0.22 in each case. 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

[12] For example, see Carroll and Summers (1991), Kambourov and Manovskii (2009) and Guvenen (2007).

full- versus part-time employment. We also explored compositional effects for different combinations of these categories. We find that 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 investigates the robustness of the experience-profile estimates.

Inclusion of the Self-Employed In the main analysis of the paper, we keep only wage earners and exclude any workers with self-employment income because of 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). We find that when we include the self employed in the twelve countries for which self-employed income data are available, the estimated returns to experience are virtually identical with and without the self-employed. For brevity, the results are shown in the Online Appendix, in Figure A.4.

As an additional robustness check, we regress the steepness of the profiles at twenty years of experience on GDP per capita and the fraction of workers that are self-employed as reported by the World Bank's World Development Indicators. The coefficient on GDP per capita is large (0.05) and statistically significant (standard error 0.0133), which means that income is positively associated with the steepness of the profiles for two countries with the same proportion of self-employed workers. Thus, the cross-country results are not only an artifact of the possibility that there are more self-employed workers in poor countries and self-employed workers have steeper profiles than other workers in poor countries. In contrast, the coefficient on the fraction self-employed is small in magnitude (0.007) and statistically insignificant (standard error 0.006). This means that for two countries with the same income, there is no association between the share of self-employed workers and the height of the experience-wage profiles. These results are not shown in Tables due to space constraints.

Other Sample Restrictions Thus far, our results include all individuals earning a wage and working full time, regardless of sex or sector of work. In addition, we do not restrict 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 female labor supply, or the timing of female entry into or exit out of the labor force. Another concern is that workers in the public sector may earn wages that are not closely tied 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-wage profiles under several different sample restrictions. The first includes part-time workers in addition to full-time workers. The second and third restrict the sample to be only male workers and male private-sector workers. The fourth restricts the sample to be only non-agricultural workers. The last two restrict the sample by keeping only workers older than 18, and only workers older than 22, respectively. Panel (a) of Table 2 presents the correlation between the height of the experience-wage profile and GDP per capita, as well as the coefficient from a regression of the former on the latter, under these alternative sample restrictions. The correlation in the benchmark estimate from Section 3.2 is 0.60. Under the alternative sample restrictions, the correlations range from 0.43 to 0.59 and are all significant at the 5% level or lower. The slope in the benchmark is 0.20 and significant at the one percent level, while the slopes range from 0.14 to 0.24 under the alternative restrictions and all significant at the five percent level or lower. 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 two alternative definitions of potential experience.

The first of these makes the more standard assumption, made by Caselli (2005), that all workers begin work at age six or whenever they finish schooling and hence sets *experience = age - schooling – 6.* The second 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.2, 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 between the heights at 20 years of potential experience and log GDP per capita are 0.50 and 0.59 in the two cases, and the slope coefficient of a regression of the former on the latter are 0.17 and 0.21 respectively. Thus, our main result is not an artifact of our choice of definition for potential experience.

Experience-Earnings Profiles One widely studied alternative to experience-wage profiles are experience-*earnings* profiles. In our data, these two variables are highly correlated and the the slope of the experience-earnings profiles is steeper than that of the experience-wage profiles.[13] Thus, cross-country differences in experience-earnings profiles are even more substantial than cross-country differences in experience-wage profiles. The reason for this is that hours worked increase over the lifecycle at a faster rate in richer countries than poorer countries, at least in our set of countries.

Age-Wage Profiles Another alternative to experience-wage profiles are *age*-wage profiles. In our data, these profiles are also flatter in poor countries than in rich countries.[14]

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 the Online Appendix, we show that this is not the case.[15]

Related is the question of whether our result for the returns to experience is an artifact of our choice for estimating the returns to schooling. To investigate this, 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). In particular, this is that the first four years of schooling have a thirteen percent return, the next four have a ten percent return, and all others have a seven percent return. We then estimate the returns to experience by restricting the returns to schooling to be a constant ten percent, following the exercise of

[13] Online Appendix Figure A.12 plots the heights of these profiles against log GDP per capita for our set of countries.

[14] The height of these profiles at age forty for all countries are plotted in Online Appendix Figure A.13. The correlation between the height of the profile at age forty and log GDP per capita is 0.65.

[15] See Online Appendix Figure A.8, which that shows the estimated returns to schooling for the countries in our sample. They range from three percent to seventeen percent per year of schooling with a mean return of nine percent. The figure also shows that the return to schooling is at best weakly correlated with GDP per capita. This is consistent with previous estimates. See Hsieh and Klenow (2010) and the references within.

Hsieh and Klenow (2010), which assumes this return in all countries. The slope coefficient from a regression of the heights at 20 years of experience and the log of GDP per capita is 0.21 in both cases. For brevity, this is not presented in tables. This is quite similar to the 0.20 found in our benchmark case. Thus, our main result does not appear to be an artifact of the way we estimate returns to schooling relative to the literature.

Additional Sensitivity Tests In addition to the robustness checks presented in this section, we conducted many others that we do not discuss for brevity. For example, we provide evidence that our results are not driven by measurement error in age or schooling; see Section A.3 and Section A.4 of the Online Appendix. We also find 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; restricting the maximum years of experience to be fifty years; and using the *Current Population Survey* in the United States instead of the Census.

4 Development Accounting

In this section, we illustrate 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) and Caselli (2005), in constructing measures of the aggregate physical and human capital stocks across countries using data on the average quantities and returns to schooling and potential experience. We depart from the previous literature by allowing the return to experience to differ across countries. 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.

Conceptually, we differ from existing studies in the following way. Existing studies eliminate all productivity differences across countries and estimate the fraction of cross-country income differences that can be accounted for with quantities of observable factors of production. In contrast, we only restrict aggregate production functions to be the same across countries but allow human capital production functions to vary. We then empirically identify what amounts to cross-country TFP differences in human capital production.

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

$$h_{it} = \exp(g(s_{it}) + f(x_{it})), \tag{9}$$

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 wage 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

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

and g and f are estimated in the wage regression (3). Analogously, we define the aggregate experience human capital stock per worker as the average of the individual stocks across individuals and over time

$$H^X = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t} h_{it}^X. \tag{10}$$

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. Computing human capital this way makes three assumptions that are standard in the development accounting literature: (i) workers earn their marginal products, (ii) workers supply their entire human capital to the labor market, and (iii) human capital is valued in efficiency units. These assumptions imply that a worker's human capital is proportional to his wage.[16]

[16] Figure A.9 plots the average potential experience for all countries in our sample against GDP per capita, and shows a modest positive correlation between the average potential experience level and GDP per capita. However, as we show in Section A.5 of the Online Appendix, differences in average potential

Figures 7a - 7d plot the implied experience human capital against per capita GDP for each country. For these figures, the experience human capital stocks are calculated using the quintic specification in equation (6), and each figure corresponds to a different restriction on cohort and year effects, analogous to Figures 1-5. These figures display a strong and significant relationship between human capital from experience and income levels. 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 Online 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:

$$H = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t} h_{it}. \tag{11}$$

The estimates of these human capital stocks are based on our estimated returns to schooling and experience from the quintic specification. Compare (10) and (11) and 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* take into account experience.

Table 3 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 and the second measure is the slope of a linear regression of log human capital stocks on log GDP per capita. The first measure is reported in column (1) and shows that simple dispersion of human capital stocks, as measured by the log variation, is somewhat larger for schooling

experience account for little cross-country variation in experience human capital stocks. This is consistent with the conclusions of Caselli (2005) and Bils and Klenow (2000) that cross-country differences in average potential experience are of modest importance from in accounting for income differences.

than for experience, but both are of the same order of magnitude. The latter measure is reported in column (2) and shows that a one-percent increase in log GDP per capita corresponds to a 0.21-percent 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 is 0.15 percent. These results show that experience and schooling contribute roughly equally to generate the differences in human capital stocks between rich and poor countries.[17]

Finally, the third row of Panel (a) in Table 3 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 3 show that these numbers change somewhat when we use the estimates from the 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 always present.

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, $\alpha = 1/3$, which is standard in this literature.

[17]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.

Following Caselli (2005), we calculate the measure:

$$success_1 = \frac{\mathrm{var}(\ln Y_{KH})}{\mathrm{var}(\ln Y)}, \tag{12}$$

where $Y_{KH} = K^{\alpha}H^{1-\alpha}$ is the component of output due to factors of production. Intuitively, $success_1$ represents the fraction of actual variation in log output per worker that would be present if countries differed only by stocks of human and physical capital. Note that this measure does not take into account 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 artificially increases $\mathrm{var}(\ln Y_{KH})$. In light of this caveat, we also report the slope of a regression of $\ln Y_{KH}$ on $\ln Y$.

Table 4 presents these measures when we calculate aggregate human capital stocks either from only schooling, from only experience or from both schooling and experience. Panel (a) shows the results using our cross-sectional estimates of human capital stocks. When human capital is measured by only using schooling as in most of the literature, $success_1$ is equal to 0.40. Recall that in Table 3, 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 4: the second row reveals that when human capital is measured only using experience, $success_1$ is 0.40. In other words, schooling and experience human capital taken alone are roughly equally important determinants of cross-country income differences. Finally, when both schooling and experience are taken into account, the measure of success increases substantially, up to 0.63. From the slope of the regression of $\ln Y_{KH}$ on $\ln Y$, reported in column (2), calculating human capital from both education and experience increases not only the total variability of $\ln Y_{KH}$ across countries, but also its correlation with $\ln Y$. Panels (b), (c) and (d) show that similar findings apply when we construct human capital using our estimates with controls for time or cohort effects.

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

$$success_2^j = \frac{Y_{KH}^{US}/Y_{KH}^j}{Y^{US}/Y^j}. \tag{13}$$

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.[18] Table A.3 first reports Caselli's (2005) numbers for output and physical capital in the 4th and 5th columns. The estimates for $success_2^j$ are presented in the last two columns. 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 of cross-country income differences than does the existing literature. Most countries still have large TFP gaps with the United States, but adding experience helps close the gaps.

4.4 Comparison to Existing Accounting Exercises

We now summarize our development accounting results by illustrating the effects of each departure that we take from existing accounting exercises and their influences on our final result. The results are shown in Table 5, and all results use our data. We begin, in Panel (a), with a specification similar to the one used by Klenow and Rodriguez-Clare (1997), and proceed step-by-step to the specification in our benchmark exercise, in Panel (e), making one change at a time.

The specification in Panel (a) of Table 5 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). The first column presents the dispersion of human capital across countries, measured as the variance of the logarithm of the stock of country-specific human capital. The second column presents $Success_1$. It shows that taking human capital due to both schooling and experience into account produces a measure of

[18] 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.

0.44, which is similar to the value of 0.39 reported in Caselli (2005).

Panel (b) of Table 5 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 increases $success_1$ from 0.42 to 0.51. 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 0.51 to 0.63. 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 Table 4: $success_1$ is 0.63.[19]

5 Interpretation of Experience-Wage Profiles

In this section, we consider some explanations of why experience-wage profiles would be flatter in poor countries. While it is beyond the scope of this paper to conclusively distinguish between alternative theories, this section nonetheless serves several purposes. First, it shows that two broad theories of human capital accumulation differ in their mapping between wages and human capital over the lifecycle, and that this has important implications for our development accounting results. Second, it illustrates how our development accounting conclusions change quantitatively when we measure experience human capital stocks through a Ben-Porath model of human capital accumulation. Third, it shows how our findings relate to some existing theories of cross-country income differences. Finally, it discusses suggestive evidence against alternative theories that postulate that factors other than human capital accumulation can affect experience-wage profiles.

[19] The results in Table 5 show that our conclusions are due to allowing the returns to experience to vary across countries *and* the more accurate approximation of the experience-wage profile. To illustrate the importance of the functional form more clearly, Figure A.10 in the Online Appendix repeats our empirical exercises from Section 3, but uses a linear-quadratic specification for estimating the experience-wage profiles. Panel (a) shows that the quadratic experience-wage profiles provide a poor approximation of the fully flexible ones whereas a quintic specification is much more accurate. Panel (b) plots the height of both the quadratic and quintic experience-wage profiles at twenty years of experience against countries' income levels, and shows only a weak relationship for the quadratic profiles (black line) and a much stronger one for the quintic ones (light grey line).

5.1 Theories of Passive Human Capital Accumulation

First, we consider models where human capital is passively accumulated. The simplest possible interpretation of flat experience-wage profiles in poor countries is that the nature of work in developing countries simply offers limited scope for skill improvement over the lifecycle. This can, in turn, be due to reasons such as worse training opportunities, simpler technologies, fewer and weaker social interactions, or worse management practices in developing countries (Lucas, 2009; Lucas and Moll, 2011; Perla and Tonetti, 2011).[20]

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

$$\dot{h}(t) = F(h(t), t), \tag{14}$$

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 ε:

$$w(t) = \bar{\omega} h(t) \exp(\varepsilon), \quad t > s. \tag{15}$$

The following special case is instructive because it maps back to our empirical model in Sections 3 and 4 exactly:

$$\dot{h}(t) = F(h(t), t) = \begin{cases} \theta(t) h(t), & t \in [0, s] \\ \phi(x(t)) h(t), & t \in (s, T]. \end{cases} \tag{16}$$

[20] 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.

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

$$\log h(t) = g(s) + f(x(t)), \tag{17}$$

where $g(s)$ and $f(x)$ are the cumulative returns to schooling and experience.[21] Substituting into (15) yields an equation linking wages, schooling and potential experience that has the same form as our estimating equation (3)

$$\log w(t) = \log \bar{\omega} + g(s) + f(x(t)) + \varepsilon. \tag{18}$$

Viewed through the lens of this simple model, flat experience-wage 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).

Importantly, under these theories, one infers lifecycle increases in human capital stocks directly from increases in wages. Thus, the mapping between wages and productivity is just as assumed in developing accounting.

5.2 Theories of Active Human Capital Accumulation

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 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): $\dot{h} = F(h, \ell)$, where ℓ are time inputs into the production of human capital. 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

[21] 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 (17) is the same functional form as our "human capital production function" (1) which is also the one used by Bils and Klenow (2000).

considered to be in school if $\ell(t) = 1$. In Ben-Porath type models, the time paths for $\ell(t)$ 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 the one characterized by equation (16), we can again obtain an equation for the wage that has the same form as our estimating equation (3):

$$\log w = \log \bar{\omega} + g(s) + \underbrace{\log(1 - \ell(x)) + \tilde{f}(x)}_{f(x)} + \varepsilon, \tag{19}$$

where $\tilde{f}(x)$ is the cumulative human capital return to experience.[22] In Ben-Porath type models, there are two reasons for upward-sloping experience-wage 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-wage profiles, $f(x)$, would reflect both.[23]

The implication for development accounting is that in models of active human capital accumulation, one cannot infer increases in human capital from experience-wage profiles alone. Thus, under these theories, the development accounting conclusions of the previous section are an upper bound on the importance of lifecycle human capital differences. Section 5.3 below assesses how quantitatively important this might be for the development accounting conclusions of the previous section.

From the perspective of theories of active human capital accumulation, flat experience-wage profiles in poor countries reflect low investment. 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

[22] The special case analogous to equation (16) is $\dot{h} = F(h, \ell) = \theta(\ell)h$ if $\ell = 1$ and $\dot{h} = F(h, \ell) = \phi(\ell)h$ if $\ell < 1$. The cumulative return to experience is again defined as $\tilde{f}(x) = \int_0^x \phi(\ell(\tilde{x}))d\tilde{x}$.

[23] We thank Lutz Hendricks for pointing this out to us. Relative to a standard development accounting exercises like ours, the Ben-Porath model departs from the assumption that workers supply their entire human capital to the labor market.

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-wage 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 et al. (2010), which shows how the accumulation of schooling human capital can amplify TFP differences across countries.

Flat experience-wage 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, which is emphasized in studies such as Acemoglu et al. (2001), 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 et al., 2011). Similarly, it could be allocative distortions in poor countries that reduce human capital accumulation over the lifecycle (Bhattacharya et al., 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.

5.3 Quantitative Role of Human Capital Investment Time

In this section, we explore how our development accounting conclusions change when we measure experience human capital stocks through a Ben-Porath model of human capital accumulation. As we explained above, models of active human capital accumulation such as the Ben-Porath model have the feature that wages rise with experience both because human capital increases and because investment time decreases. The goal of this section is to disentangle increases in human capital from decreases in investment time through the lens of a Ben-Porath model. We can then re-do our standard development accounting exercise using the human capital stocks implied by the model, and ask whether there are still substantial differences in these stocks across countries.

For simplicity and transparency we consider a model in which time is the only factor in producing human capital. In particular, we assume that human capital accumulates according to $\dot{h} = \varphi(\ell)h$, where ℓ is the worker's time spent investing in new human capital. We assume further that $\varphi(\ell) = B\ell^{\gamma} - \delta$, where B and γ govern efficiency and returns to scale in human capital investment and δ is the depreciation rate of existing capital. Finally, we assume away human capital accumulation during schooling. Workers solve the problem

$$\max_{\ell(t), t \geqq 0} \int_0^T e^{-rt} \left[\omega(1-\tau(t))h(t)(1-\ell(t))\right] dt, \tag{20}$$

subject to $\dot{h} = \varphi(\ell)h$, where $\tau(t)$ is a "wedge" that determines the human capital accumulation decision over time. These wedges can be thought of as any factor which gives workers a disincentive to accumulate more human capital, and which potentially varies with a worker's potential experience (in this case, t).

To quantify the importance of human capital investment time for measuring cross-country experience human capital stocks, we proceed as follows. We first assume that the human capital production function is the same in all countries. Next, we pick the $\tau(t)$ paths for each country so as to match the country's experience-wage profile exactly. Finally, we recover the implied paths for investment and human capital, $\ell(t)$ and $h(t)$, for each country. In Section A.6 of the Online Appendix, we show how this can be done in the current framework by using the fact that optimizing workers will choose not to invest in the final period, i.e. $\ell(T) = 0$.

The parameter values we use in the quantitative exercise are $B = 0.19$, $\gamma = 0.94$ and $\delta = 0$, which are taken from Manuelli and Seshadri's (2010) cross-country analysis of the Ben-Porath model. Their efficiency and scale parameters are disciplined to be consistent with the U.S. age-wage profiles and observed inputs to human capital production. Their depreciation rate is chosen based on the observation that wage profiles do not systematically decline at the end of the lifecycle.[24]

Online Appendix Figure A.11 presents the human capital and investment profiles for the United States, as an illustration. Early on, workers spend just over one third of their time investing in human capital. Over the lifecycle, their investment time declines steadily until eventually reaching zero. Human capital increases rapidly over the lifecycle and then eventually levels off. The wage rise is steeper than the rise in human capital, reflecting both the increase in capital and the decrease in investment time. Countries with flatter experience-wage profiles differ in that they have less investment and smaller increases in human capital over the lifecycle.

When we redo the development accounting results using the experience human capital implied by the model, we find that $success_1$ rises to 0.50, up from 0.40 in the world without experience human capital. This is lower than the 0.63 of the benchmark calculations, but still represents a substantial increase in the importance of factors. We also find that the slope of a regression of $\ln Y_{KH}$ on $\ln Y$ increases from 0.52 to 0.59. This implies that adding human capital from experience still increases the correlation between actual income and income in a world with only factor differences.

In summary, when human capital is measured through the lens of a Ben-Porath model of human capital investment, the quantitative importance of experience human capital is lower than in our benchmark analysis. However, the main qualitative point of our

[24] The interpretation of their scale parameter and our parameter γ differs slightly. This is for two reasons: first, their formulation features both time and non-time inputs into human capital accumulation, whereas we abstract from the latter for simplicity. Second, we postulate an accumulation technology that is linear in human capital rather than being subject to slight diminishing returns. Both departures are made entirely for tractability, as they allow us to obtain analytic solutions for the time path of wages given time allocation decisions.

study stands since importance of human capital in accounting for income differences is still substantially increased.

5.4 Alternative Explanations

We note that there are several theories besides those that we discuss above that postulate that factors other than human capital accumulation affect the shape of experience-wage 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.[25] In many theories of long-term contracting, frictions such as moral hazard or limited commitment on the part of workers lead 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 more pronounced in poor countries, these theories would predict more backloading in poor countries, which implies that our estimates understate the difference in the steepness of profiles between rich and poor countries.[26] Some theories also suggest reasons for front-loading in wage-contracts. For example, this could be because of limited commitment on the side of firms, or if firms implicitly lend to financially constrained workers (e.g., Azariadis, 1988). Front-loading would cause experience-wage profiles to appear flatter than in the frictionless case. 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-wage 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).

[25] To formalize this, assume that human capital is accumulated passively as in (16), 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

$$\log w = \log \bar{\omega} + g(s) + \underbrace{\log(1+\tau(x)) + \tilde{f}(x)}_{f(x)} + \varepsilon. \tag{21}$$

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

[26] Similarly, 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.

Currently, there is little empirical evidence on the extent of market frictions across countries. But we believe that these alternative explanations are unlikely to drive our cross-country results for several reasons. First, studies of the United States agree that despite the presence of the frictions discussed above, human capital accumulation is the most important source of wage growth, at least 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.[27] Second, in a companion paper, Lagakos et al. (2013), we document that among new U.S. immigrants, returns to foreign experience are higher for immigrants from rich countries than immigrants from poor countries. Since all wages are paid in the United States, this is inconsistent with the alternative that differences in experience-wage profiles are driven by different wage-setting structures across countries. Providing a more conclusive answer on the determinants of the cross-country wage-profiles is an important avenue for future research.

6 Conclusion

A large literature has concluded that human and physical capital account for less than half of cross-country income differences (Klenow and Rodriguez-Clare, 1997, Hall and Jones, 1999, and Caselli, 2005). Likely due to data limitations, this literature has found that taking into account human capital from experience does not change the explanatory power of human and physical capital. This paper draws on new evidence which supports a substantially different conclusion. Using better data than what were available to earlier studies, we document that experience-wage profiles are steeper in rich countries than poor countries. This suggests that workers in rich countries accumulate more human capital through experience than workers in poor countries. We find that taking this into account significantly increases the contribution of observable factors of production in accounting for international income differences.

We demonstrate that our empirical findings are consistent with the large body of theories that postulate that workers accumulate human capital, actively or passively, over the life-cycle. We also provide some speculative evidence against alternative interpretations

[27] These studies vary in their assessment of the exact contribution of each mechanism (e.g., Altonji et al. (2009) and Topel and Ward (1992)).

in which life-time earnings dynamics are an outcome of factors other than human capital accumulation.

Our research suggests that providing a more conclusive answer for the determinants of cross-country experience-wage profiles is an important avenue of future research. More generally, exploring the determinants of lifecycle human capital accumulation and how they vary across countries is likely to be a fruitful endeavor for understanding cross-country income differences.

References

Acemoglu, Daron, Simon Johnson, and James A. Robinson, "The Colonial Origins of Comparative Development: An Empirical Investigation," *American Economic Review*, December 2001, *91* (5), 1369–1401.

Aguiar, Mark and Erik Hurst, "Deconstructing Lifecycle Expenditure," *Journal of Political Economy*, 2013, *97.*

Altonji, Joseph G., Anthony Smith, and Ivan Vidangos, "Modeling Earnings Dynamics," NBER Working Papers 14743, National Bureau of Economic Research February 2009.

Azariadis, Costas, "Human Capital and Self-Enforcing Contracts," *Scandinavian Journal of Economics*, 1988, *90* (4), 507–28.

Barro, Robert J and Jong-Wha Lee, "International Data on Educational Attainment: Updates and Implications," *Oxford Economic Papers*, July 2001, *53* (3), 541–63.

Ben-Porath, Yoram, "The Production of Human Capital and the Life Cycle of Earnings," *Journal of Political Economy*, 1967, *75*, 352.

Bhattacharya, Dhritiman, Nezih Guner, and Gustavo Ventura, "Distortions, Endogenous Managerial Skills and Productivity Differences," mimeo, Arizona State University 2012.

Bils, Mark and Peter J. Klenow, "Does Schooling Cause Growth or the Other Way Around?," NBER Working Papers 6393, National Bureau of Economic Research February 1998.

_ and _ , "Does Schooling Cause Growth?," *American Economic Review*, December 2000, *90* (5), 1160–83.

Burdett, Kenneth, "A Theory of Employee Job Search and Quit Rates," *The American Economic Review*, 1978, *68* (1), pp. 212–220.

_ and Dale T Mortensen, "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, May 1998, *39* (2), 257–73.

Carroll, Christopher D. and Lawrence H. Summers, "Consumption Growth Parallels Income Growth: Some New Evidence," in "National Saving and Economic Performance" NBER Chapters, National Bureau of Economic Research, 1991, pp. 305–348.

Caselli, Francesco, "Accounting for Cross-Country Income Differences," in Philippe Aghion and Steven Durlauf, eds., *Handbook of Economic Growth*, Vol. 1, Elsevier, 00 2005, chapter 9, pp. 679–741.

Deaton, Angus, *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy*, The World Bank, 1997.

Erosa, Andres, Tatyana Koreshkova, and Diego Restuccia, "How Important Is Human Capital? A Quantitative Theory Assessment of World Income Inequality," *Review of Economic Studies*, October 2010, *77* (4), 1421–1449.

Galor, Oded and Joseph Zeira, "Income Distribution and Macroeconomics," *Review of Economic Studies*, 1993, *60* (1), 35–52.

Gennaioli, Nicola, Rafael La Porta, Florencio Lopez-de-Silanes, and Andrei Shleifer, "Human Capital and Regional Development," *Quarterly Journal of Economics*, forthcoming.

Gollin, Douglas, "Getting Income Shares Right," *Journal of Political Economy*, April 2002, *110* (2), 458–474.

Guvenen, Fatih, "Learning Your Earning: Are Labor Income Shocks Really Very Persistent?," *American Economic Review*, June 2007, *97* (3), 687–712.

_ , Burhanettin Kuruscu, and Serdar Ozkan, "Taxation of human capital and wage inequality: a cross-country analysis," Working Paper 2011.

Hall, R. E., "Technical Change and Capital from the Point of View of the Dual," *The Review of Economic Studies*, 1968, *35* (1), pp. 35–46.

Hall, Robert E. and Charles I. Jones, "Why Do Some Countries Produce So Much More Output Per Worker Than Others?," *The Quarterly Journal of Economics*, February 1999, *114* (1), 83–116.

Hanushek, Eric A. and Dennis D. Kimko, "Schooling, Labor-Force Quality, and the Growth of Nations," *American Economic Review*, December 2000, *90* (5), 1184–1208.

Hendricks, Lutz, "How Important Is Human Capital for Development? Evidence from Immigrant Earnings," *American Economic Review*, March 2002, *92* (1), 198–219.

Herrendorf, Berthold and Todd Schoellman, "Why is Measured Productivity so Low in Agriculture?," Working Paper 2011.

Heston, Alan, Robert Summers, and Bettina Aten, *Penn World Table Version 7.0* Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania May 2011.

Hsieh, Chang-Tai and Peter J. Klenow, "Development Accounting," *American Economic Journal: Macroeconomics*, January 2010, *2* (1), 207–23.

_ and _ , "The Life Cycle of Plants in India and Mexico," Working Paper, Stanford University 2012.

Huggett, Mark, Gustavo Ventura, and Amir Yaron, "Sources of Lifetime Inequality," *American Economic Review*, 2011, *101* (7), 2923–54.

Hurst, Erik, Geng Li, and Ben Pugsley, "Are Household Surveys Like Tax Forms: Evidence from Income Underreporting of the Self Employed," *Review of Economics and Statistics*, Forthcoming.

Jones, Benjamin F., "The Human Capital Stock: A Generalized Approach," NBER Working Papers 17487, National Bureau of Economic Research 2011.

Jovanovic, Boyan, "Job Matching and the Theory of Turnover," *Journal of Political Economy*, October 1979, *87* (5), 972–90.

Kambourov, Gueorgui and Iourii Manovskii, "Accounting for the Changing Life-Cycle Profile of Earnings," Working Paper 2009.

King, Miriam, Steven Ruggles, J. Trent Alexander, Sarah Flood, Katie Genadek, Matthew B. Schroeder, Brandon Trampe, and Rebecca Vick, *Integrated Public Use Microdata Series, Current Population Survey: Version 3.0. [Machine-readable database]*, University of Minnesota, 2010.

Klenow, Pete and Andres Rodriguez-Clare, "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?," in "NBER Macroeconomics Annual 1997, Volume 12" NBER Chapters, National Bureau of Economic Research, 1997, pp. 73–114.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Lifecycle Human Capital Accumulation Across Countries: Lessons from U.S. Immigrants," Technical Report, UC San Diego, type=https://sites.google.com/site/davidlagakos/home/research 2013.

Lazear, Edward P, "Why Is There Mandatory Retirement?," *Journal of Political Economy*, December 1979, *87* (6), 1261–84.

Lemieux, Thomas, *The "Mincer Equation" Thirty Years After "Schooling, Experience, and Earnings"*, Springer,

Lucas, Robert E., "Ideas and Growth," *Economica*, 2009, *76* (301), 1–19.

_ **and Benjamin Moll**, "Knowledge Growth and the Allocation of Time," NBER Working Papers 17495, National Bureau of Economic Research October 2011.

Manuelli, Rodolfo and Ananth Seshadri, "Human Capital and the Wealth of Nations," Working Paper, University of Wisconsin 2010.

Michelacci, Claudio and Vincenzo Quadrini, "Financial Markets and Wages," *Review of Economic Studies*, 04 2009, *76* (2), 795–827.

Minnesota Population Center, *Integrated Public Use Microdata Series, International: Version 6.1 [Machine-readable database]*, University of Minnesota, 2011.

Murphy, Kevin M and Finis Welch, "Empirical Age-Earnings Profiles," *Journal of Labor Economics*, April 1990, *8* (2), 202–29.

Perla, Jesse and Christopher Tonetti, "Endogenous Risk and Growth," mimeo, NYU 2011.

Psacharopoulos, George, "Returns to Investment in Education: A Global Update," *World Development*, 1994, *22* (9), 1325–43.

Schoellman, Todd, "Education Quality and Development Accounting," *The Review of Economic Studies*, March 2012, *3* (1), 133–175.

Seshadri, Ananth and Nicolas Roys, "The Organisation of Production and Economic Development," Working Paper, University of Wisconsin Madison 2012.

Shastry, Gauri Kartini and David N. Weil, "How Much of Cross-Country Income Variation is Explained By Health?," *Journal of the European Economic Association*, 04/05 2003, *1* (2-3), 387–396.

Topel, Robert H and Michael P Ward, "Job Mobility and the Careers of Young Men," *The Quarterly Journal of Economics*, May 1992, *107* (2), 439–79.

Weil, David N., "Accounting for The Effect of Health on Economic Growth," *The Quarterly Journal of Economics*, 08 2007, *122* (3), 1265–1306.

Table 1: Returns to Experience and GDP per Capita

	Corr(Height$_{20}$, GDP)	Slope(Height$_{20}$, GDP)
	(1)	(2)
Benchmark (No cohort or time effects)	0.60***	0.20***
Restriction 1: All growth is due to cohort effects	0.42	0.14
Restriction 2: All growth is due to time effects	0.58**	0.13**
Restriction 3: Growth is equally due to time and cohort effects	0.52*	0.13*

Notes: Column (1) shows the correlation coefficient between the height of the experience-wage profile at 20 years of experience and log per capita GDP in 2010 at PPP. Column (2) presents the coefficient of from a bivariate regression. Restrictions 1, 2 and 3 refer to the estimated returns to potential experience using the Deaton-Hall method. The sample for the benchmark includes all 35 countries. The sample for the Deaton-Hall estimates includes 12 countries. *,** and *** denote statistical significance at the 10%, 5% and 1% levels.

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

	Corr($Height_{20}$, GDP) (1)	Slope($Height_{20}$, GDP) (2)
Benchmark	0.60***	0.20***
	(a) Alternative Sample Restrictions	
Include Part-Time Workers	0.51***	0.14***
Male Workers	0.54***	0.24***
Male Private Workers	0.55***	0.23***
Non-Agricultural Workers	0.53***	0.18***
Older than 18 Years Workers	0.59***	0.19***
Older than 22 Years Workers	0.43**	0.15**
	(b) Alternative Definitions of Potential Experience	
Start Work at Age 6	0.50***	0.17***
Start Work at Age 15	0.59***	0.21***

Notes: Column (1) shows the correlation coefficient between the height of the experience-wage profile at 20 years of experience and log per capita GDP in 2010 at PPP. Column (2) presents the coefficient of from a bivariate regression. The sample for the benchmark includes all 35 countries. *,** and *** denote statistical significance at the 10%, 5% and 1% levels.

Table 3: Variance of Human Capital Stocks Across Countries

Human Capital Measure	Var(log(H)) (1)	Slope(log(H), log(GDP)) (2)
	(a) Benchmark	
Schooling	0.12	0.15
Experience	0.09	0.21
Schooling + Experience	0.26	0.36
	(b) Restriction 1: All Growth is due to Cohort Effects	
Schooling	0.11	0.11
Experience	0.14	0.04
Schooling + Experience	0.40	0.16
	(c) Restriction 2: All Growth is due to Time Effects	
Schooling	0.07	0.17
Experience	0.07	0.18
Schooling + Experience	0.17	0.35
	(d) Restriction 3: Growth is Equally due to Cohort and Time Effects	
Schooling	0.08	0.14
Experience	0.08	0.11
Schooling + Experience	0.24	0.25

Notes: Column (1) presents the cross-country variance in human capital stocks that take into account human capital from schooling, experience and experience + schooling. Column (2) presents the coefficient of the bivariate regression between the log of human capital and the log of 2010 GDP per capita at PPP. In Panels (b)-(d), restrictions 1, 2 and 3 refer to the estimated returns to potential experience using the Deaton-Hall method in countries with multiple cross-sections of data spanning fifteen or more years. The sample in Panel (a) includes 35 countries. The samples used in Panels (b) - (d) include 12 countries.

Table 4: Development Accounting

Human Capital Measure	Success_1 (1)	Slope(log(Y_{KH}), log(GDP)) (2)
	(a) Benchmark	
Schooling	0.40	0.53
Experience	0.40	0.56
Schooling + Experience	0.63	0.65
	(b) Restriction 1: All Growth is due to Cohort Effects	
Schooling	0.33	0.51
Experience	0.28	0.43
Schooling + Experience	0.51	0.52
	(c) Restriction 2: All Growth is due to Time Effects	
Schooling	0.34	0.56
Experience	0.31	0.53
Schooling + Experience	0.49	0.66
	(d) Restriction 3: Growth is Equally due to Cohort and Time Effects	
Schooling	0.33	0.53
Experience	0.28	0.48
Schooling + Experience	0.47	0.59

Notes: Column (1) presents the cross-country variance of log Y_{KH} (from from schooling, experience and experience + schooling) divided by the cross-country variance in of log per capita 2010 GDP. Y_{KH} is output per worker assuming that countries differ only in their stocks of human and physical capital per worker. Column (2) presents the coefficient from a bivariate regression. In Panel (a), the sample includes 35 countries. In Panels (b)-(d), restrictions 1, 2 and 3 refer to the estimated returns to potential experience using the Deaton-Hall method. The samples include 12 countries.

Table 5: Relation to Literature

Human Capital Measure	Var(log(H)) (1)	Success1 (2)
(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	0.32
Schooling + Experience	0.12	0.51
(d) Hall-Jones Schooling + Country-Specific Quintic Returns to Exp		
Schooling	0.05	0.37
Experience	0.08	0.42
Schooling + Experience	0.18	0.63
(e) Benchmark: Country-Specific Returns to Schooling (Linear) and Exp (Quintic)		
Schooling	0.12	0.40
Experience	0.09	0.40
Schooling + Experience	0.26	0.63

Notes: Column (1) presents the cross-country variance of the log of human capital (from from schooling, experience and experience + schooling). Column (2) presents the cross-country variance of log Y_{KH} divided by the cross-country variance in of log per capita 2010 GDP, where Y_{KH} is output per worker assuming that countries differ only in their stocks of human and physical capital per worker. Panel (a) computes human capital stocks using a linear-quadratic Mincer regression and the average returns to schooling and experience as in Klenow and Rodriguez-Clare (1997). In our sample, the average coefficients on schooling, experience and experience^2 are 0.092, 0.048 and -0.00076. Panel (b) uses the same specification except for imposing diminishing returns to schooling using the methodology of Hall and Jones (1999): assume that *g(s)*, where *s* is the years of schooling, is piecewise linear with a slope of 0.13 for s<=4, 0.10 for 4<s<=8 and 0.07 for 8<s. Panel (c) allows the returns to experience to vary across countries, but retains a quadratic specification. Panel (d) is identical to panel (c), except that it uses a quintic specification. Panel (e) additionally allows the returns to schooling to vary (linearly) across countries.

Figure 1: Fully Flexible Experience-Wage Profiles – India, Mexico and the United States

Notes: This figure plots the coefficients of the dummy variables for the years of experience.

Figure 2: Returns to Experience vs. GDP per Capita – All Countries

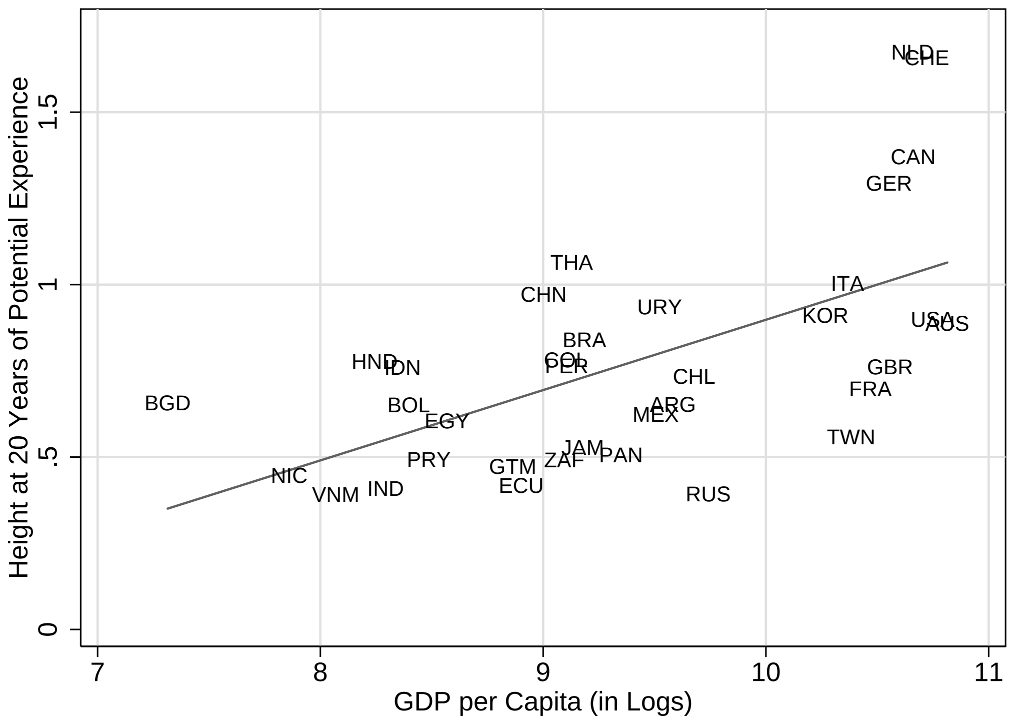


Figure 3: Returns to Experience vs. GDP per Capita – Restriction 1: All Growth is due to Cohort Effects

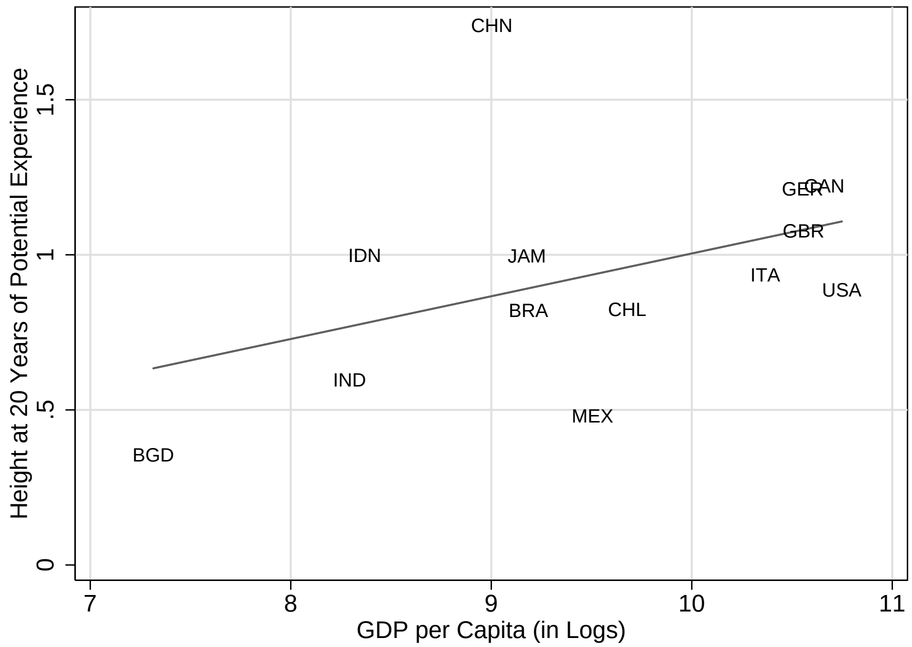


Figure 4: Returns to Experience vs GDP per Capita –Restriction 2: All Growth is due to Time Effects

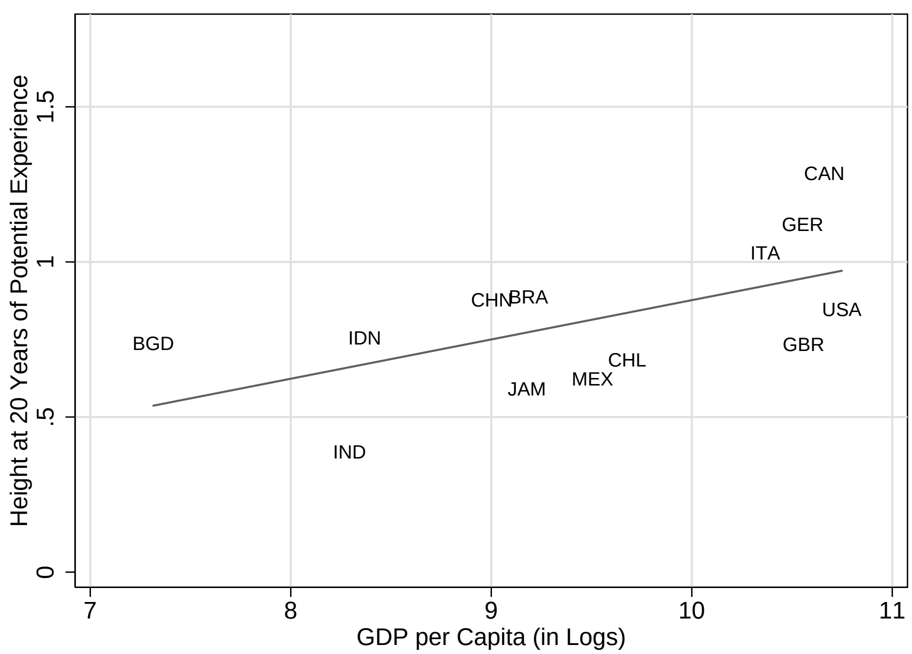


Figure 5: Returns to Experience vs. GDP per Capita – Restriction 3: Growth is equally due to Cohort and Time Effects

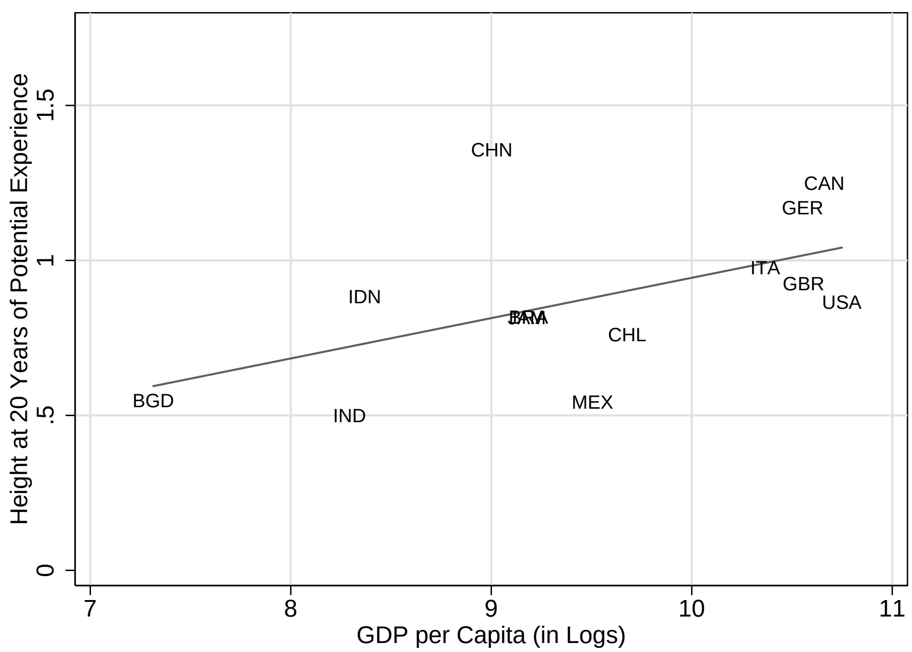
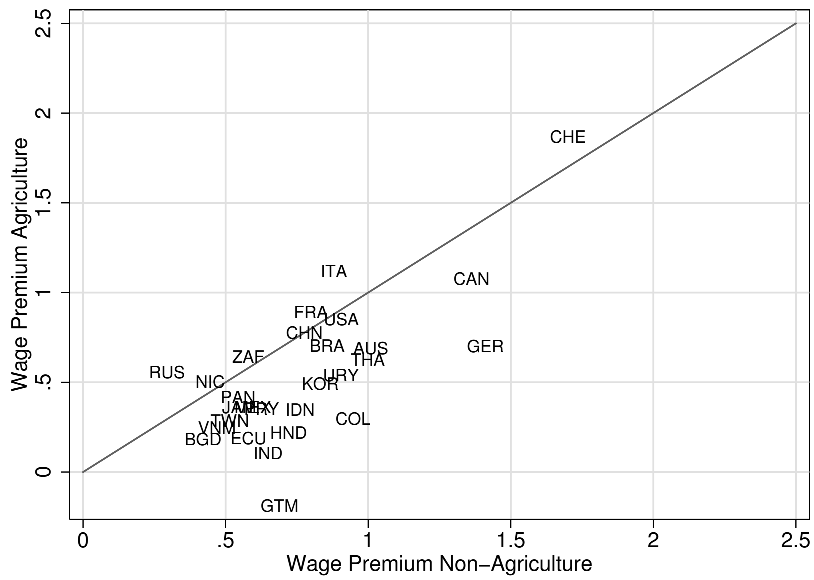
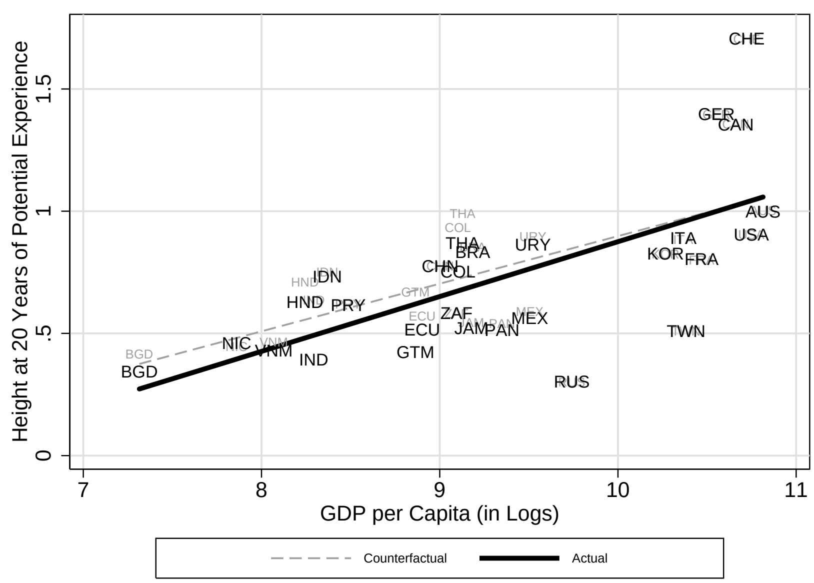


Figure 6: Returns to Experience in Agriculture and Non-Agriculture



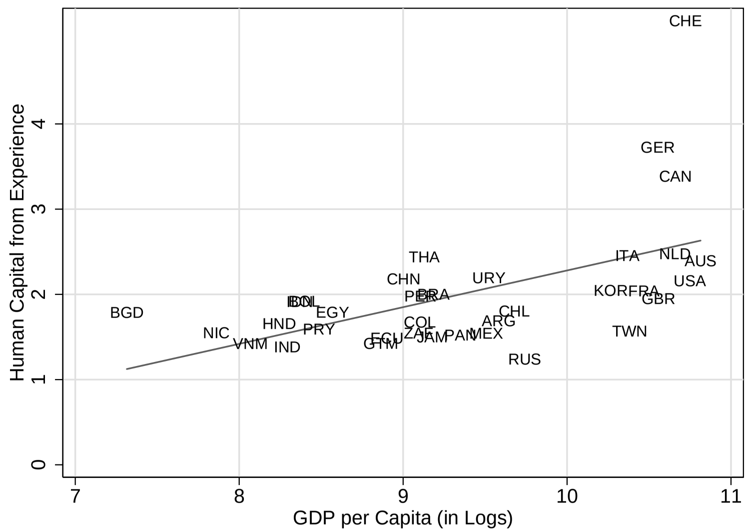
(a) Height of Profiles at 20 Years of Experience by Sector



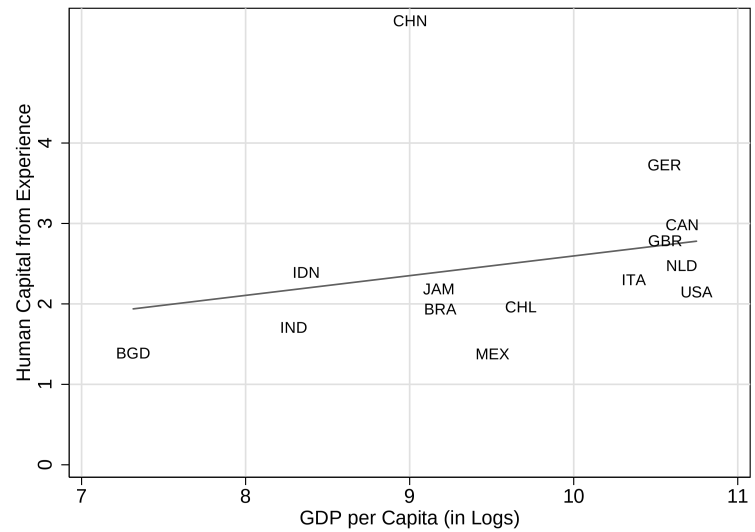
(b) Counterfactual: U.S. Employment Share in Agriculture

Figure 7: Implied Human Capital from Experience versus GDP per capita

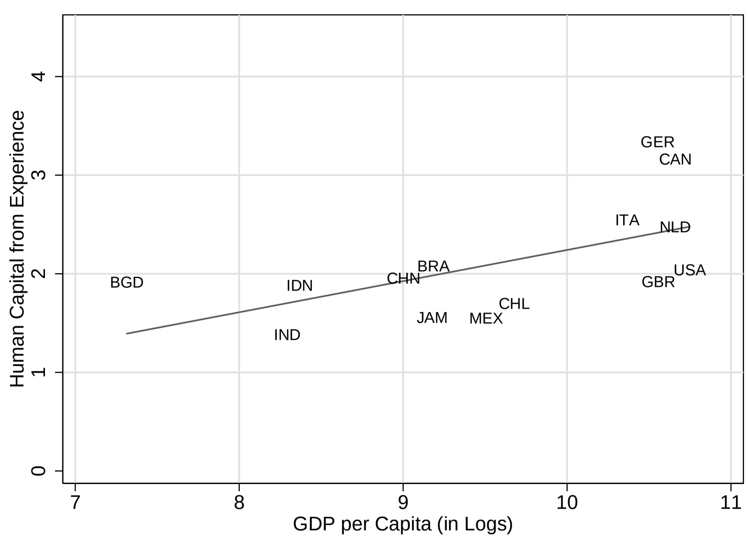
(a) Benchmark



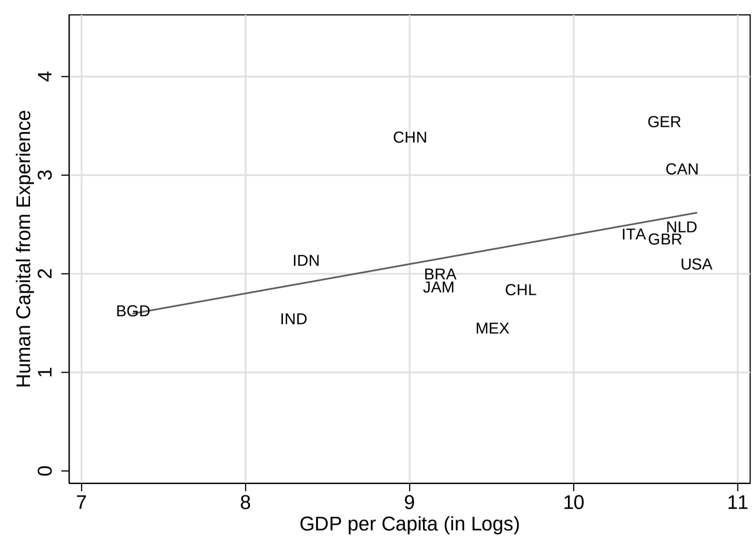
(b) Restriction 1: All Growth Due to Cohort Effects



(c) Restriction 2: All Growth Due to Time Effects



(d) Restriction 3: Half of Growth Due to Time Effects



A Online Appendix – Not for 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 et al., 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,* 1995, 2000, 2005 and 2010, 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),* 1992, 1994, 1996, 1998, 2000, 2003, 2006 and 2009, from the Chilean Ministry of Planning and Cooperation.
- China: *Urban Household Surveys* (0.01% of urban households, 27 cities), 1988 to 2005 yearly; *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, 1983, 1987, 1993, 1999 and 2004, available from IPUMS.
- Indonesia: *Family Life Survey,* National Labour Force Survey (SAKERNAS), 1988 to 1994 and 1996 to 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% 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.
- 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) and Italy, 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 et al., 2011).

A.2 Restrictions for Identification of Cohort and Time Effects

This section adds some additional structure to our conceptual framework in Section 3.1 that gives more precise interpretations to cohort and time effects, and then uses it to derive meaningful restrictions on cohort and time effects that can be used to separately identify them using the Deaton-Hall method.

A Framework for Thinking about Cohort and Time Effects. Section 3.1 motivated our main estimating equation (4) from a simple model of human capital but left unspecified the reason why the skill price ω_{ct} is cohort- and time-specific. We here provide a simple model that fills this gap and is also consistent with the development accounting exercise in Section 4. There is a representative firm with a constant returns production function

$$Y_t = F\left(K_t, Z_t \sum_{c \in C_t} X_c H_{ct}\right), \tag{22}$$

where Y_t denotes output, K_t capital, and C_t the set of cohorts working at time t. $H_{ct} = \sum_{i=1}^{N_{ct}} h_{ict}$ is the aggregate human capital of cohort c at time t and its efficiency depends on two factors: cohort-neutral efficiency Z_t, and cohort-specific efficiency X_c. This production function can be usefully written as

$$Y_t = F\left(K_t, A_t H_t\right), \tag{23}$$

where $H_t = \sum_{c \in C_t} H_{ct}$ is the aggregate human capital stock in year t and the efficiency of aggregate human capital A_t has two determinants $A_t = Z_t \bar{X}_t$ where

$$\bar{X}_t \equiv \sum_{c \in C_t} X_c \frac{H_{ct}}{H_t}. \tag{24}$$

Note that A_t is what the development accounting literature refers to as TFP. Aggregate human capital efficiency, A_t, can improve over time for two reasons: *i*) directly, due to increases in cohort-neutral human capital efficiency; and *ii*) indirectly, due to changes in the composition of cohorts active in the labor market. For example, suppose that young cohorts are more productive than old ones. Then human capital efficiency will improve over time as old cohorts exit the labor force and young cohorts enter.

From the profit maximization problem of firms, we can now derive an expression for the skill price ω_{ct} in terms of the primitives of this simple model:

$$\omega_{ct} = \frac{\partial Y_t}{\partial H_{ct}} = F_L(\kappa_t, 1) Z_t X_c, \tag{25}$$

where $\kappa_t \equiv K_t/(A_t H_t)$ is capital per units of "effective human capital". On a balanced growth path, κ_t would equal a constant. As in equation (3) this can be written as $\omega_{ct} = \bar{\omega} \exp(\gamma_t + \chi_c)$ where the cohort and time effects are given by

$$\bar{\omega} \exp(\gamma_t) \equiv F_L(\kappa_t, 1) Z_t, \quad \exp(\chi_c) \equiv X_c. \tag{26}$$

The time effect γ_t captures changes in cohort-neutral productivity Z_t and capital accumulation κ_t, and the cohort effect χ_c captures changes in cohort-specific productivity X_c.

Restrictions on Cohort and Time Effects. To impose meaningful restrictions on cohort and time effects, consider the evolution of aggregate labor productivity (or more precisely "aggregate human capital productivity")

$$\text{MPH}_t = F_L(\kappa_t, 1) A_t = F_L(\kappa_t, 1) Z_t \bar{X}_t. \tag{27}$$

First, note that on a balanced growth path, with κ_t constant, the growth rate of labor productivity MPH_t would simply equal that of aggregate labor efficiency A_t. Not surprisingly then given our discussion above, labor productivity growth can also be decomposed into a part "due to time effects", i.e. economy-wide changes affecting everyone, and a part "due to cohort effects", i.e. improvements specific to individual cohorts. To see this use (26) to write

$$\text{MPH}_t = \bar{\omega} \exp(\gamma_t + \bar{\chi}_t), \tag{28}$$

where $\bar{\chi}_t \equiv \log \bar{X}_t$. Equation (28) is the key equation we use to derive meaningful restrictions on cohort and time effects. The basic idea is to decompose the time series for MPH_t into a trend component and a cyclical component and to make assumptions on whether the trend component ("labor productivity growth") is attributed to time or to cohort effects.

In practice, this is executed in the following way. First, it is convenient to define time periods in deviations from the sample mean, i.e. such that $\frac{1}{T}\sum_{t=0}^{T} t = 0$, and similarly renormalize γ_t and $\bar{\chi}_t$ such that $\frac{1}{T}\sum_{t=0}^{T} \gamma_t = \frac{1}{T}\sum_{t=0}^{T} \bar{\chi}_t = 0$ (an appropriate choice of the constant $\bar{\omega}$ does the trick). Second, the series for γ_t and $\bar{\chi}_t$ can be decomposed into a trend component and a cyclical component

$$\gamma_t = g_\gamma t + u_{\gamma,t}, \quad \bar{\chi}_t = g_\chi t + u_{\chi,t},$$

where

$$g_\gamma = \frac{\sum_{t=0}^{T} \gamma_t t}{\sum_{t=0}^{T} t^2}, \quad g_\chi = \frac{\sum_{t=0}^{T} \bar{\chi}_t t}{\sum_{t=0}^{T} t^2}. \tag{29}$$

Intuitively, one simply runs a regression of γ_t and χ_t on time, thereby decomposing each time series into a trend component and a component that is orthogonal to the time trend. Finally, from (28), aggregate labor productivity is

$$\log \text{MPH}_t = \log \bar{\omega} + g_M t + u_{M,t},$$

where $g_M = g_\gamma + g_\chi$ and $u_{M,t} = u_{\gamma,t} + u_{\chi,t}$. The different restrictions we use are then simply different ways of splitting g_M between g_γ and g_χ. The three restrictions for which we present results in the main text are as follows.

Restriction 1: the time trend in labor productivity growth is entirely due to cohort effects:

$$g_M = g_\chi, \quad g_\gamma = 0.$$

From (29) this implies the linear restriction $\sum_{t=0}^{T} \gamma_t t = 0$, i.e. that time effects are orthogonal to a time trend and capture only cyclical variation. This is exactly the same restriction as equation (2.94) in Deaton (1997).

Restriction 2: the time trend in labor productivity growth is entirely due to year effects:

$$g_M = g_\gamma, \quad g_\chi = 0.$$

From (29) this implies the linear restriction $\sum_{t=0}^{T} \bar{\chi}_t t = 0$ or

$$\sum_{t=0}^{T} \log\left(\sum_{c\in C_t} \exp(\chi_c)\frac{H_{ct}}{H_t}\right) t = 0. \tag{30}$$

Note that the human capital stocks H_{ct} enter this restriction. Since the construction of human capital stocks requires estimating equation (4), it is necessary to use an iterative procedure.

Restriction 3: a share θ of the time trend in labor productivity growth is due to year effects:

$$g_\gamma = \theta g_M, \quad g_\chi = (1-\theta)g_M.$$

From (29), this implies the linear restriction

$$\theta\sum_{t=0}^{T} \bar{\chi}_t t = (1-\theta)\sum_{t=0}^{T} \gamma_t t. \tag{31}$$

It can be seen that restrictions 1 and 2 are the special cases $\theta = 0$ and $\theta = 1$. In the main text, we represent results for the case $\theta = 1/2$.

A.3 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 measurement error in age may lead to attenuation bias in our estimated returns to experience, and since this problem may affect poor countries more than rich countries, one may be concerned that our cross-country finding is due to measurement error in age data.

To investigate this further, we construct an auxiliary dataset for the United States in which 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 A.5a in the Online Appendix presents the results. As the figure shows, 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 ninety percent 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.

A.4 Measurement Error in Years of Schooling

For most countries, direct measures of the years that individuals spent in school are not available. We therefore rely on educational attainment data (e.g., "some secondary school" and "secondary school completed") in order to construct the "years of schooling" variable. Moreover, the coarseness of the educational attainment categories differs across countries. One might be concerned, therefore, that mis-measurement of years of schooling (and hence potential experience) may be driving our results.

To investigate this possibility further we create two auxiliary schooling variables for the United States and use them to re-estimate the U.S. experience-wage profile. The first auxiliary variable imputes schooling years using only information on degree attainment, such as primary school completion, secondary school completion, and so forth. This is similar to what we observe in some of the developing countries in our sample. The second auxiliary variable classifies secondary school graduates or higher as having twelve years of schooling and all others as having no schooling. This is meant to see how important an extreme amount of measurement error in schooling years may be.Figure A.5b in the Online Appendix shows that the actual and auxiliary profiles for the United States, and the actual profile of India as a frame of reference. While the actual and auxiliary U.S. profiles certainly differ, the differences are modest compared to the differences between the U.S. profile and that of India. In addition, the noisy education measures make the profiles modestly steeper, not flatter. We conclude that our finding of flatter experience-wage profiles in poorer countries is unlikely to be driven by mismeasured years of schooling.

A.5 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.

A.6 Ben-Porath Model of Human Capital Accumulation

To measure human capital stocks through the lens of the Ben Porath model of Section 5.3, we proceed as follows. Given $h(0) = 1$, the human capital at experience level x is

$$\log h(x) = \int_0^x \phi(\ell(s))ds. \tag{32}$$

Since $w = \bar{\omega}(1-\ell)h\exp(\varepsilon)$, the wage regression is

$$\log w = \log(\bar{\omega}(1-\ell(0))) + \log\left(\frac{1-\ell(x)}{1-\ell(0)}\right) + \int_0^x \phi(\ell(s))ds + \varepsilon. \tag{33}$$

As mentioned above, we assume that the technology ϕ is known and the same across all countries, and that all cross-country variation in investment decisions is driven by the wedge $\tau(t)$. The time allocation, $\ell(x)$, can then be identified as follows. First, we have an experience-wage profile $f(x)$ from the data, and we know that:

$$f(x) = \log\left(\frac{1-\ell(x)}{1-\ell(0)}\right) + \int_0^x \phi(\ell(s))ds. \tag{34}$$

Differentiating,

$$f'(x) = -\frac{\ell'(x)}{1-\ell(x)} + \phi(\ell(x)) \Leftrightarrow \tag{35}$$

$$\ell'(x) = \left[\phi(\ell(x)) - f'(x)\right](1-\ell(x)).$$

In any Ben-Porath model, it will be true that just before retirement at $x = T$, people do not invest in human capital: $\ell(T) = 0$. So given functions $f(x)$ and $\phi(\ell)$, this is a simple differential equation in $\ell(x)$ with a terminal condition at $\ell(T) = 0$. It can be solved very efficiently with a finite difference method.

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, 2000-2010	41
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
United Kingdom	1992-2009	18
United States	1960, 1970, 1980, 1990, 2000, 2005	46

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

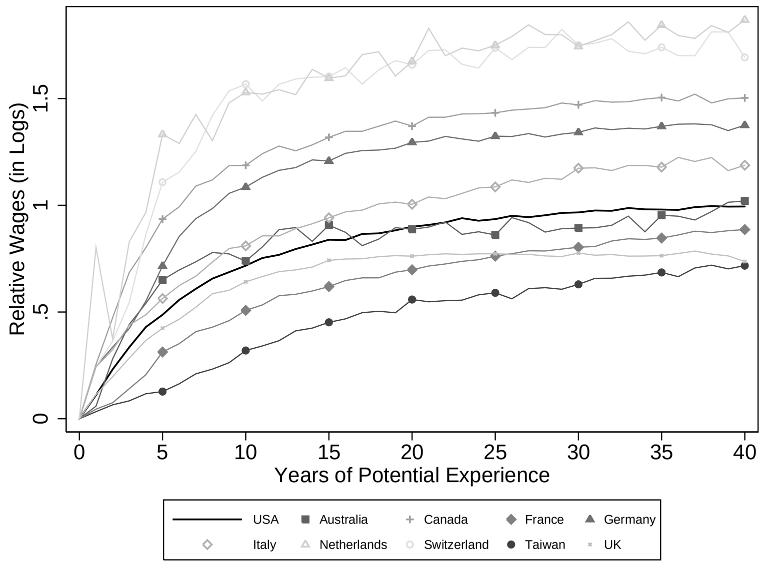
	(1) Benchmark	(2) Country-specific Returns	(3) Country-specific Levels
	(a) Human Capital Stocks from Experience		
Slope(log(H),log(GDP))	0.21***	0.20***	0.03***
	(b) Human Capital Stocks from Education		
Slope(log(H),log(GDP))	0.15**	-0.03	0.19***

Notes: The table reports the coefficient of the bivariate regression between the log of human capital and the log of 2010 GDP per capita at PPP. The sample for the benchmark includes all 35 countries. *,** and *** denote statistical significance at the 10%, 5% and 1% levels.

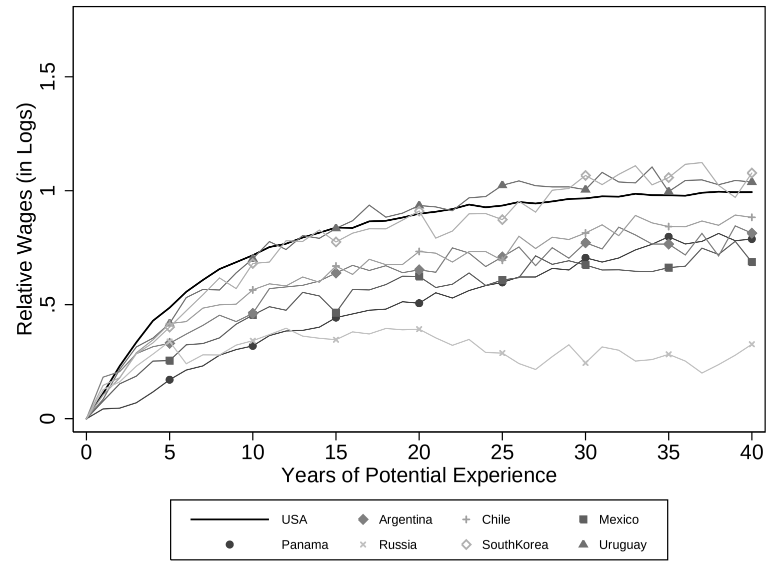
Table A.3: Aggregate Human Capital and Development Accounting

	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
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Argentina	0.76	0.78	0.58	0.45	0.39	0.74	0.88
Australia	0.81	1.11	0.89	0.81	0.95	0.95	0.89
Bangladesh	0.39	0.83	0.32	0.11	0.05	0.56	0.64
Bolivia	0.99	0.89	0.84	0.12	0.06	0.31	0.34
Brazil	0.78	0.93	0.70	0.33	0.31	0.57	0.62
Canada	0.82	1.57	1.26	0.79	0.98	0.91	0.68
Chile	0.86	0.84	0.70	0.41	0.29	0.67	0.78
China	0.99	1.01	0.98	0.09	0.06	0.22	0.22
Colombia	0.61	0.78	0.46	0.21	0.12	0.59	0.72
Ecuador	0.47	0.69	0.32	0.22	0.20	0.62	0.81
Egypt	0.48	0.83	0.39	0.22	0.06	0.90	1.03
France	0.58	0.95	0.54	0.79	1.08	1.10	1.16
Germany	0.71	1.73	1.21	0.75			
Guatemala	0.66	0.66	0.42	0.23	0.09	0.70	0.93
Honduras	0.75	0.77	0.56	0.12	0.08	0.34	0.41
India	0.56	0.64	0.34	0.09	0.04	0.39	0.54
Indonesia	0.71	0.89	0.61	0.17	0.11	0.45	0.50
Italy	0.63	1.14	0.70	0.89	1.11	1.17	1.09
Jamaica	0.88	0.70	0.60	0.13	0.14	0.28	0.36
Korea, Rep.	1.00	0.95	0.91	0.60	0.78	0.65	0.69
Mexico	0.63	0.71	0.44	0.37	0.35	0.72	0.92
Netherlands	0.93	2.26	2.05	0.80	0.98	0.85	0.50
Nicaragua	0.44	0.72	0.31	0.10	0.08	0.40	0.51
Panama	0.60	0.71	0.41	0.27	0.25	0.60	0.77
Paraguay	0.86	0.74	0.61	0.21	0.11	0.49	0.61
Peru	1.06	0.92	0.94	0.18	0.18	0.30	0.33
Russia	0.78	0.58	0.44	0.25			
SouthAfrica	1.59	0.72	1.09	0.38	0.22	0.46	0.60
Switzerland	1.02	2.41	2.49	0.77	1.27	0.70	0.39
Taiwan	0.88	0.73	0.62	0.62	0.44	0.89	1.13
Thailand	1.50	1.13	1.53	0.23	0.30	0.27	0.26
United Kingdom	1.18	0.90	1.05	0.71	0.70	0.71	0.77
United States	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Uruguay	0.48	1.02	0.48	0.36	0.24	0.96	0.96
Vietnam	0.40	0.66	0.26	0.06			

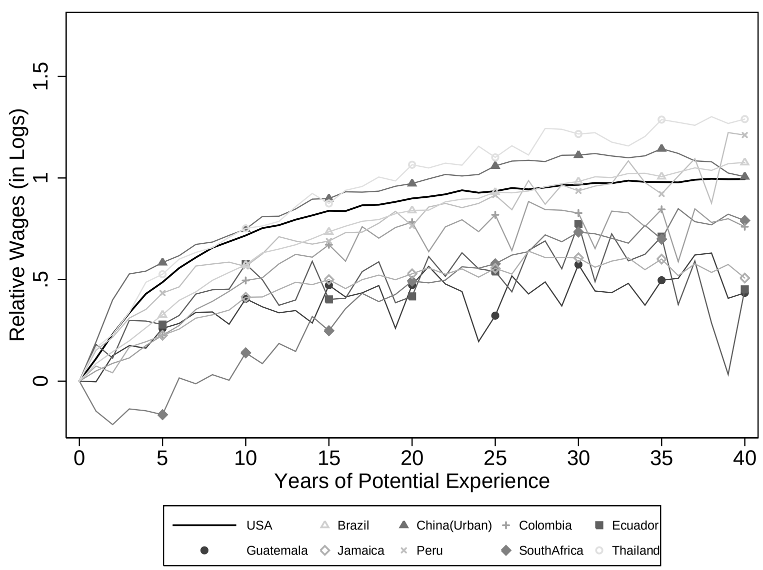
Figure A.1: Fully Flexible Experience-Wage Profiles by GDP-per-capita Quartile



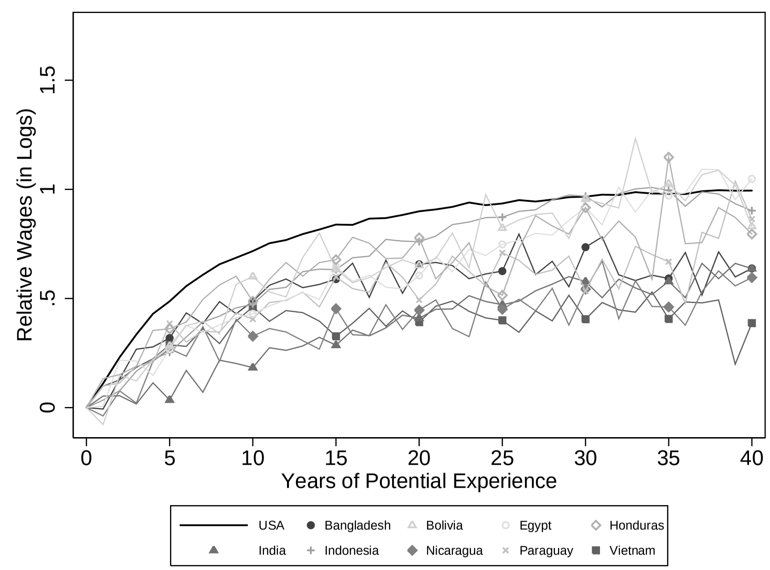
(a) Top Quartile



(b) Second Quartile



(c) Third Quartile



(d) Poorest Quartile

Figure A.2: Fully Flexible Experience-Wage Profiles with Confidence Intervals

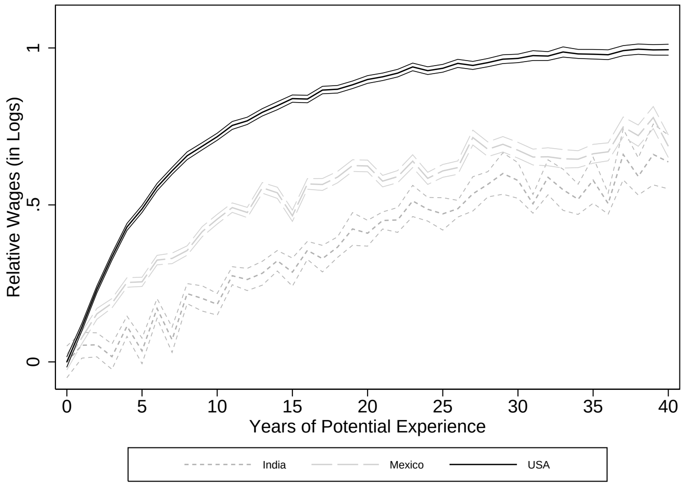


Figure A.3: Fraction of Individuals with Positive Wages by Age

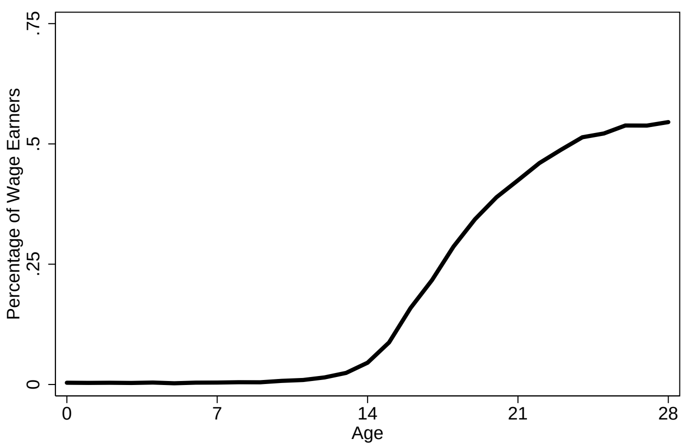


Figure A.4: Returns to Experience Including the Self-Employed

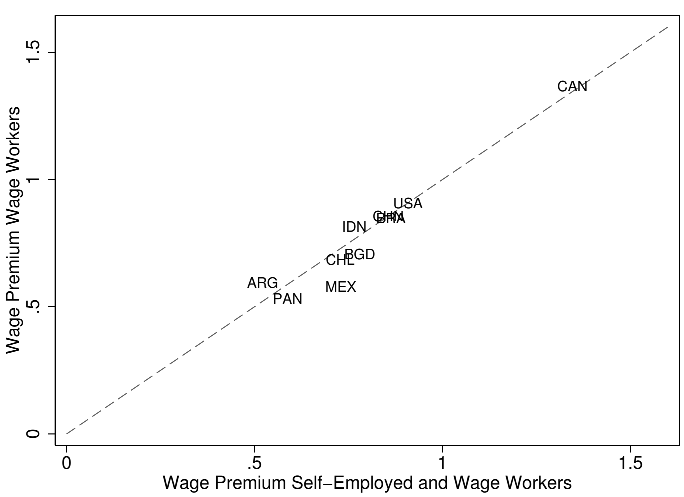
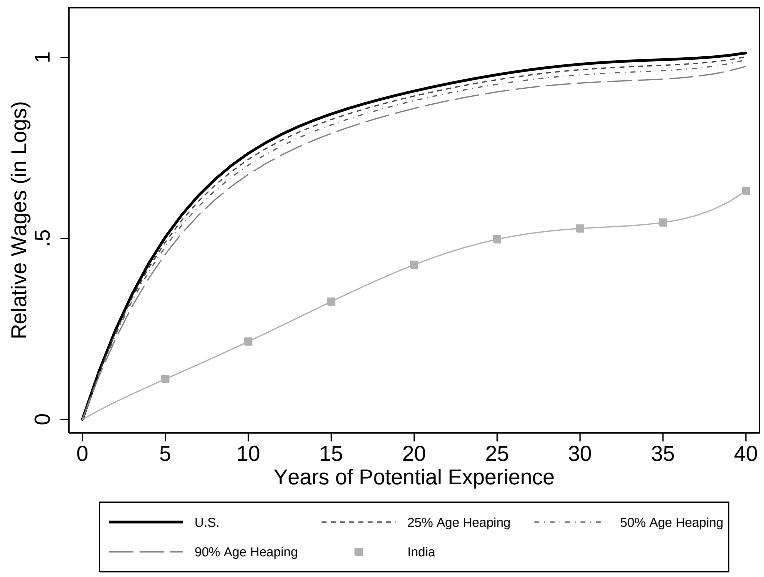


Figure A.5: Robustness to Measurement of Age and Education

(a) Adjusted for Age Heaping



(b) Adjusted for Differences in Education Reporting

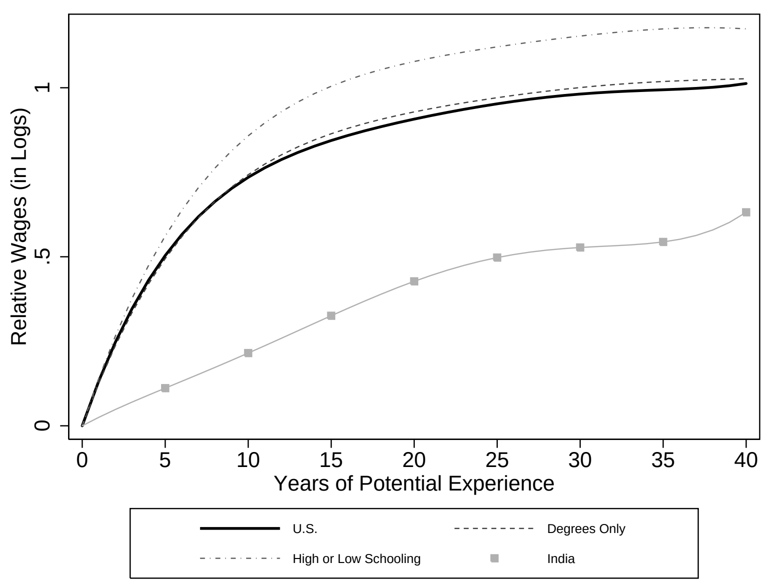


Figure A.6: Deaton-Hall Estimates for China: All Growth Due to Cohort Effects

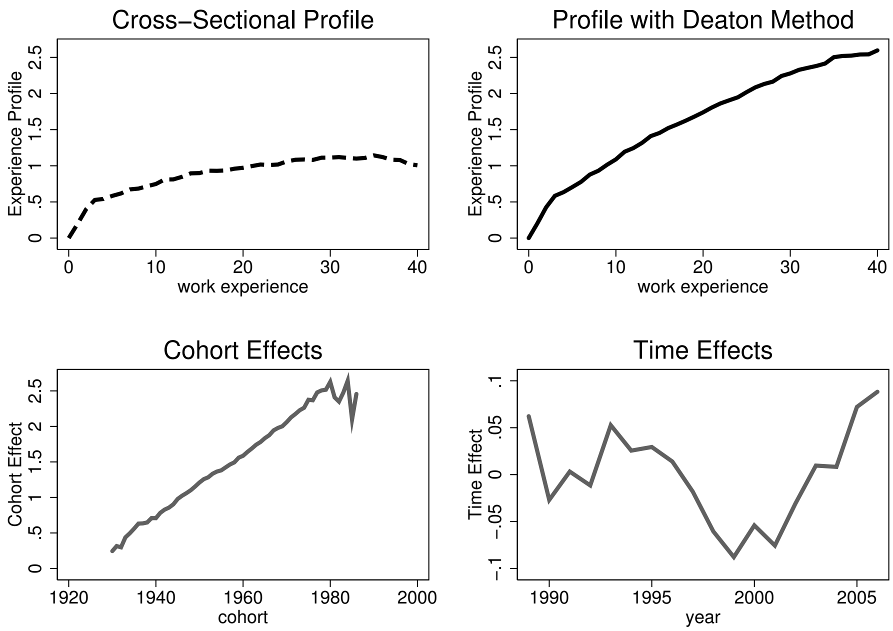


Figure A.7: Deaton-Hall Estimates for China: All Growth Due to Time Effects

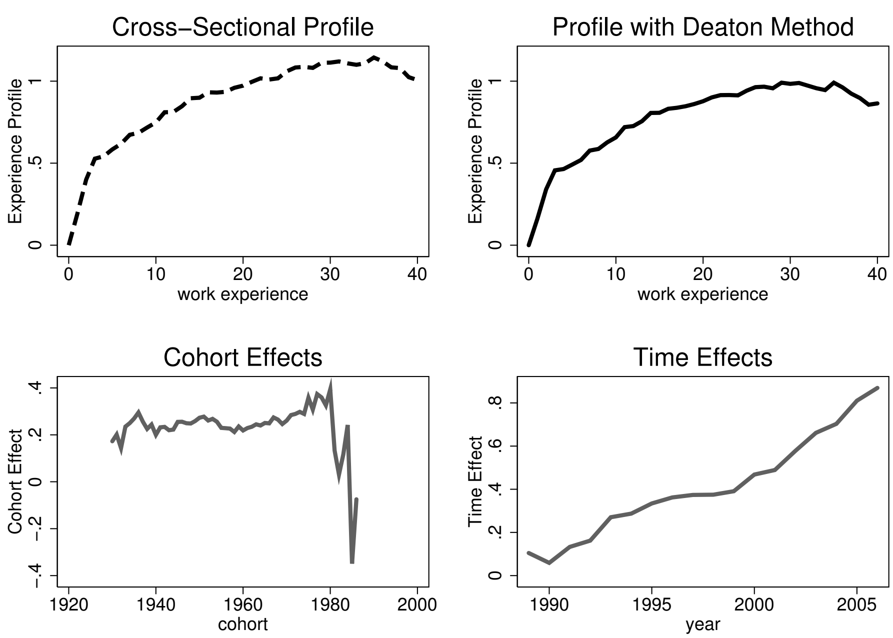


Figure A.8: Estimated Returns to Schooling versus GDP per capita

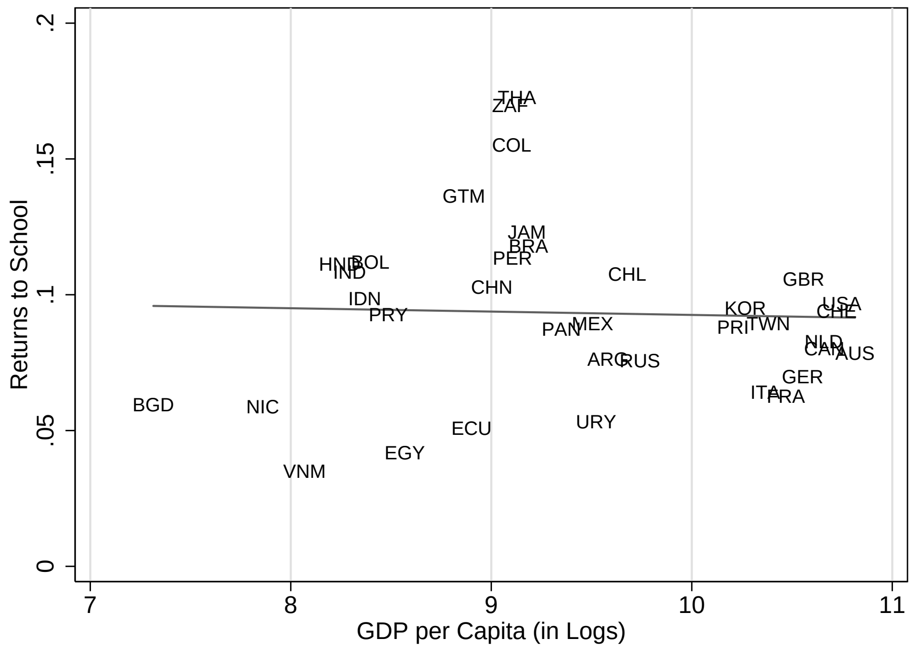


Figure A.9: Average Experience versus GDP per capita

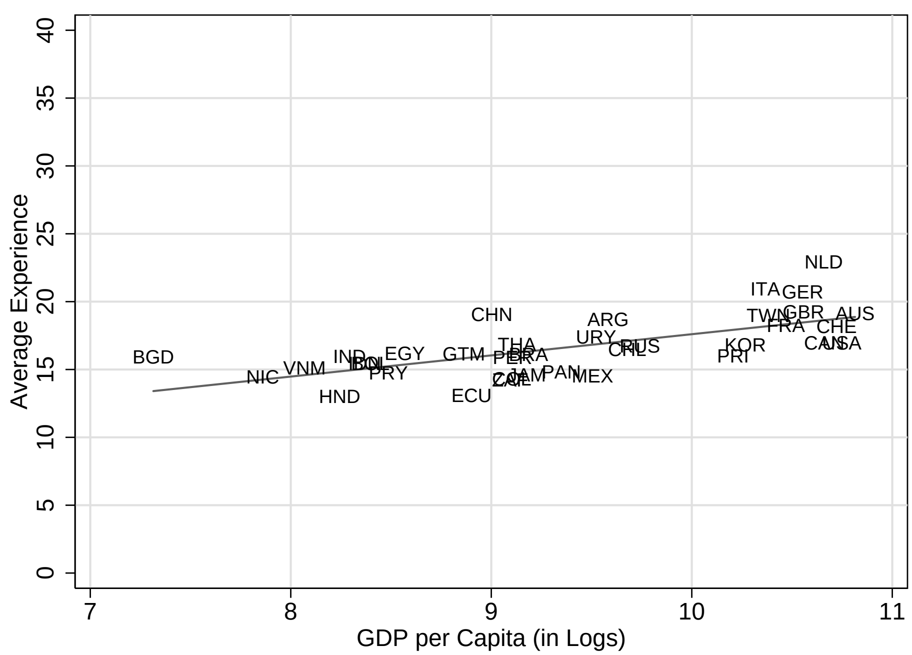
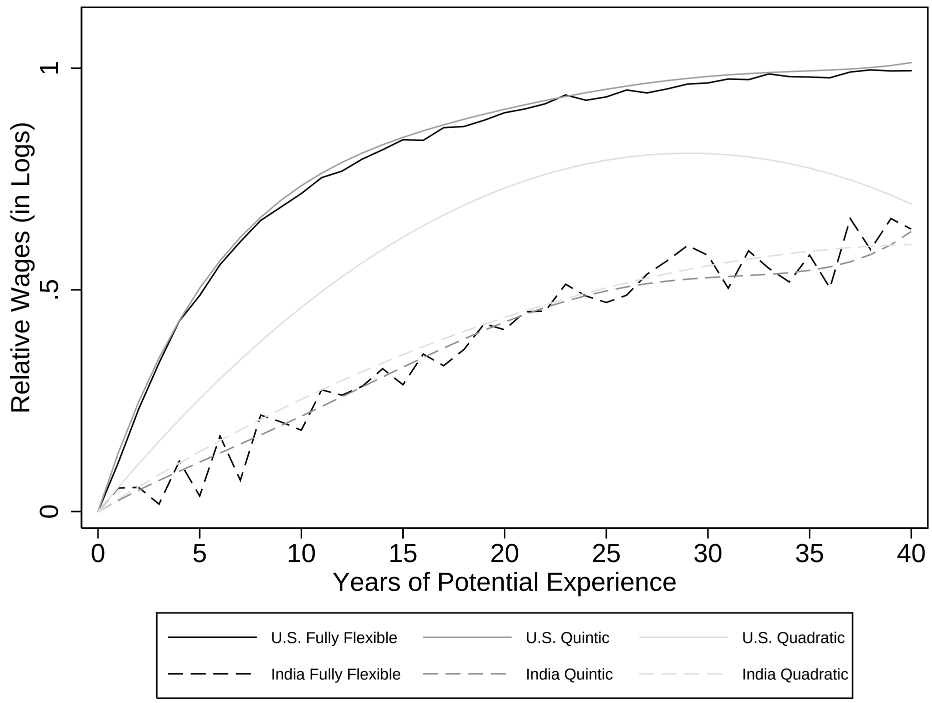


Figure A.10: Quadratic Experience-Wage Profiles, Cross-Sectional Estimates

(a) Experience-Wage Profiles for Select Countries



(b) Height of Profiles at 20 Years of Experience versus GDP per capita

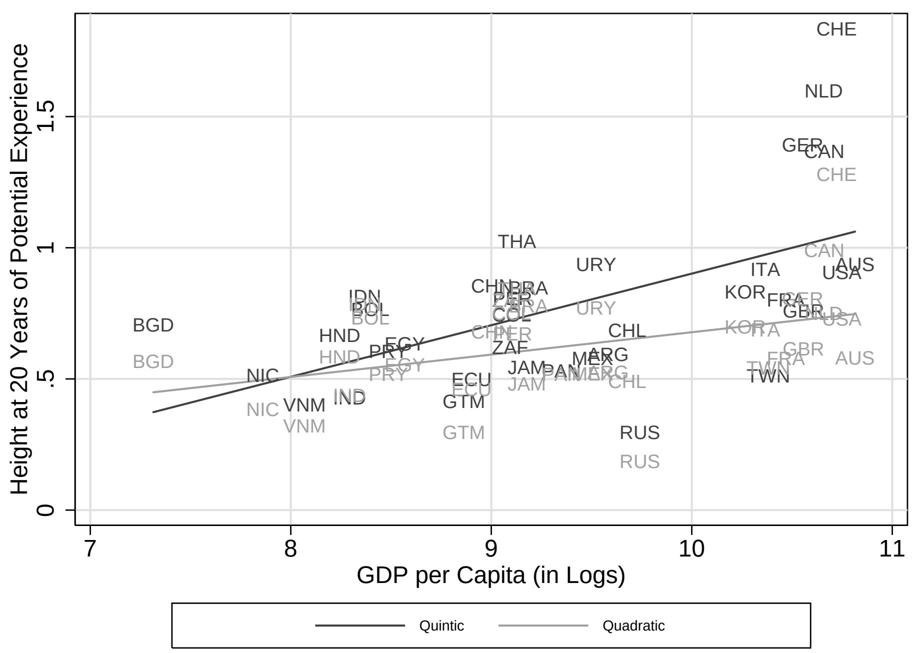
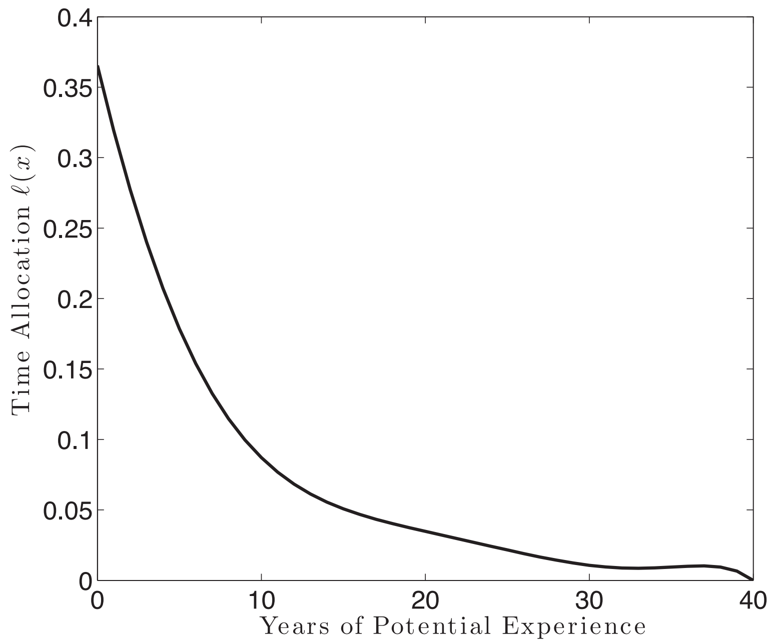


Figure A.11: Wages, Human Capital and Investment in Ben-Porath Model

(a) Profile of Investment



(b) Profiles of Wages and Human Capital

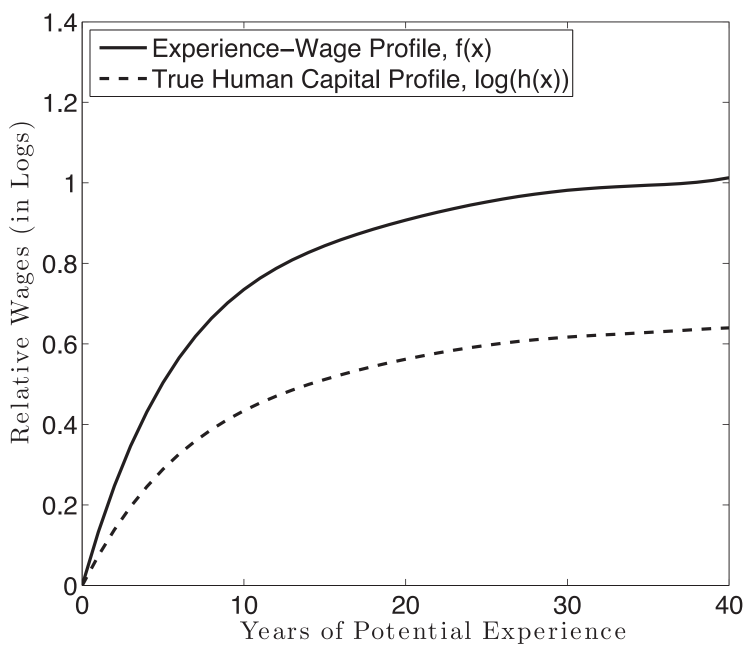


Figure A.12: Height of Experience-*Earnings* Profiles versus GDP per capita

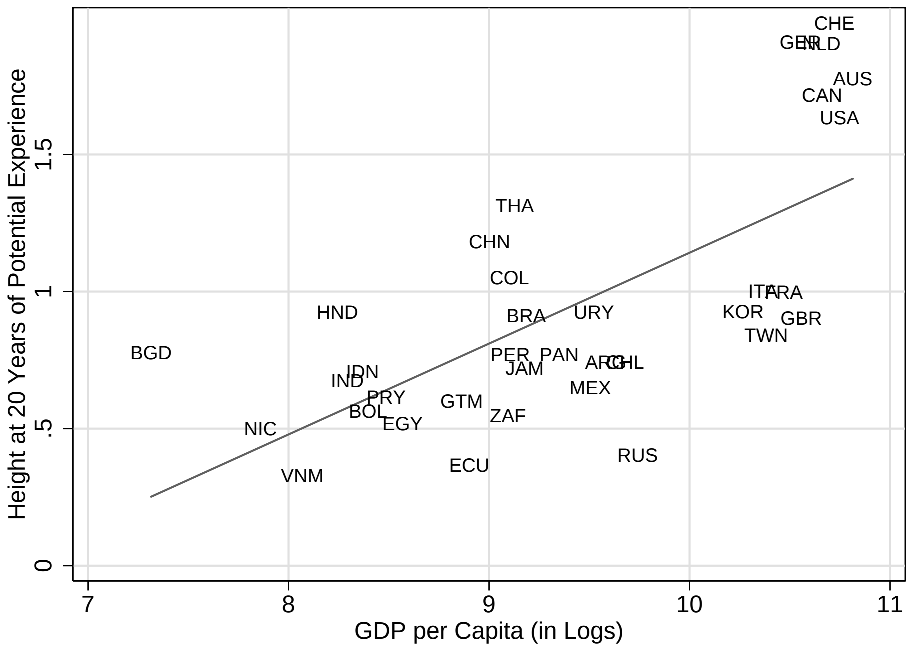


Figure A.13: Height of *Age*-Wage Profiles versus GDP per capita