Experience Matters:

Human Capital and Development Accounting*

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Abstract

Using recently available large-sample micro data from 36 countries, we document that experience-earnings profiles are flatter in poor countries than in rich countries. Motivated by this fact, we conduct a development accounting exercise that allows the returns to experience to vary across countries but is otherwise standard. When the country-specific returns to experience are interpreted in such a development accounting framework – and are therefore accounted for as part of human capital – we find that human and physical capital differences can account for almost two thirds of the variation in cross-country income differences, as compared to less than half in previous studies.

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1 Introduction

Understanding the determinants of cross-country income differences is one of the central aims of development and growth economics. An important first step in addressing this difficult question is to assess what fraction of these income differences are due to observable factors of production, namely physical and human capital. One of the main challenges in such development accounting exercises is the measurement of human capital stocks. Klenow and Rodriguez-Clare (1997) and Hall and Jones (1999) first addressed this difficulty by constructing human capital stocks from country-level measures of educational attainment. This was further refined by studies that accounted for additional aspects of human capital, such as schooling quality (Barro and Lee, 2001; Hanushek and Kimko, 2000; Hendricks, 2002; Schoellman, 2012), experience (Klenow and Rodriguez-Clare, 1997), and health (Weil, 2007; Shastry and Weil, 2003).[1] However, even with the most expansive definitions of human capital, human and physical capital together account for less than half of the variation in cross-country income differences (see for example, Caselli, 2005; Hsieh and Klenow, 2010). In other words, more than half of the variation in cross-country income differences is accounted for by the residual total factor productivity (TFP).

In this study, we document a new fact: experience-earnings profiles are flatter in poor countries than in rich countries. Then, motivated by this fact, we conduct a development accounting exercise that allows the return to experience to vary across countries but is otherwise standard. The accounting exercise implies that cross-country differences in human capital due to experience are much larger than previously thought, and that human and physical capital differences account for almost two thirds of the variation in income across countries, compared to less than half in earlier studies.

Our study proceeds in three steps. The first step is to collect recently available large-sample micro data for 36 countries. These data, which comprise over 200 household surveys, provide several important benefits. First, the large sample sizes – at least five thousand but often many more individuals per survey – allow us to estimate the returns to experience with minimal restrictions

[1] Barro and Lee (2001) construct quality of schooling measures by using student-teacher ratios and government spending on education. Hanushek and Kimko (2000) measure quality with test scores. Weil (2007) and Shastry and Weil (2003) account for health using data on adult mortality rates. Bils and Klenow (2000) also construct human capital stocks taking into account the levels of both schooling and experience, though with substantially less detailed data than in the current study. Hendricks (2002) and Schoellman (2012) both use returns to schooling for immigrants to the United States to estimate country differences in schooling quality.

on functional form. Second, the comparable sampling frames across countries provide substantial scope for making international comparisons. Finally, the availability of multiple surveys for most countries allows to control (to some extent) for cohort effects or time effects in our estimates, and check that the cross-sectional estimates of the experience-earnings profiles are not driven by spurious factors correlated with time such as aggregate growth, or those correlated with cohorts, such as improvements in health.

The second step is to document the returns to experience for each country. Absent theoretical predictions about the functional form of experience-earnings profiles, we begin our empirical analysis by allowing the returns to experience to vary fully flexibly for each additional year of experience. These fully flexible estimates show that experience-earnings profiles in poor countries are typically flatter than those in rich countries.[2] Our finding that experience-earnings profiles are flatter in poorer countries than richer countries is robust to a number of alternative specifications and sample restrictions. For example, profiles still appear flatter in poor countries when we control for either time or cohort effects, restrict the sample in a variety of ways, or use alternative definitions of potential experience.

The third step is to interpret our findings in a development accounting exercise. While there are potentially other frameworks in which our findings can be important, development accounting is a natural application for illustrating the economic significance of the fact we document. The reason is that, under the standard assumptions of development accounting, flatter experience-earnings profiles in poor countries imply that workers have less human capital from experience in poor countries.[3] We calculate the part of human capital due to experience and show that this is positively correlated with income, and similar in magnitude to the human capital due to schooling on average. Putting these together we find that the contribution of physical and human capital in accounting for cross-country income differences increases from less than one-half to almost two-thirds.

While it is beyond the scope of this paper to explain conclusively why experience-earnings

[2] We also find that the estimated experience-earnings profiles are highly nonlinear is important because it means that the commonly used linear-quadratic Mincerian specification cannot accurately measure true experience-earnings profiles. Instead, we find that a quintic specification is needed to provide an accurate approximation to the fully flexible specification. The need of higher order polynomials is consistent with the findings of Murphy and Welch (1990), who argue that at least a quartic specification is needed to match age-earnings profiles in the United States.

[3] The standard assumptions of development accounting are that workers earn their marginal products and supply their entire human capital to the labor market, and that human capital is valued in efficiency units. We discuss departures from these assumptions in section 4.5.

profiles are flatter in poor countries than rich countries, we nonetheless explore several potential explanations for the facts we document. We examine whether our findings can be explained by cross-country differences in the composition of workers in terms of sectors of work or educational level. We find that such composition effects explain a relatively small fraction of the cross-country differences in the steepness of experience-earnings profiles. In light of this, we discuss some existing theories that can potentially shed light on the causes of our findings. In particular, we note that the finding that experience-earnings profiles are flatter in poorer countries is consistent with a class of theories in which TFP and experience human capital accumulation are complementary, in the sense that low TFP in poor countries depresses the incentives to accumulate human capital. Two prominent examples from this literature are the work of Erosa et al. (2010) and Manuelli and Seshadri (2010).

Perhaps the most important limitation of our study is that our data cover only 36 countries, and represent much but far from all of the world's population. The countries in our sample represent 68% the world's population and range between the 1st (United States) and 83rd percentile (Bangladesh) of the world income distribution. Notably, we exclude most of the very poorest countries in the world, such as those in Sub-Saharan Africa.[4] In addition, our results cover wage earners but not the self-employed, who we exclude for measurement reasons, as we discuss below.

Our study adds directly to the existing literature on development accounting discussed at the beginning of the introduction. One conceptual difference between our study and the previous literature is the following. 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. Another important difference between our study and the existing literature is that we collect large-sample micro data to estimate country-specific experience-earnings profiles. Lacking such data, past studies have typically relied on secondary estimates from small and often non-representative samples. Also related to this is our ability to fully take into account the non-linearity of experience-earnings

[4]The richest country in our sample is the United States and the poorest is Bangladesh. The percentile rankings are based on per capita income reported by the World Development Indicators for 2005-11.

profiles, whereas past studies have relied on Mincer-quadratic estimates of returns to experience obtained from other studies.[5]

Our study is most closely related to Klenow and Rodriguez-Clare (1997) and Bils and Klenow (2000). These two studies allow the *levels* of – but not the *returns* to – experience to vary across countries and find that this has little effect on estimated human capital stocks of poor countries relative to rich ones.[6] Our study complements these studies by allowing both the levels of and the *returns* to experience to vary across countries, finding that the latter significantly increases cross-country gaps in human capital stocks. Our results complement the work of Mankiw et al. (1992), Erosa et al. (2010), Manuelli and Seshadri (2010), Jones (2011) and Gennaioli et al. (2011), each of which emphasize the importance of human capital for explaining cross-country differences.[7]

While development accounting motivates our study, we acknowledge that there are potentially many other interpretations of our estimates of country-specific experience-earnings profiles, which are beyond the scope of this study to comprehensively discuss. In the context of the literature beyond development accounting, the empirical patterns that we document should be interpreted as new facts that may be helpful for guiding future theories of cross-country differences in economic performance. In this sense, our study is similar in spirit to some recent studies that document productivity patterns across countries with survey data. For example, Hsieh and Klenow (2009) document differences in the distributions of revenue productivity and firm sizes between China, India and the United States. Hsieh and Klenow (2011) refine the analysis by documenting differences in productivity over the life-cycle of firms between Mexico, India and the United States. Similarly, Bloom and Reenen (2007) and Bloom et al. (2010) document cross-country differences in managerial

[5]For example, studies such as Bils and Klenow (1998) use estimates obtained by Psacharopoulos (1994) and Krueger and Pischke (1992), which often use non-representative and small samples of data and estimate the returns to experience with a Mincer-quadratic functional form.

[6]This is due to the fact that the positive effect of longer life expectancy and later retirement on the levels of experience in rich countries is offset by the negative effect of more years of schooling on the level of experience (e.g, higher schooling means that workers enter the labor force later in life).

[7]The specific mechanisms differ across studies. Mankiw et al. (1992) proxy for human capital with educational attainment and do not take into account human capital from experience. Schoellman (2012) estimates that schooling quality is lower in poor countries than rich countries using returns to schooling for immigrants to the United States, and finds that after schooling quality is accounted for, human capital differences are twice as large as standard estimates constructed with country-specific returns to schooling. Jones (2011) points out that one critical assumption of traditional development accounting is that different skill types are perfect substitutes in production and argues that relaxing this assumption can substantially amplify the role of human capital in accounting for cross-country income differences (and even close the entire income gap between rich and poor countries if high and low skill types are sufficiently complementary). Manuelli and Seshadri (2010) and Erosa et al. (2010) use Ben-Porath style models to back out the implied quality differences in human capital across countries, and argue that these differences are quantitatively substantial.

practices and productivity.

This paper is organized as follows. Section 2 describes the data and sample of countries. Section 3 documents our new fact, namely that experience-earnings profiles are flatter in poor countries than rich countries. Section 4 conducts a development accounting exercise which incorporates differences in returns to experience across countries. Section 5 examines several potential reasons why experience profiles are flatter in poor countries. Section 6 offers concluding remarks.

2 Data

Our analysis uses large-sample household survey data from a set of 36 countries. The surveys we employ satisfy two basic criteria: (i) they are nationally representative or representative of urban areas; and (ii) they contain data on labor income for at least five thousand individuals. We make use of multiple surveys for each country whenever data are available. The final sample comprises of 203 surveys spanning the years 1960 to 2011. The complete list of countries and data sources are listed in the Data Appendix.[8]

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

The main analysis uses individual-level data on age, years of schooling, labor income and the number of hours worked. We restrict attention to individuals with zero to 45 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. In the majority of surveys, we measure labor income as monthly wages or salaries from both primary and secondary jobs. Similarly, in the majority of surveys, we measure hours as the actual hours worked at both primary and secondary jobs. The Data Appendix provides details for each country.

We also restrict attention to workers that are wage earners, as opposed to self employed. We do

[8]We attempted to obtain data for every country in the world with a population greater than one million people.

so for three main reasons. First, conceptually, the income of the self employed consists of a payment to labor and a payment to capital, and in our data (as in most other data) it is hard to distinguish them (Gollin, 2002). Second, self-employed income often accrues in practice to the household, not the individual, making it hard to know how to treat self-employed income reported at the individual level. Third, self-employed individuals tend to under-report their income when asked directly, and often report revenues instead of income (Deaton, 1997).

We define experience as "potential experience" such that *experience = age – schooling – 6* for all individuals with eight or more years of schooling, and *experience = age – 14* for individuals with fewer than eight years of schooling.[9] 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 14 in our countries; see Figure A.4.[10]

We define an individual's wage to be her labor income divided by the reported number of hours that she worked. The majority of our surveys report the number of hours worked over the past week or some recent reference week. In the few countries without these 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.

For most countries, we have surveys for two or more years. For these countries, we can control for cohort effects or year effects in our estimates. For Argentina and China our data are representative of the urban population, and for all the remaining countries our data are nationally representative.

3 Returns to Experience Across Countries

3.1 Conceptual Framework

A simple model of human capital, similar to the one proposed by Bils and Klenow (1998), motivates the empirical estimation. Human capital of individual i, who is a member of cohort c at

[9] Note that a large literature in labor economics using U.S. data has examined experience-earnings profiles and the extent to which they reflect human capital accumulation over the lifecycle as opposed to other factors such as job shopping or job seniority. Consistent with our focus on potential experience, studies such as Altonji et al. (2009) find that human capital accounts for most of the growth of earnings over a career and that job seniority and job mobility play decidedly smaller roles. While other studies such as Topel and Ward (1992) and Bagger et al. (2011) have argued that the contribution of job search is somewhat larger than that postulated by Altonji et al. (2009), they all agree that human capital accumulation is the most important source of wage growth at least in the early phase of workers' careers, which is also the phase that cross-country differences in returns to experience that we document are most pronounced.

[10] Later in Section 3.4 we show that our results are robust to alternative definitions of potential experience.

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 define human capital to be only the part of earnings due to schooling or experience. 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. This assumption will allow us to identify individual human capital stocks directly from individual wages.[11] 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:[12]

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

Substituting (1) and (3) into (2) and taking logs, we obtain

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

The main goal of our paper is to empirically estimate the function $f(\cdot)$ and assess how it varies across countries. Our first empirical exercise is to estimate equation (4) under the assumption that there are no cohort or time effects, $\gamma_t = \psi_c = 0$. Then, we will show that the results are robust to including cohort and time effects to the extent possible.

[11] We discuss possible departures from this assumption later in Section 4.5. We will also provide a set of weaker assumptions under which we can identify aggregate human capital stocks, but can no longer identify individual human capital. See Section B.

[12] An alternative formulation would have been to let human capital, as opposed to skill prices, depend on cohort quality: $h_{ict} = \exp(g(s_{ict}) + f(x_{ict}) + \psi_c), \omega_t = \bar{\omega} \exp(\gamma_t)$. However, with this specification, it is no longer true that the human capital stock of an individual with $s = x = 0$ is one, a normalization we imposed because it defines human capital to be that part of wages that is only due to schooling or experience.

3.2 Benchmark Results

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

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

where D_{ict}^x is a dummy variable for a worker's number of 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, $\phi_x = f(x)$. That is, the coefficient estimate corresponding to each experience level, x, identifies the experience-earnings profile evaluated at point x. We first estimate this equation without including either cohort or time effects, $\gamma_t = \psi_c = 0$.

Figure 1 presents the main finding of the paper, which is that experience-earnings profiles are flatter in poor countries than rich countries. Panel (a) displays the experience-earnings profiles for six large representative countries in our sample.[13] The steepest profile of the six is the United States, which is also the richest. Germany has the next steepest profile, followed by China, Brazil, Mexico and finally India. To more clearly see how the steepness of the profiles vary by income for all countries in our sample, Panel (b) plots the height of the estimated profiles evaluated at twenty years potential experience, which is the roughly the average experience level of most countries in our sample, against the log of GDP per capita at PPP. As can be seen from the figure, the experience-earnings profiles in poor countries are systematically flatter than those in rich countries. The correlation between the height of the profiles at 20 years and log GDP per capita is 0.61, and is significant at well below the 1% level.

Importantly, Figure 1a illustrates that the returns to experience are highly non-linear over experience levels and cannot be accurately summarized a linear-quadratic Mincerian specification, a fact that has been pointed out by Murphy and Welch (1990) for the United States. We find instead that a quintic specification can accurately and parsimoniously approximate the true experience-earnings profile.[14] This can be written as:

[13]The estimated profiles for all of the countries in our sample are displayed in Appendix Figures A.2a-A.2d. The countries are grouped according to their position on the world income distribution.

[14]This is important because it implies that past studies that relied on external estimates using a linear-quadratic

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

where the log wage of individual i of cohort c during year t is a function of the years of schooling, s_{ict}; and the years of experience, x_{ict}. This is a special case of the model presented in the previous section with $g(s) = \theta s$ and $f(x) = \sum_{k=1}^{5} \phi_k x^k$. Figure 2a plots the predicted experience-earnings profiles based on our quintic estimates. It shows that the quintic estimates closely resemble the fully flexible estimates in Figure 1a. Thus, for simplicity, we will use the quintic specification in all of our estimates henceforth.[15]

3.3 Controlling for Cohort and Time Effects

In this section, we investigate the effect of controlling for time or cohort effects. This could be important if there are many changes in aggregate conditions over time (e.g. periods of rapid economic growth) or if there are significant changes in the productivity of workers across cohorts (e.g., changes in the health of younger cohorts of workers). Given the fast economic growth of many developing economies such as China during the time-period of our study, the omission of such controls could be particularly important for poor countries.

To address the potentially influences of time or cohort effects, we estimate the returns to experience either controlling for *i*) cohort fixed effects or *ii*) time fixed effects. Since there are often large intervals of time between the waves of data for some of the countries in the sample, we construct birth-cohort categories of twenty birth-year intervals. The cohort fixed effects are therefore dummy variables that take the value of one if a worker belongs to a birth-cohort category.

In Figure 3, we plot the predicted profiles based on the estimates of equation (6) when year controls are included. There is little difference from the predicted profiles based on the cross-sectional estimates shown in Figure 2. The correlation between log GDP per capita and the profile heights at twenty years experience is 0.63, and is significant at the 1% level. The fact that we find little change over time is not altogether surprising since our data cover a relatively short time period for most countries, often less than ten years. Figure 4 plots the predicted profiles for the returns to

measure of experience could suffer from misspecification bias. We revisit this issue in Section 4.4 to follow.

[15]The correlation between the height of the profiles at 20 years of experience from the quintic specification and log GDP per capita equals 0.61 which is identical to the correlation when using the fully flexible specification. Also all of our results are robust to using the fully flexible specification in (5). They are not reported for brevity but are available upon request.

experience when birth-cohort fixed effects are included in equation (6). As the figure shows, adding cohort effects makes some differences in the estimates for particular countries, but does not change the overall result. The correlation falls slightly to 0.57 and is still significant at the 1% level.

Finally, we present the predicted profiles based on estimates controlling for time and cohort controls. Note that we are able to do this with the quintic specification because this functional form allows there to be more degrees of freedom than the fully flexible estimation.[16] The predicted experience-earnings profiles shown in Figure 5 lie broadly between those with only time effects in Figure 3 and only cohort effects in Figure 4. The correlation between the profile heights and log GDP per capita is 0.63 and significant. Also in this vein, we estimated the experience profiles using controls for both cohort and time effects using the method suggested by Deaton (1997). Our results were quite similar to those of Figure 5, so we omit them for brevity.

The estimates in this section show that our finding of flatter experience-earnings profiles in poor countries is robust to the inclusion of cohort or time controls. Of course our controls are not perfect here, as many of our countries do not have samples dating far back in time, such as the United States. Nevertheless, our available data suggest that our estimated profiles with cohort or year controls are similar to our bechmark estimates.

3.4 Alternative Sample Restrictions and Measures of Experience

In this section we show that our finding of flatter experience profiles in poor countries is present under a variety of sample restrictions and alternative measures of potential experience. For simplicity we continue to focus on the correlation between the height of the profile at twenty years of experience and the log of GDP per capita.

Table 1 shows that the correlation in the Benchmark estimates (of Section 3.2) is 0.61 and significant at the 1% level. The panel that follows presents the correlation coefficients for male workers, private-sector workers, full-time workers, male private-sector workers, male private full-time workers, and non-agricultural workers. The correlations range from 0.54 to 0.67, and are all significant at the 1% level. We conclude that our finding is robust to alternative sample restrictions.

The middle panel of Table 1 reports the correlation for alternative definitions of potential ex-

[16]In the fully flexible specification it is impossible to simultaneously control for both time and cohort effects due a well-known collinearity problem, namely that schooling, experience, year and birth year are linked through the identity $t = age_{ict} + c = s_{ict} + x_{ict} + 6 + c$. The quintic specification gets around this problem, but cohort and time effects are then identified off functional form.

perience. The first of these assumes that all workers begin work at age 6 if not in school, and hence sets *experience = age - schooling – 6.* The next three take the same definition of potential experience but restrict the sample to males, private-sector males and full-time private-sector males. The last assumes that all workers begin work no earlier than age 15, and hence sets *experience = age – schooling – 6* for all individuals with nine or more years of schooling, and *experience = age – 15* for other workers. The correlations range from 0.46 to 0.56 when experience is assumed to start accruing at age 6, and is 0.67 when experience begins only at age 15. In all cases the correlations are statistically significant at below the 1% level. Thus, our finding is robust to plausible alternative definitions of potential experience.

The last panel of Table 1 makes alternative assumptions about how returns to school are measured. In the first, we estimate the returns to experience under the restriction that returns to schooling satisfy the non-linear function used by Hall and Jones (1999). In the second, we estimate the returns to experience restricting the returns to schooling to be a constant 10%, as in Hsieh and Klenow, 2010. In the first exercise, the correlation between the profile heights and the log of GDP per capita is 0.63 and significant; in the second, the correlation is 0.65 and significant. We conclude that our finding is not driven from our estimated returns to schooling differing from previous estimates in the literature.

3.5 Measurement Error in Reported Age

One concern is that the flatter profiles in poor countries are driven by measurment error in reported age in poor countries. In several poor countries, for example, it is apparent that age has been reported for many individuals to the nearest five years (see for example India in Figure A.2). This phenomenon has been called "age heaping" in the literature (Shryock and Siegel, 1976). To the extent that age heaping is more prevalent in poor countries than rich countries, attentuation bias could result in estimated profiles that are flatter in poor countries.

To investigate the potential quantitative effect of bias caused by heaping, we construct a new auxiliary dataset for the United States where we take the actual U.S. data and 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 6a shows that increasing the fraction of the sample to which we introduce measurement error does bias downward the profiles, but the effect is not quantitatively large. Even in the extreme case when we allow 90% of the U.S. population to mis-report their age, the profile is still far above that of India. We conclude that our results are not driven by biases induced through age-heaping.

3.6 Additional Sensitivity Tests

We also find that our results are robust to different functional forms for estimating the returns to schooling, in particular higher order polynomials, fully flexible returns to education, alternative imputation methods for hours worked in countries with no hours data. We also find that our results do not substantively change when cutting the maximum years of experience at 40, 45 or 50 years. Finally, given the large labor economics literature that studies the returns to experience using the *Current Population Survey* (CPS), we replicate our estimates with these data to check that our results for the U.S. experience earnings profiles are not driven by our choice of data. Figure 6b shows that the experience-earnings profiles estimated from Census data and from CPS data are nearly identical.

4 Aggregate Human Capital and Development Accounting

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

4.1 Human Capital from Experience

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

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

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

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

Our estimates for aggregate human capital stocks due to experience are simply the integral of estimated the experience-earnings profiles from the previous section (i.e., the area beneath the profiles), using the distribution of work experience from the data.[17]

Figures 7a-7d plot the implied human capital from experience against per capita GDP for each country during this period. For these figures, the human capital stocks from experience are calculated using the quintic specification in equation (6) and each figure corresponds to a different combination for the inclusion of cohort and year controls. These figures show clearly that there is a strong positive relationship between human capital from experience and income levels, with correlations ranging from 0.60 to 0.62 and always significant at the 1% level. The estimates of experience human capital stocks for each country that are used in the figures are reported in Table A.1 in the Appendix.

4.2 Total Human Capital Stocks Due to Both Schooling and Experience

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

$$H = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_t}\sum_{i=1}^{N_t} h_{it}. \tag{7}$$

The estimates of these human capital stocks are based on our estimated returns to schooling and experience from our quintic specification.

Table 2, panel (a), summarizes our country-specific estimates of aggregate human capital stocks and presents two measures of the cross-country dispersion of total human capital stocks. The first measure we use is the log variation in human capital stocks, and the second measure is the ratio of the human capital stock of the country at the 90th percentile in the world income distribution to that at the 10th percentile. The 90th percentile country has an experience human capital stock

[17] The distributions of work experience in our six representative countries are displayed in Figure A.2. Figure A.3 plots the average potential experience for all countries in our sample against GDP per capita. Our data show little variation in the average experience level across countries, as in the findings of Caselli (2005) and Bils and Klenow (2000).

that is 1.96 times as large as that of the 10th percentile. For the sake of comparison, we also present the difference in the human capital stock from schooling, which equals 1.86. This is the measure traditionally used by the literature. These results show that cross-country differences in human capital due to experience (as measured by the 90/10 ratio) are roughly as big as those due to schooling. When dispersion is instead measured using the log variation in column (1), it becomes somewhat larger for schooling than for experience human capital stocks, but both are of the same order of magnitude.[18]

Finally, the third row of panel (a) in Table 2 reports the dispersion of total human capital stocks, where we take into account both schooling and experience. It shows that taking into account cross-country differences in returns to experience (going from row one to three) roughly doubles the dispersion in human capital across countries. Panel (b) of Table 2 shows that these numbers change somewhat when we include cohort and year effects, but that our main finding – that allowing returns to experience to vary across countries increases cross-country human capital gaps – is robust to their inclusion. The results reported in Table 2 are constructed from the country-specific estimates reported in Appendix Tables A.1 and A.2.

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 review 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, K is its physical capital stock, A is total factor productivity and H is our measure of the human capital stock. The capital share is assumed to equal $\alpha = 1/3$.

We follow Caselli (2005) and calculate his measures, *Success-1* and *Success-2*, that are designed to measure the fraction of cross-country income differences explained by factors of production only

$$
\begin{aligned}
success_1 &= \frac{\operatorname{var}(\ln Y_{KH})}{\operatorname{var}(\ln Y)}, \\
success_2 &= \frac{Y_{KH}^{90}/Y_{KH}^{10}}{Y^{90}/Y^{10}},
\end{aligned}
$$

[18] 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 is roughly the same across countries.

where $Y_{KH} = K^{\alpha}H^{1-\alpha}$ is the component of output explained by factors of production.

Intuitively, Success-1 is the fraction of the variance of log GDP per capita that is explained by human and physical capital. Similarly, Success-2 is the fraction of 90th-to-10th percentile ratio of GDP that is explained by these factors of production.

Table 3 presents these measures of success for different measures of the aggregate human capital stocks. When human capital is identified by only schooling as in most of the literature, the two measures of success are between forty and fifty percent. Recall that in Table 2, we showed that cross-country differences in experience human capital are roughly as big as those in schooling human capital. This is reflected in Table 3: comparing the first and the second row reveals that schooling and experience human capital are roughly equally important determinants of cross-country income differences.

Finally, when both schooling and experience are taken into account as in the third row, both measures of success increase dramatically. Physical and human capital taken together now account for roughly two-thirds of the variation in cross-country income differences as compared to less than half when experience is not taken into account.

We can also conduct our development accounting exercise "country-by-country". To do this, we report a slightly modified version of "Success-2"

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

This is the fraction of the income gap between the United States and one of the poorer countries that can be explained by factors of production only. Table A.3 first reports Caselli's numbers for output and physical capital in columns (1) and (2). The estimates for Success-2 are presented in rows (3)-(7). The results indicate that taking into account cross-country differences in returns to experience when calculating aggregate human capital stocks allows one to account for a substantially larger fraction of cross-country income differences than the existing literature. Note that for some countries (e.g., Italy) and under some specifications, our estimates even modestly over-predict the GDP gap to the United States when taking experience into account. Taken literally, this implies that the estimated human capital in these countries is so low relative to the United States, that the only way of accounting for the observed income gap is for these countries to have "higher" TFP than the United States.

4.4 Comparison to Existing Accounting Exercises

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

The specification in panel (a) computes human capital stocks using a linear-quadratic Mincer specification and the average returns to schooling and experience as in Klenow and Rodriguez-Clare (1997).[19] Success1, when taking into account human capital due to both schooling and experience, is only 0.35 (panel (a), third row, third column), which is considerably less than the result of one-half that we have cited as the upper-bound from the existing literature.

Panel (b) uses the same specification, but imposes diminishing returns to schooling as in Hall and Jones (1999).[20] This is also similar to Bils and Klenow (2000). Success1 is essentially unchanged at 0.34. Panel (c) allows returns to experience to vary across countries, but retains the quadratic specification for estimating the returns to experience. This induces an increase in Success1 from 0.34 to 0.45. Panel (d) allows the returns to experience to vary across countries *and* uses the our main quintic functional form for estimating the returns to experience. This causes Success1 to further increase from 0.45 to 0.60. Panel (e) additionally allows returns to schooling to vary across countries (estimated using a linear control for the years of schooling). This produces our main results shown in Tables 2 and 3: Success1 is 0.64.

The results in Table 4 show that our finding that human and physical capital contribute to two-thirds instead of less than one-half of cross-country income differences is due to our allowing the returns to experience to vary across countries *and* the more accurate approximation of the experience-earnings profile from using of a quintic functional form. To see the importance of the flexible functional form more clearly, Figure 8 repeats our empirical exercise from section 3, but use

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

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

a linear-quadratic specification for estimating the experience-earnings profiles. It shows that the quadratic experience-earnings profiles in panel (a) provide a poor approximation to the fully flexible ones in Figure 1a. Moreover, Panel (b) plots the height of the quadratic experience-earnings profiles at twenty years of experience against countries' income levels and show only a weak relationship.

4.5 Relaxing the Assumptions of Development Accounting

In this section we explore what happens when we relax some of the assumptions of development accounting with regards to human capital. The three assumptions in question are: first, that a worker's wage equals her marginal product of capital; second, that individuals supply their entire human capital to the market; and third, that human capital is valued in efficiency units. These assumptions imply that a worker's human capital is proportional to his wages as in equation (1) and hence allow us to identify individual human capital stocks directly off individual wages.

Some alternative interpretations depart from these assumptions but still interpret cross-country differences in experience-earnings profiles as differences in human capital accumulation. That is, they postulate alternative *mappings* from earnings profiles to human capital profiles. For example, Ben-Porath (1976) type models depart from the assumption that individuals supply their entire human capital to the market. Individuals instead use some of their time for human capital accumulation, for example as on-the-job training. Therefore, upward-sloping experience-earnings profiles may reflect a declining fraction of time devoted to training.[21] Interpreted in a Ben-Porath type framework, our empirical finding that experience-earnings profiles are flatter in poor countries than in rich ones still reflects cross-country differences in human capital accumulation. But the *quantitative mapping* between the two may be quite different.[22]

An alternative class of models of human capital accumulation are learning-by-doing models. Even in this class of models, the mapping between earnings and human capital profiles may differ

[21] In these models, individuals devote a fraction ℓ_{ict} of their time endowment to human capital accumulation and the remaining $1 - \ell_{ict}$ to working. The mapping from wages to human capital (1) therefore has to be modified to include the fraction of time (and therefore human capital) supplied to the market: $w_{ict} = \omega_{ct} h_{ict}(1 - \ell_{ict}) \exp(\varepsilon_{ict})$. A rising w_{ict} may thus be due to a declining ℓ_{ict}.

[22] For example, Kuruscu (2006) argues that in a calibrated Ben-Porath model, relatively large fractions of time devoted to training have only small effects on lifetime income and human capital accumulation. Therefore, large cross-country differences in experience-earnings profiles may reflect smaller differences in human capital profiles (instead of the two being proportional as in our benchmark exercise). But the exact quantitative mapping would depend on (i) the exact type of Ben-Porath model used (for example, how the human capital production function depends on time- and non-time inputs), (ii) what exactly drives cross-country differences in time devoted to training (for example, whether these are caused by differences in human capital accumulation technologies or tax policies), and (iii) the exact functional forms and parameter values that are being used.

from the one in our benchmark exercise. For example, suppose that different employers offer different learning opportunities and that potential employees find their employers through competitive search. Then employees at firms will pay for good learning opportunities by accepting starting wages below their marginal product, again altering the quantitative mapping between human capital and wages.

One class of theories in which wages do not equal marginal products feature long term contracts between workers and their firms (as in the work of Lazear (1979)). In the presence of moral hazard or commitment frictions, firms may then "backload" wage payments to incentivize their employees thereby offering a wage profile that is steeper than their human capital profile. To the extent that frictions that result in backloading are more pronounced in poor countries, however, such theories would predict that experience-earnings profiles in poor countries should be *steeper* than those in rich countries, that is the opposite of what we find.[23][24]

We note that as long as a worker's average wages over their lifecycle equal their average productivity, then our estimates will still accurately identify the *aggregate* stock of human capital. The reason is that in such an environment, the area under the measured experience profile will be equal to the area under the profile that reflects the worker's true productivity. We prove this formally in Appendix B, and illustrate our point in a numerical example.

One class of theories of long-term contracting that does have the potential of delivering the observed cross-country differences in experience-earnings profiles has been proposed by Azariadis (1988) and Bernhardt and Timmis (1990) among others: if workers are financially constrained but have signed a long-term contract with a firm, then that firm can act as a "lender of last resort" for its workers, implicitly lending to them by offering a wage profile that is flatter than in the frictionless case. Note, however, that this is a theory of flat *tenure*-earnings rather than flat *experience*-earnings profiles because it relies on a worker staying with the same employee (see also Guiso et al., 2010). For this class of theories to generate the flat experience-earnings profiles that we document, worker turnover in poor countries would have to be considerably lower than that in the United States.

[23] Similarly, Michelacci and Quadrini (2009) postulate that financially constrained firms that sign optimal long-term contracts with workers may implictly borrow from their workers, thereby offering steeper wage profiles than in the frictionless case. To the extent that firms in poor countries are more financially constrained than in rich countries, this theory would again predict the opposite of our empirical finding.

[24] Of course, certain types of frictions may also result in less backloading. We discuss one example in the last paragraph of this section.

5 Potential Mechanisms

In this section, we explore several mechanisms for why experience-earnings profiles are flatter in poor countries than rich countries.

5.1 Composition Effects

First, we ask whether compositional differences of workers across countries are behind the flatter profiles in poor countries. This could be the case for example, if profiles are generally flatter among agricultural workers than non-agricultural workers, as documented by Herrendorf and Schoellman (2011, Figure 4b) for the United States. Compositional differences might also matter across educational groups. Several studies have shown that college graduates have steeper *age*-earnings profiles than high school graduates (Carroll and Summers, 1991, Figures 10.7a and 10.8a; Guvenen, 2007, Figure 2; Kambourov and Manovskii, 2009, Figures 3,6,8 and 10; Elsby and Shapiro, 2012, Figure 3).

Agriculture A key difference between rich and poor countries is that poor countries tend to have a much larger share of workers in agriculture than rich countries. To consider the role that this composition difference may play in our development accounting exercise, we extend our simple model in section 3.1 to allow for differences in human capital accumulation across sectors. In particular, we now allow the human capital production functions (1) to be different for agriculture (sector A) and non-agriculture (sector N). Human capital of individual i at time t in country j is now

$$h_{itj} = \exp(g_j(s_{itj}; D_{itj}) + f_j(x_{itj}; D_{itj})),$$

where $D \in \{A, N\}$ is the sector that individual i is active in at time t. As before, the functions $f_j(\cdot\ ; A)$ and $f_j(\cdot\ ; N)$ can be identified from the experience-earnings profiles for agriculture and non-agriculture, i.e. we estimate equation (4) separately for each of the two sectors. Having done so, we construct aggregate human capital from experience in sector $D \in \{A, N\}$ and country j as

$$H^X_{D,j} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{N_{Dt,j}}\sum_{i:D_{itj}=D}\exp(f_j(x_{itj}; D)), \tag{8}$$

where $N_{Dt,j}$ is the number of individuals in country j at time t that are employed in sector $D \in \{A, N\}$. Aggregate experience human capital in country j is then simply a weighted average of the sectoral experience human capital stocks

$$H_j^X = \ell_{A,j} H_{A,j}^X + (1 - \ell_{A,j}) H_{N,j}^X,$$

where $\ell_{A,j}$ is the employment share in agriculture in country j. Figure 9a shows the height of the experience earnings profile at twenty years of experience in agriculture plotted against that in non-agriculture. It can be seen that all countries except Italy and France lie below the 45 degree line; i.e., for all countries except Italy, the experience-earnings profiles in agriculture are flatter than those in non-agriculture. Thus, the finding documented by Herrendorf and Schoellman (2011, Figure 4b) for the United States also holds for most other countries in our sample.

To assess the quantitative importance of the cross-country differences in the proportions of workers engaged in agriculture in understanding why that experience earnings profiles of poor countries are flatter, we conduct the following counterfactual exercise. We ask: what would a country's experience human capital be if that country had the U.S.'s employment share in agriculture? We compute the following counterfactual experience human capital stock for each country j

$$\tilde{H}_j^X = \ell_{A,US} H_{A,j}^X + (1 - \ell_{A,US}) H_{N,j}^X.$$

If all of cross-country differences in experience human capital stocks were due to sectoral differences, then this counterfactual would eliminate all such differences. Figure 9b graphs the counterfactual human capital stocks (those using U.S. agricultural employment shares) against the actual human capital stocks. If composition effects explained all of cross-country differences in experience human capital stocks, all countries would lie on a straight horizontal line at the level of the U.S. human capital stock. But instead, all countries lie near the 45 degree line – i.e., counterfactual human capital stocks are very similar to the actual ones. Thus, differences in agricultural employment shares across countries do not appear to be driving our results.

To make this point more rigorously, we decompose the variance of the logarithm of experience human capital stocks that we reported in Table 2 as follows

$$\underbrace{\operatorname{var}\left(\ln H^X\right)}_{\text{dispersion in } H^X} = \underbrace{\operatorname{var}\left(\ln H^X\right) - \operatorname{var}\left(\ln \tilde{H}^X\right)}_{\substack{\text{part due to} \\ \text{composition effects}}} \quad + \quad \underbrace{\operatorname{var}\left(\ln \tilde{H}^X\right)}_{\substack{\text{part due to} \\ \text{within-sector diff's in } H^X}}$$

Panel (a) of Table 5 reports the results of this decomposition. Differences in employment shares between agriculture and non-agriculture explain a modest thirteen percent of the log variation in experience human capital stocks across countries.

Schooling Another important compositional difference between rich and poor countries is that workers in poor countries attain fewer years of schooling. We now explore the extent to which this difference drives our results by allowing the returns to experience to vary by the different levels of schooling in the human capital production function in equation (1). We now allow for a functional form that is non-separable in schooling and experience, $h_{it} = \exp(m(s_{it}, x_{it}))$. If the function m has a positive cross-derivative, then schooling and experience are complements, which captures the idea that one has to "learn (in school) how to learn (on the job)". If instead m has a negative cross-derivative, this would suggest that schooling and experience are substitutes.

We work with a simple cutoff specification that allows for different returns to experience according to whether a worker has "high" (H) or "low" (L) educational attainment, i.e. whether his years of schooling are larger or smaller than some cutoff $\bar{s}$ that is common across countries

$$h_{itj} = \exp(g_j(s_{itj}; D_{itj}) + f_j(x_{itj}; D_{itj})) \quad \text{where} \quad D_{itj} = \begin{cases} L, & s_{itj} \leq \bar{s} \\ H, & s_{itj} > \bar{s} \end{cases}.$$

We define the threshold to be at ten years of schooling, $\bar{s} = 10$, which is the highest level for which we have a sufficient number of observations above and below the threshold in all countries. The aggregate experience human capital stock for a given schooling categories is then again simply the average human capital across all individuals in that category, that is calculated as in equation (8). Figure 9c shows the height of the experience-earnings profile for workers with low schooling (less than ten years) plotted against the height for those with high schooling (more than ten years). Perhaps surprisingly, in many countries (including the United States), workers with low educational attainment have *steeper* experience-earnings profiles than their educated counterparts.[25]

Next, we conduct a similar counterfactual exercise as earlier and compute the implied experience human capital stocks if all countries had the same share of highly educated individuals as the United States. Figure 9d plots the counterfactual human capital stocks against the actual stocks. Many countries lie *below* the 45 degree line, suggesting that the cross-country gaps in the counterfactual human capital stocks are even larger than those in the actual human capital stocks. Panel (c) of Table 5 reports the fraction of cross-country dispersion in experience human capital stocks that is due to schooling composition effects. The number is negative. Thus, our result are not driven by differences in the educational composition of workers across countries.

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 vs female, urban versus rural, and full- versus part-time employment. We also explored compositional effects for different combinations of these categories. None of these decompositions are important for explaining cross-country differences in the returns to experience. The fraction of cross-country dispersion in experience human capital explained by composition effects never exceeds fifteen percent. These results are not reported for brevity and are available upon request.

5.2 Existing Theories that are Consistent with our Finding

While it is beyond the scope of this paper to provide a conclusive explanation or an exhaustive discussion for all of the possible causes for the positive relationship between income and the steepness of experience-earnings profiles that we uncover in the data, we note that this finding is consistent with several bodies of existing theoretical work.

TFP Our empirical findings are consistent with the class of theories in which TFP and experience human capital accumulation are complementary, in the sense that an increase in TFP raises the

[25]This contrasts with the opposite pattern that is typically found for *age*-earnings profiles shown in the literature (and in our data) (Carroll and Summers, 1991; Guvenen, 2007; Kambourov and Manovskii, 2009). Appendix C discusses in more detail the reasons why *experience*-earnings profiles are steeper for workers with low schooling even though their *age*-earnings profiles are steeper.

As was the case in the agriculture decomposition, a plot of experience human capital stocks across sectors is essentially a rescaled version of the plot of the height of experience-earnings profiles, Figure 9c. Thus, we omit it for the sake of brevity.

returns to the accumulation of experience human capital. A prominent recent example from this class of theories is a study by Manuelli and Seshadri (2010). Their framework is a Ben-Porath type model in which human capital accumulation requires both time and non-time inputs (i.e. goods inputs, for example books, equipment, or buildings). Low TFP thus implies that the price of non-time inputs is high relative to the wage per unit of human capital. This, in turn, implies that individuals purchase fewer non-time inputs and accumulate less human capital, both within school and on the job. A symptom is flat experience-earnings profiles.

Social Interactions The findings are also related to the class of theories that focuses on the importance of social interactions for learnings such as Lucas (2009); Lucas and Moll (2011); Perla and Tonetti (2011). These theories 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.

6 Conclusion

This paper uses newly available large-sample micro data from 36 countries to document a new fact: experience-earnings profiles are flatter in poor countries than rich countries. We show that the fact appears under a variety of sample restrictions, several alternative definitions of potential experience, and when controlling for time or cohort effects.

While this fact may have many different economic implications, we highlight its importance in one natural application, namely accounting for income differences across countries. In particular, we conduct a development accounting exercise which allows the return to experience to vary across countries but is otherwise standard. We find that the importance of human and physical capital is roughly twice that of previous estimates, accounting for up to two-thirds of income differences compared to less than one half in previous studies (such as those of Caselli, 2005 and Hsieh and Klenow, 2010). The intuition behind our finding is straightforward. By restricting returns to experience to be similar across countries, previous developing accounting exercises understated the importance of cross-country differences in human capital from experience. In contrast, our exercise implies that international differences in human capital from experience are in fact substantial.

There are many potential explanations for why experience-earnings profiles are flatter in poor countries than rich countries. One broad explanation is that workers in poorer countries have less incentive to accumulate human capital. For example, Erosa et al. (2010) and Manuelli and Seshadri (2010) show that the Ben-Porath model of human capital accumulation predicts that when aggregate TFP is lower, workers face higher costs of accumulating human capital in terms of foregone consumption, and therefore accumulate less. Another possibility is that the higher prevalence of extractive institutions in poorer countries (emphasized by e.g. 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 life-cycle wage growth (Guvenen et al., 2011).

A second broad explanation is that workers in developing countries have less opportunity to improve their skills over their lifetime than their counterparts in rich countries. One class of theories in this vein emphasizes the importance of social interactions for learning (Lucas, 2009; Lucas and Moll, 2011; Perla and Tonetti, 2011). Lower skill accumulation by workers could also be the result of worse management practices in developing countries, as documented by Bloom and Reenen (2007) and Bloom et al. (2010). More generally, the same factors which cause firms to grow less quickly over the lifecycle in poor countries (Hsieh and Klenow (2011)) may explain why workers accumulate skills less quickly.[26] Understanding the root causes of cross-country differences in experience-earnings profiles is an important avenue for future research. Our study is just a small step forward in this agenda.

[26]Seshadri and Roys (2012) propose a theory that can potentially explain both facts simultaneously.

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Appendix

A Data Appendix

The surveys we employ in our analysis are listed below for each country. All surveys are nationally representative unless noted. 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,* 2000, from the Bangladesh Bureau of Statistics, available from the FAO RIGA database.

- Brazil: *Recenseamento Geral do Brazil, Censo Demográfico,* 1970 (5% sample), 1980 (5% sample), 1991 (5.8% sample), and 2000 (6% sample), from the Instituto Brasileiro de Geografia e Estatística (IBGE), available from IPUMS, and *Pesquisa Nacional por Amostra de Domicilios,* yearly from 2001 to 2010, from IBGE.

- Canada: *Census of Canada,* 1971 (1% Sample), 1981 (2% Sample), 1991 (3% Sample) and 2001 (2.7% Sample), available from IPUMS.

- Chile: *National Socioeconomic Characterization Survey (CASEN),* 2000 and 2009, from the Chilean Ministry of Planning and Cooperation.

- China: *Urban Household Surveys* (0.01% of urban households, 27 cities), year from 1989 to 2005; *representative of urban areas.*

- Ecuador: *Estudio de Condiciones de Vida,* 1995, from the Instituto Nacional de Estadística y Censos, available from the FAO RIGA database.

- 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).

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

- Indonesia: *Family Life Survey,* 2000, from RAND, available from the FAO RIGA database.

- Italy: *Survey on Household Income and Wealth*, 1991, 1993, 1995, 1998, 2000, 2002, 2004, 2006, 2008, 2010, from the Bank of Italy.

- Jamaica: *Population Census*, 1982, 1991 and 2001, (10.0% samples) from the Statistical Institute of Jamaica, available from IPUMS.

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

- 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.

- Peru: *Encuesta Nacional de Hogares,* 2004 and 2010, from the from the Instituto Nacional de Estadística y Informática.

- Puerto Rico: *Census of Population and Housing,* 1970 (1% Sample), 1980 (5% Sample), 1990 (5% Sample) , 2000 (5% Sample) ; *American Community Survey*, 2005 (1% Sample), available from IPUMS.

- Russia: *Russia Longitudinal Monitoring Survey,* yearly from 2000 to 2010, available from the Carolina Population Center at the University of North Carolina, Chapel Hill.

- South Korea: *Korea Labor and Income Panel Study,* yearly from 1999 to 2008, from the Korea Labor Institute, available from the Cornell Department of Policy Analysis and Management.

- Switzerland: *Swiss Household Panel*, yearly from 1999 to 2009, from the Swiss Foundation for Research in Social Sciences, available from the Cornell Department of Policy Analysis and Management.

- Taiwan: *Survey of Family Income and Expenditure*, yearly from 1995 to 2003, available from the Research Program in Development Studies at Princeton University.

- Thailand: *Thailand Socioeconomic Survey,* 1990, 1992, 1994, 1996, 1998 and 1999, available from the Research Program in Development Studies at Princeton University.

- United Kingdom: *British Household Panel Survey,* yearly from 1992 to 2009, from the Institute for Social & Economic Research at the University of Essex.

- United States: *Census of Population and Housing,* 1960 (1% Sample), 1970 (1% Sample), 1980 (5% Sample), 1990 (5% Sample) , 2000 (5% Sample); *American Community Survey*, 2005 (1% Sample); *Current Population Survey,* yearly from 1980 to 2010; all available from IPUMS.

- Uruguay: *Extended National Survey of Households*, 2006, from the Uruguay National Institute of Statistics, available from IPUMS.

- Vietnam: *Living Standards Survey*, 1998 and *Household Living Standards Survey,* 2002, both from the General Statistics Office of Vietnam, available from the FAO RIGA.

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

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

For most countries, labor earnings and hours worked are for both primary and secondary jobs. In Argentina, Chile, France, South Korea and Uruguay, labor earnings and hours worked are for just the primary job. For Brazil (the census data) and Switzerland, we measure labor income as the total income earned of individuals reporting to be primarily wage earners (as opposed to self employed.) In most countries, earnings are reported at the monthly frequency. The exceptions are Australia, Canada, Germany, Jamaica, South Korea, and the United States, in which earnings are measured at the annual frequency, and India, in which earnings are measured at the weekly frequency. In all surveys, earnings are before taxes.

B Identifying Aggregate Human Capital Stocks when Wages≠MPL

The purpose of this Appendix is to argue that even if individuals' wages do not reflect their marginal products, our methodology still correctly identifies *aggregate* under certain conditions. Assume that human capital is produced according to

$$h_{ict} = \exp(m(s_{ict}, x_{ict})). \tag{9}$$

This is solely for generality; the formulation in section 3.1 is the special case $m(s, x) = g(s) + f(x)$. Depart from the assumption that individuals are paid their marginal products in efficiency units of human capital, and instead assume that an individual's wage is

$$w_{ict} = (\omega_{ct} h_{ict} + B_{ict}) \exp(\varepsilon_{ict}), \tag{10}$$

where B_{ict} captures deviations from the wage equals marginal product assumption (in section 3.1, $B_{ict} \equiv 0$). A potential identification problem arises if this transfer depends on schooling and/or experience. We therefore assume that

$$B_{ict} = B(s_{ict}, x_{ict}) \exp(\gamma_t + \psi_c). \tag{11}$$

The following Lemma shows that this departure from the assumption that wage equals marginal product is not an issue for *aggreggate* human capital estimates if the deviations satisfy

$$\frac{1}{T}\sum_{t=1}^{T}\frac{1}{C_t}\sum_{c=1}^{C_t}\frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}}B(s_{ict},x_{ict})=0,\quad B(0,0)=0. \tag{12}$$

This condition says that deviations take the form of zero-sum transfers across individuals and that no transfers are received by individuals with zero experience and schooling. If the distribution over age and schooling choices is stationary, (12) has the alternative interpretation of zero-sum transfers in expectation *over the lifecycle of a given individual.* This is because in a stationary environment the fraction of individuals with a given experience and schooling level is also the probability of an individual living up to the age where she attains that same experience and schooling levels.

Lemma: Assume wages equal marginal products *plus* transfers, $B_{ict}\neq 0$, but that these satisfy (12). Then the procedure in sections 3 and 4 produces biased estimates of *individual* human capital stocks, h_{ict}, but correct *aggregate* human capital stock estimates, H.

Proof: Combining equations (9) to (11), the analogue of our estimating equation (4) is now

$$\log w_{ict}=\log\bar{\omega}+m(s_{ict},x_{ict})+b(s_{ict},x_{ict})+\gamma_t+\psi_c+\varepsilon_{ict}$$

where

$$b(s_{ict},x_{ict})=\log\left(1+\frac{B(s_{ict},x_{ict})}{\bar{\omega}\exp(m(s_{ict},x_{ict}))}\right).$$

Our identification strategy still correctly identifies the intercept $\log\bar{\omega}$ because $B(0,0)=0$ and hence $b(0,0)=0$. But we can no longer separately identify the functions m and b. The slope of the experience-earnings profile are therefore biased, and we obtain biased estimates of *individual* human capital stocks

$$\hat{h}_{ict}=\exp(m(s_{ict},x_{ict})+b(s_{ict},x_{ict}))=\exp(m(s_{ict},x_{ict}))\left(1+\frac{B(s_{ict},x_{ict})}{\bar{\omega}\exp(m(s_{ict},x_{ict}))}\right)=h_{ict}+\frac{B(s_{ict},x_{ict})}{\bar{\omega}}.$$

However, *aggregate* human capital stocks are still correctly identified:

$$\hat{H} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C_t}\sum_{c=1}^{C_t}\frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}}\hat{h}_{ict} = \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C_t}\sum_{c=1}^{C_t}\frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}}h_{ict} + \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C_t}\sum_{c=1}^{C_t}\frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}}\frac{B(s_{ict}, x_{ict})}{\bar{\omega}}$$
$$= \frac{1}{T}\sum_{t=1}^{T}\frac{1}{C_t}\sum_{c=1}^{C_t}\frac{1}{N_{ct}}\sum_{i=1}^{N_{ct}}h_{ict} = H.$$

where the second to last equality follows from (12).□

Numerical Example. For simplicity abstract from cohort and year effects and set $\gamma_t = \psi_c = 0$. Assume that the human capital production has the quintic functional form

$$h_i = \exp(\theta s_i + \phi_1 x_i + \phi_2 x_i^2 + \phi_3 x_i^3 + \phi_4 x_i^4 + \phi_5 x_i^5),$$

where we use the ϕ_k estimated for the United States in section 3.2. Consider the example of long-term labor contracts and assume that transfers depend on experience in a linear-quadratic fashion, $B_i = \beta_1 x_i + \beta_2 x_i^2$, and the coefficients β_1 and β_2 are such that (12) is satisfied.[27] Panel (a) of Figure A.5 plots two examples of such transfer functions. Panel (b) plots the implied experience-earnings profiles (dashed lines) and the underlying correct human capital profile for sake of comparison (solid line). If our empirical exercise estimated either of the dashed experience-earnings profiles, we would still identify the correct *aggregate* human capital stock, that is the one corresponding to the solid experience-earnings profile.

C Experience-Earnings and Age-Earnings Profiles

In section 5.1 we documented that experience-earnings profiles for individuals with more than ten years of schooling are *flatter* than those for less than ten years of schooling. This is true even though the opposite pattern holds for *age*-earnings profiles. The purpose of this Appendix is to argue that this pattern arises relatively mechanically. In particular, going back and forth between age-earnings and experience-earnings profiles mainly involves a rescaling of the axes that differentially affects the two schooling categories and hence results in the observed pattern. We explain in detail how this

[27] We assume for simplicity that experience is distributed uniformly between 0 and $\bar{x} = 45$. Therefore, β_1 and β_2 satisfy

$$\int_0^{\bar{x}} [\beta_1 x + \beta_2 x^2]\frac{1}{\bar{x}}dx = 0 \quad \Leftrightarrow \quad \beta_1 + \beta_2\frac{2\bar{x}}{3} = 0.$$

works for the United States – other countries look similar.

Figure A.6(a) plots the age-earnings profile for the two different schooling categories. The age-earnings profiles for highly educated individuals are steeper than those of their uneducated counterparts. This is consistent with the findings documented in (Carroll and Summers, 1991: Figures 10.7a and 10.8a; Guvenen, 2007: Figure 2; Kambourov and Manovskii, 2009: Figures 3, 6, 8 and 10). Highly educated individuals start working later and at a higher starting wage. Figure A.6(b) changes the x-axis from age to experience. Figure A.6(c) additionally normalizes the logarithm of the starting wage to zero for the two schooling categories, that is rescales the y-axis. It can be seen that this rescaling of the axes generate the reversal in the relative slopes of age-earnings with respect to the experience earnings profiles.

Table 1: Correlation between Profiles and GDP per Capita under Alternative Sample Restrictions and Experience Measures

Sample Restriction/Experience Measure	Corr(GDP,Exp20)	Var(Exp20)	Max(Exp20)	Min(Exp20)
Benchmark	0.61***	0.10	1.67	0.23
Male Workers	0.67***	0.13	1.79	0.26
Private Workers	0.59***	0.11	1.67	0.29
Full-time Workers	0.65***	0.11	1.89	0.27
Male Private Workers	0.62***	0.16	1.79	0.27
Male Private Full-time Workers	0.64***	0.17	2.00	0.32
Non-agricultural Workers	0.54***	0.09	1.67	0.23
Start Work at Age 6	0.46**	0.09	1.68	0.23
Start Work at Age 6 - Male	0.55***	0.12	1.86	0.26
Start Work at Age 6 - Male Private	0.51**	0.14	1.86	0.27
Start Work at Age 6 - Male Private Full-time	0.56***	0.15	1.98	0.32
Start Work at Age 15	0.67***	0.10	1.64	0.23
Hall and Jones Return to Schooling	0.63***	0.11	1.72	0.22
Constant 10% Return to Schooling	0.65***	0.10	1.63	0.28

Notes: *significant at 5% level, **significant at 1% level, ***significant at 0.1% level

Table 2: Dispersion of Aggregate Human Capital Stocks

	Dispersion Measure					
	Var(ln H)			90-10 Ratio		
Human Capital Measure	(a) Cross-sectional Results					
Schooling	0.133			1.86		
Experience	0.090			1.96		
Schooling + Experience	0.293			3.65		
	(b) Year and Cohort Controls					
	Year	Cohort	Both	Year	Cohort	Both
Schooling	0.112	0.123	0.114	1.92	1.81	1.90
Experience	0.110	0.082	0.112	1.98	1.75	1.99
Schooling + Experience	0.326	0.300	0.337	3.80	3.18	3.78

Table 3: Development Accounting

	Success Measure					
	Success1			Success2		
Human Capital Measure	(a) Cross-sectional Results					
Schooling	0.38			0.45		
Experience	0.39			0.46		
Schooling + Experience	0.64			0.70		
	(b) Year and Cohort Controls					
	Year	Cohort	Both	Year	Cohort	Both
Schooling	0.33	0.30	0.33	0.45	0.44	0.45
Experience	0.39	0.32	0.39	0.46	0.42	0.46
Schooling + Experience	0.59	0.50	0.59	0.72	0.64	0.71

Table 4: Relation to Literature

	Dispersion Measure		Success Measure	
Human Capital Measure	Var(ln H)	90-10 Ratio	Success1	Success2
	(a) Klenow and Rodriguez-Clare			
Schooling	0.060	1.74	0.38	0.42
Experience	0.002	1.04	0.23	0.30
Schooling + Experience	0.068	1.82	0.40	0.44
	(b) Hall-Jones Schooling + Klenow and Rodriguez-Clare Experience			
Schooling	0.049	1.63	0.36	0.41
Experience	0.002	1.04	0.23	0.30
Schooling + Experience	0.057	1.72	0.38	0.42
	(c) Hall-Jones Schooling + Country-Specific Quadratic Returns to Exp			
Schooling	0.049	1.63	0.36	0.41
Experience	0.034	1.54	0.30	0.39
Schooling + Experience	0.115	2.54	0.47	0.54
	(d) Hall-Jones Schooling + Country-Specific Quintic Returns to Exp			
Schooling	0.049	1.63	0.36	0.41
Experience	0.097	1.95	0.42	0.46
Schooling + Experience	0.210	3.22	0.61	0.64
	(e) Country-Specific Returns to Schooling (Linear) and Exp (Quintic)			
Schooling	0.133	1.88	0.40	0.44
Experience	0.092	1.98	0.41	0.46
Schooling + Experience	0.297	3.72	0.64	0.70

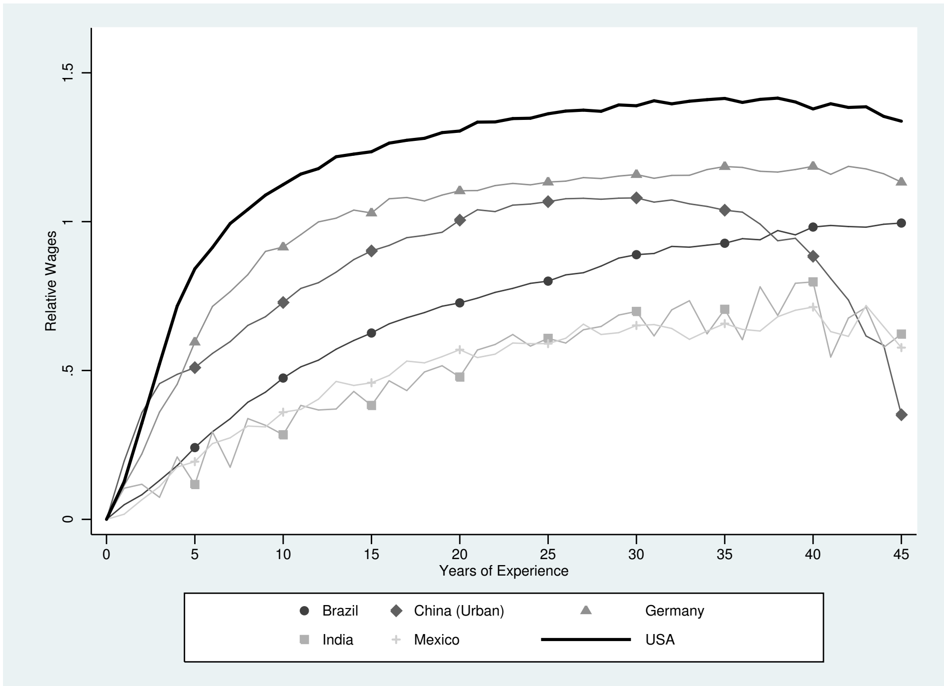
Notes: panel (a) computes human capital stocks using a linear-quadratic Mincer specification and using the *average* returns to schooling and experience as in Klenow and Rodriguez-Clare (1997). In our sample of 28 countries the average coefficients on schooling, experience and experience^2 are 0.09211, 0.04775 and -0.000758 which is similar to those in Klenow and Rodriguez Clare (1997). Panel (b) uses the same specification except for imposing *diminishing returns to schooling* using the methodology of Hall and Jones (1999), namely assuming that g(s) is piecewise linear with slope 0.13 for s<=4, 0.10 for 4<s<=8 and 0.07 for 8<s. This is also similar to Bils and Klenow (2000). Panel (c) allows returns to experience to vary across countries, but retains a quadratic specification whereas panel (d) uses a quintic specification. Panel (e) additionally allows returns to *schooling* to vary (linearly) across countries.

Table 5: Counterfactual: US Employment Share in Agriculture

	Var(ln H)
(a)Counterfactual: US Employment Share in Agriculture	
Data	0.101
Counterfactual	0.088
Fraction due to Composition Effect	0.13
Fraction due to Within-Sector Diffs	0.87
(b) Counterfactual: US Sectoral Shares in all of Agr.-Manuf.-Ser.-Govt	
Data	0.086
Counterfactual	0.073
Fraction due to Composition Effect	0.15
Fraction due to Within-Sector Diffs	0.85
(c) Counterfactual: US Share of Workers with Low Schooling	
Data	0.098
Counterfactual	0.102
Fraction due to Composition Effect	-0.04
Fraction due to Within-Sector Diffs	1.04

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

(a) Experience-Earnings Profiles for Select Countries



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

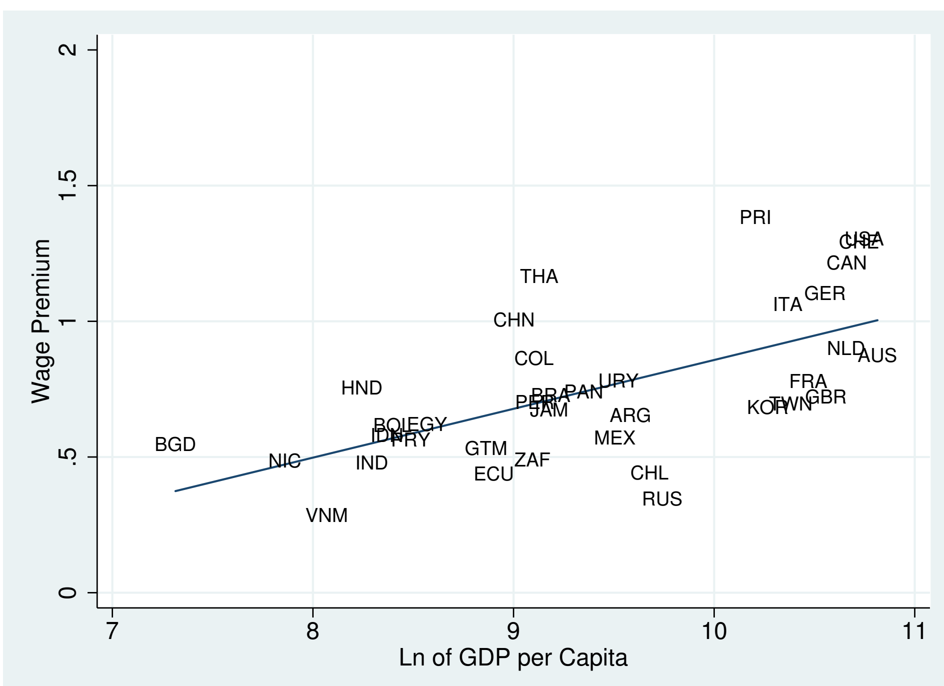
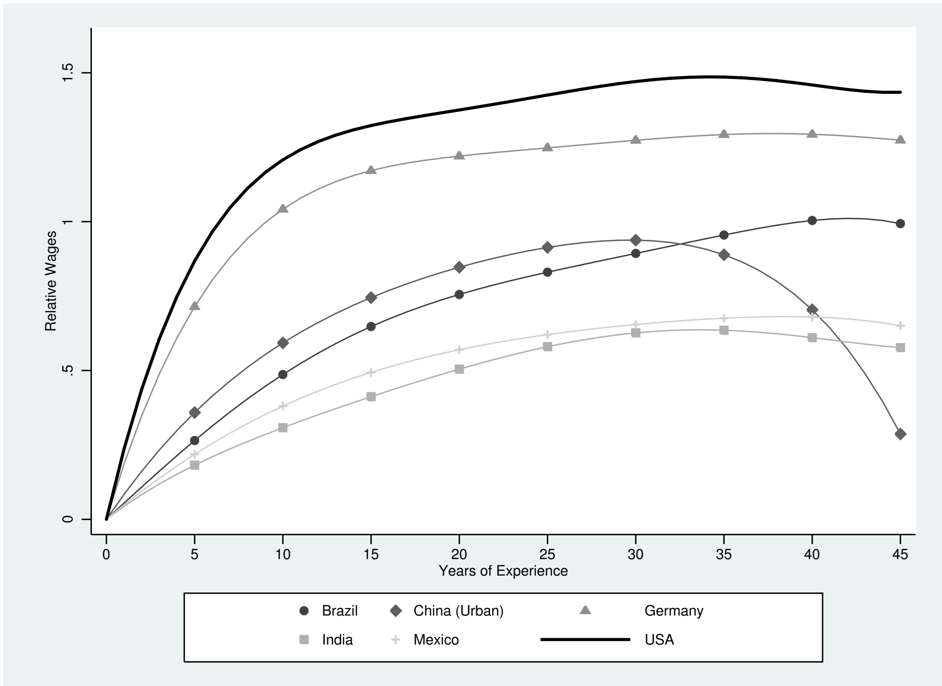


Figure 2: Quintic Experience-Earnings Profiles, Cross-sectional Estimates

(a) Experience-Earnings Profiles for Select Countries



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

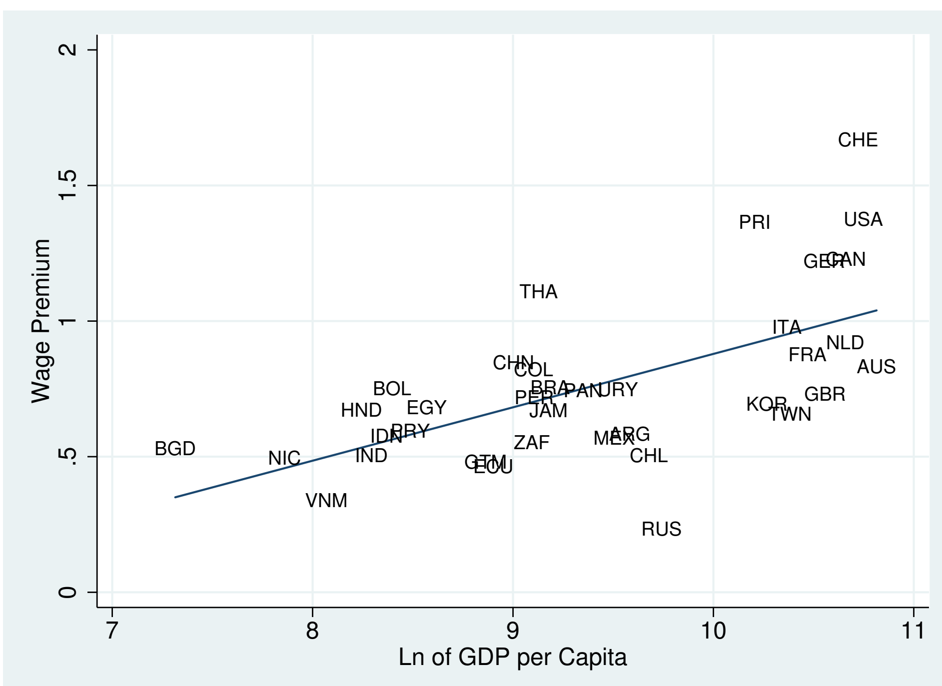
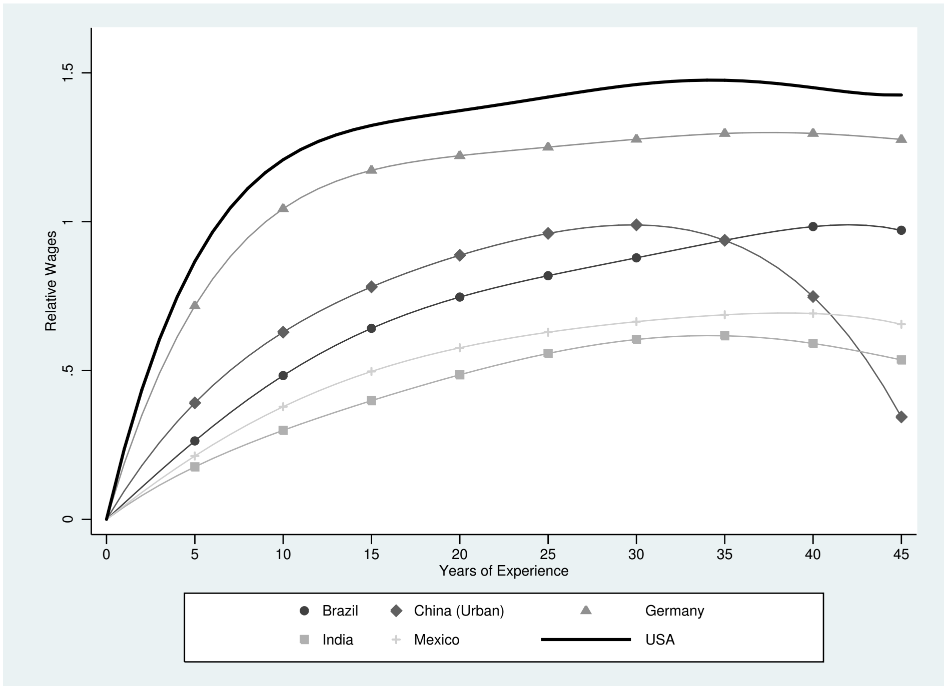


Figure 3: Quintic Experience-Earnings Profiles, Estimates with Time Effects

(a) Experience-Earnings Profiles for Select Countries



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

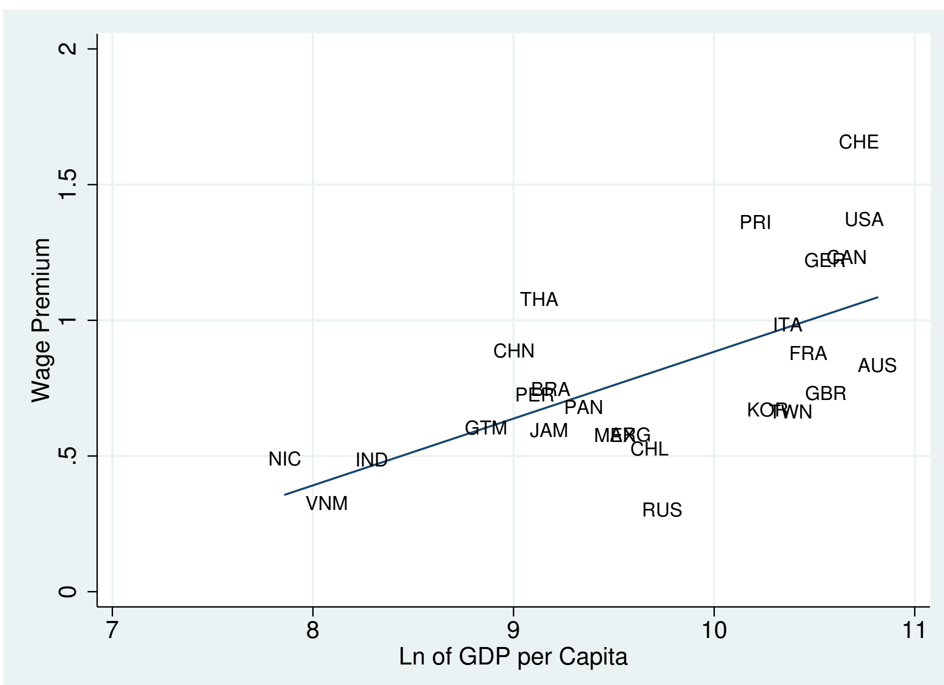
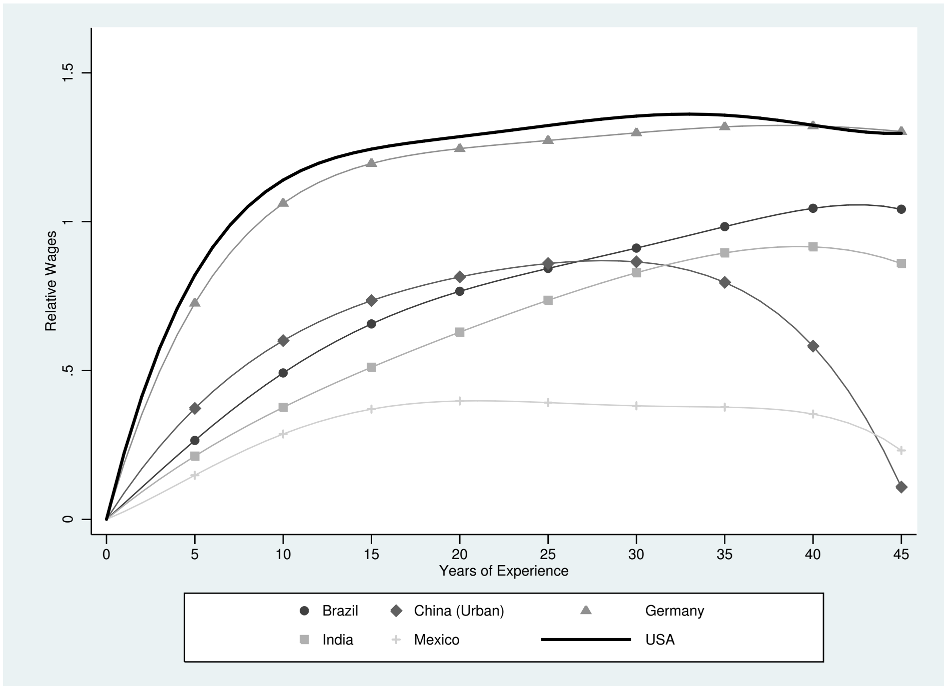


Figure 4: Quintic Experience-Earnings Profiles, Estimates with Cohort Effects

(a) Experience-Earnings Profiles for Select Countries



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

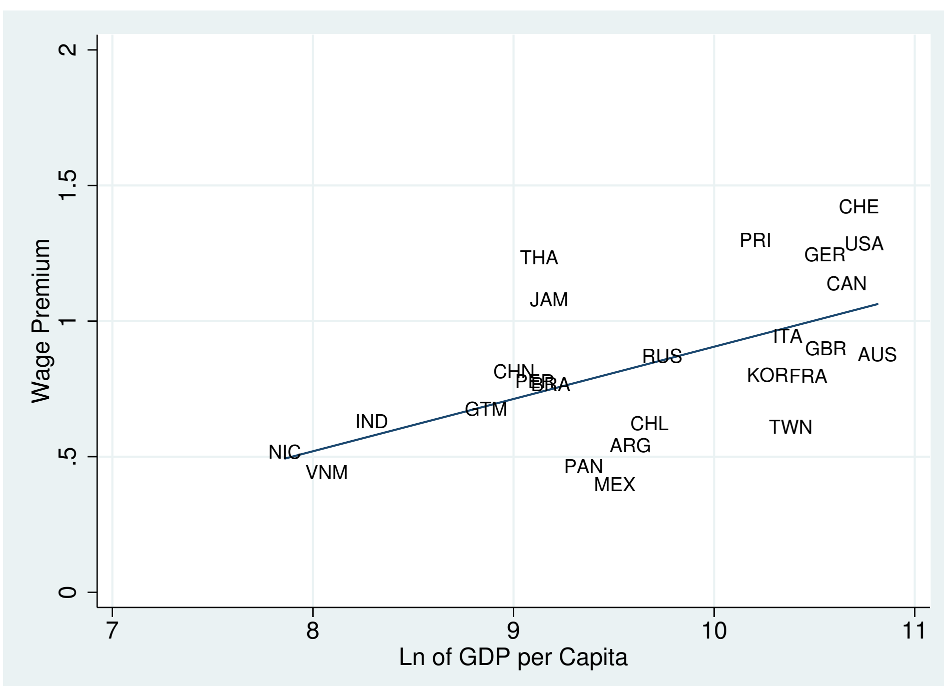
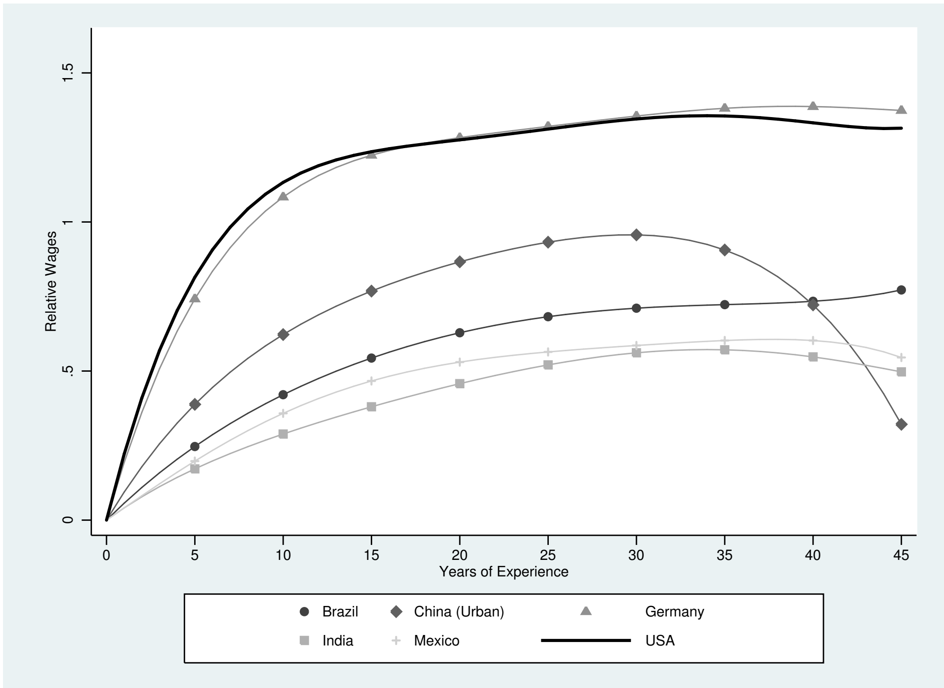


Figure 5: Quintic Experience-Earnings Profiles, Estimates with Both Time and Cohort Effects

(a) Experience-Earnings Profiles for Select Countries



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

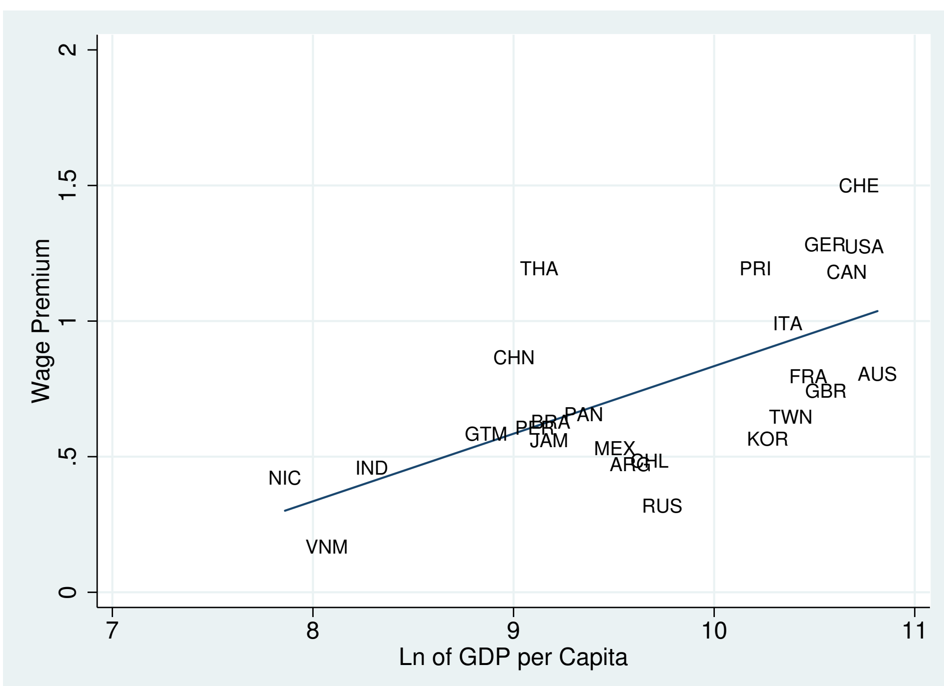
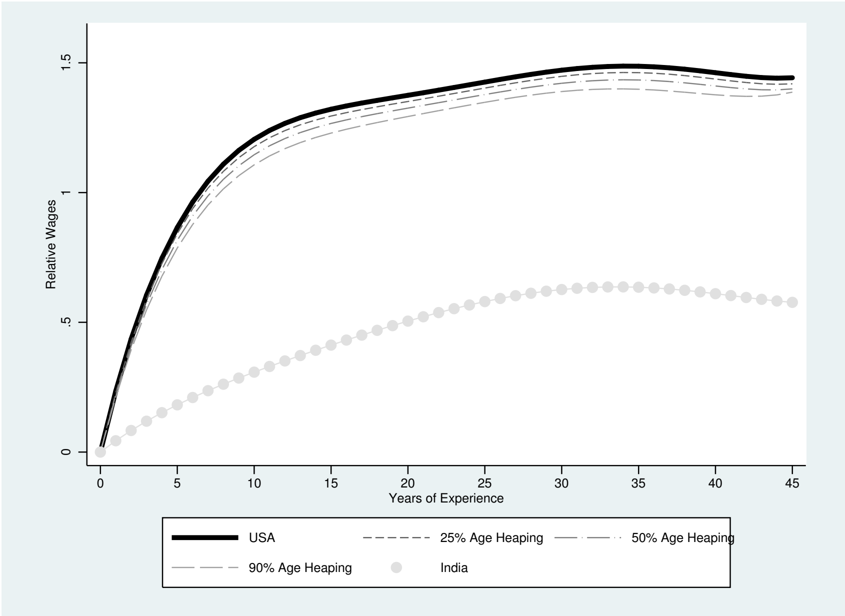


Figure 6: Returns to Experience – Robustness to Measurement Differences

(a) Adjusted for Age Heaping



(b) U.S. Census and CPS Data

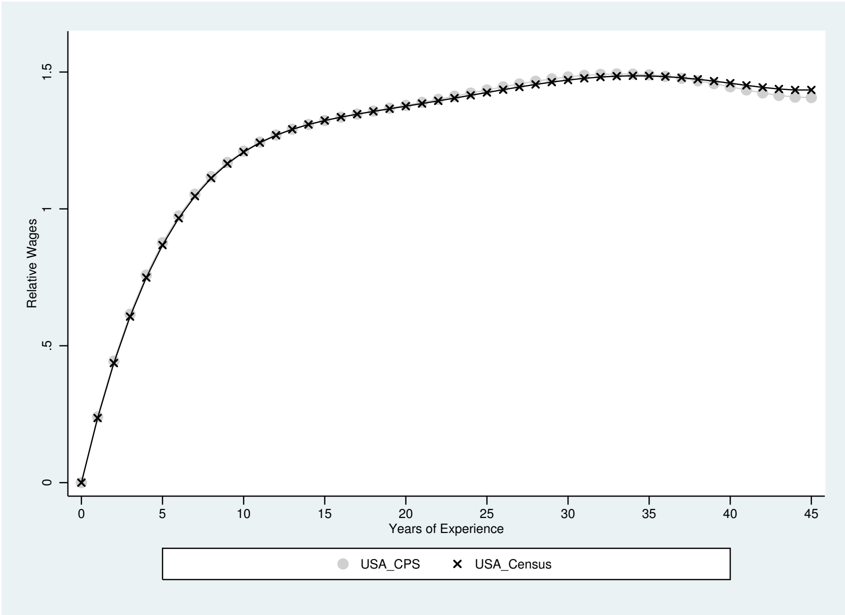
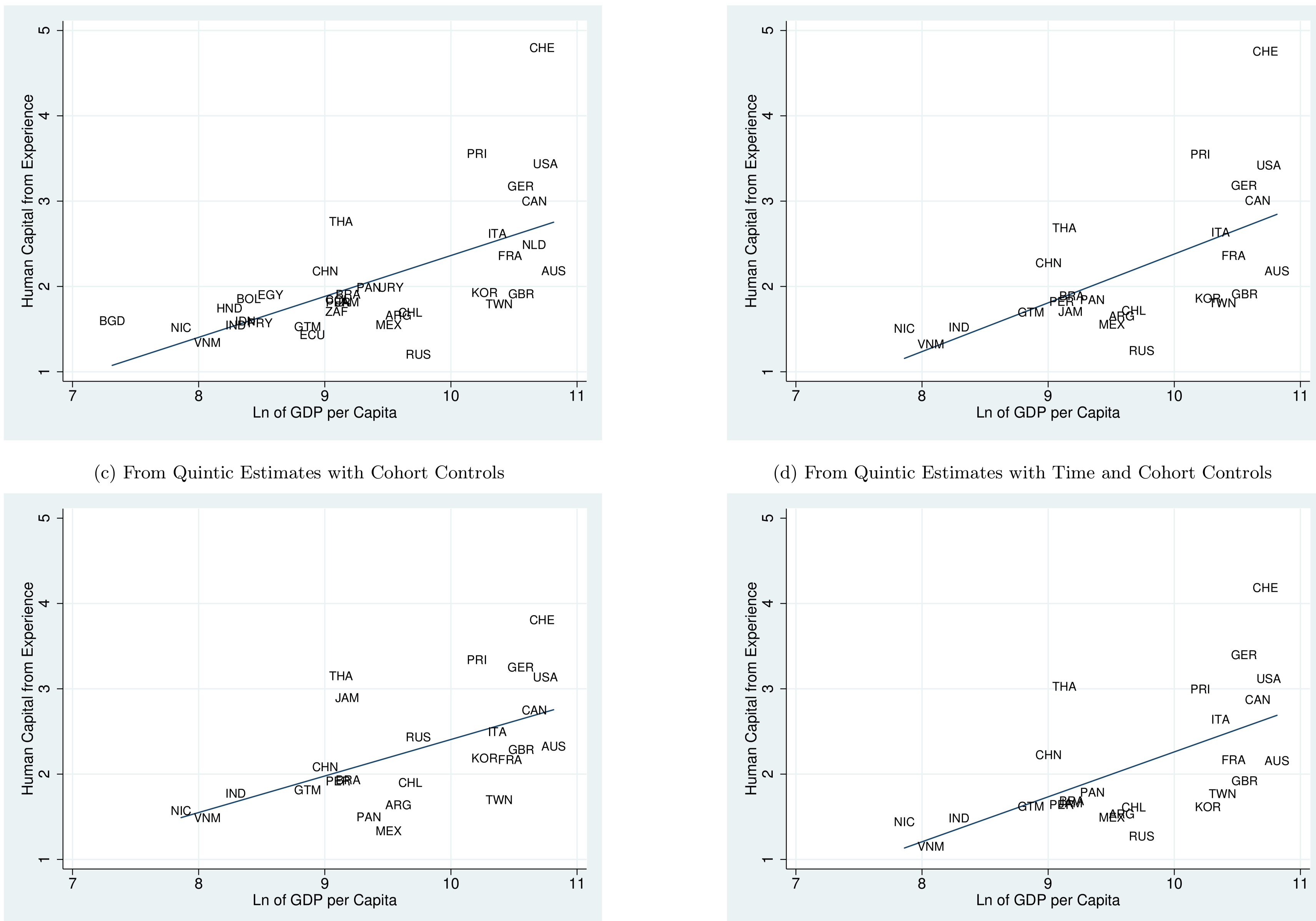


Figure 7: Implied Human Capital from Experience versus Income



(a) From Quintic Estimate

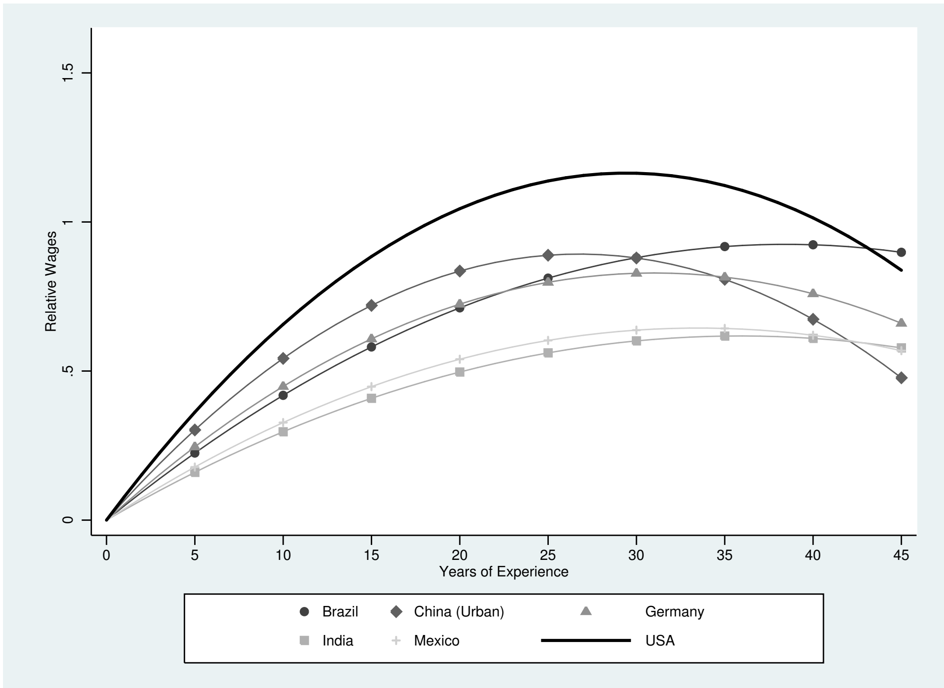
(b) From Quintic Estimates with Time Controls

(c) From Quintic Estimates with Cohort Controls

(d) From Quintic Estimates with Time and Cohort Controls

Figure 8: Quadratic Experience-Earnings Profiles, Cross-Sectional Estimates

(a) Experience-Earnings Profiles for Select Countries



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

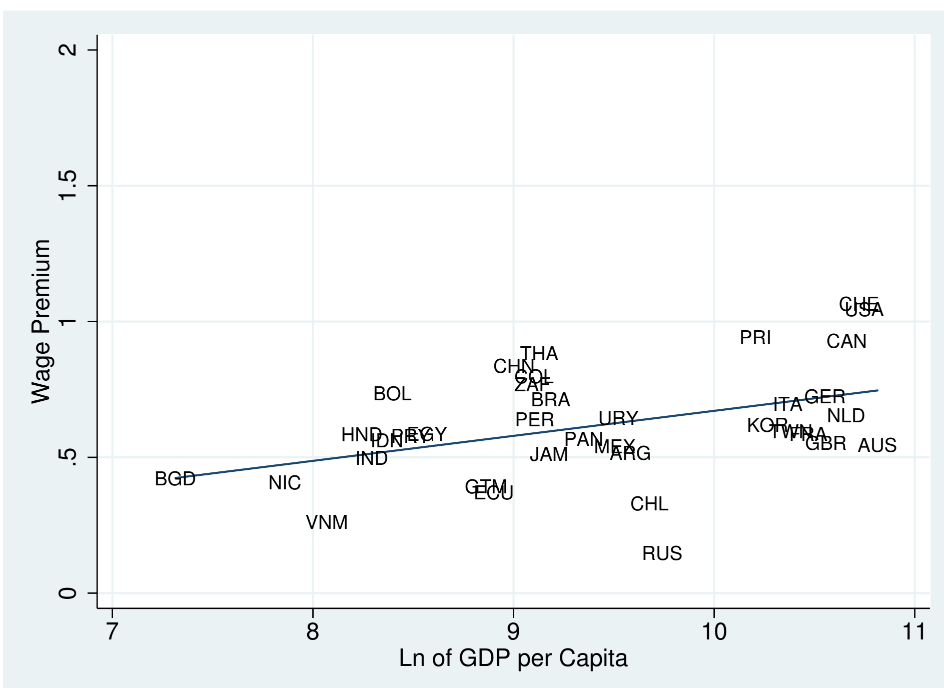
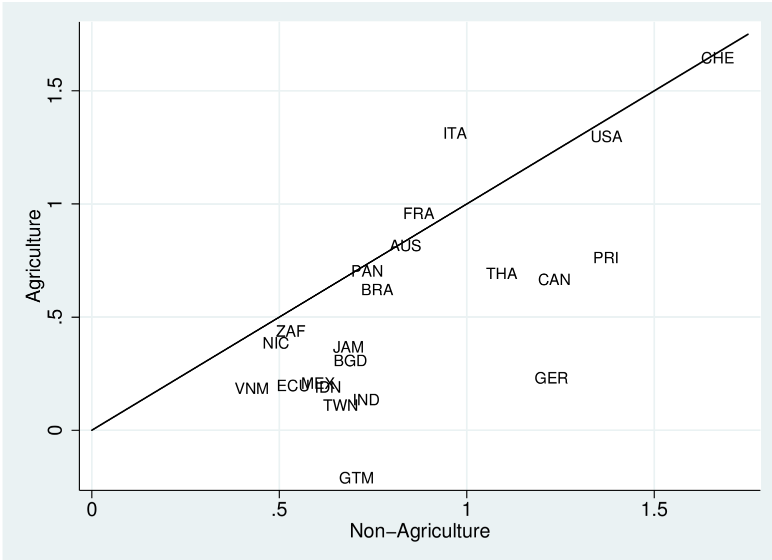
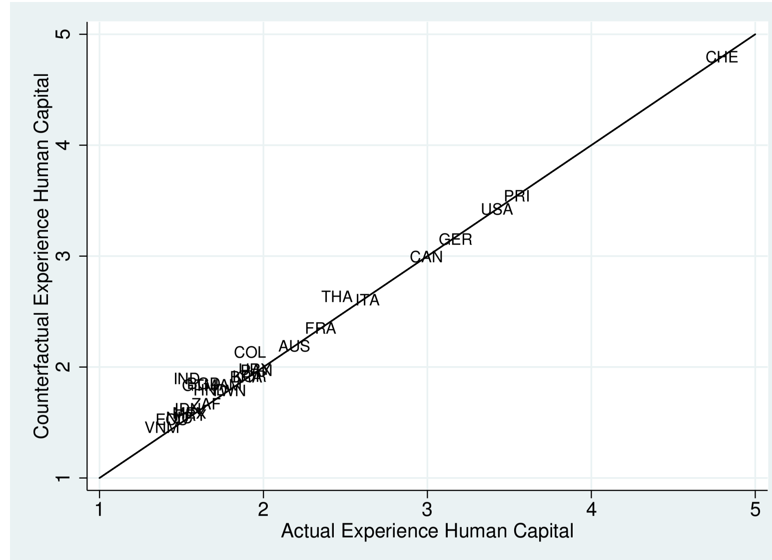


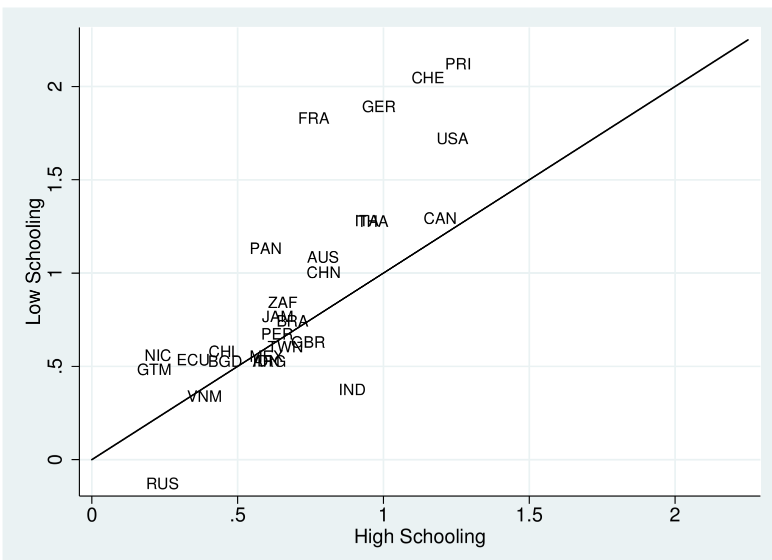
Figure 9: Worker Composition



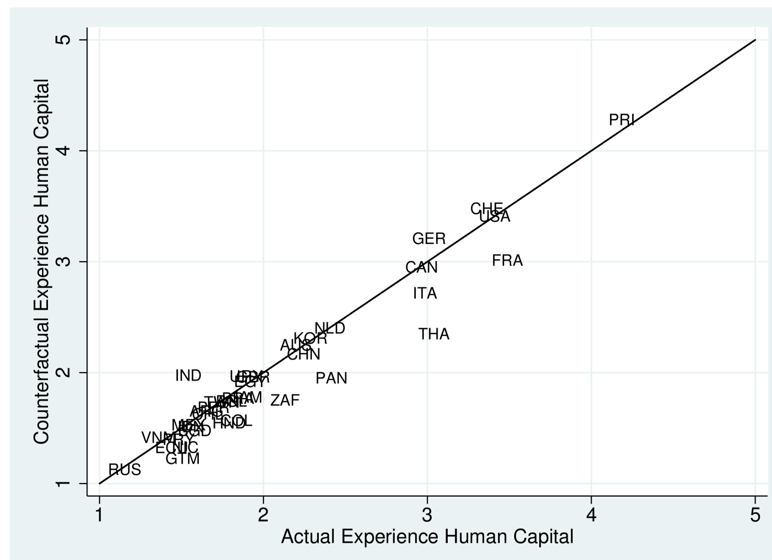
(a) Height of Profiles at 20 Years of Experience: Agriculture vs. Non-Agriculture



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



(c) Height of Profiles at 20 Years of Experience: High versus Low Schooling



(d) Counterfactual: U.S. Share of Workers with Low Schooling

Table A.1: Aggregate Human Capital from Experience

	Fully Flexible Estimation of Returns to Experience			Quintic			
	Cross-Section	Time Controls	Cohort Controls	Cross-Section	Time Controls	Cohort Controls	Both
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Experience Human Capital Relative to US						
Argentina	0.52	0.53	1.25	0.47	0.47	1.11	0.48
Australia	0.69	0.69	0.77	0.62	0.62	0.71	0.68
Bangladesh	0.55			0.46			
Brazil	0.57	0.56	0.63	0.55	0.55	0.61	0.54
Canada	0.90	0.90	0.90	0.86	0.87	0.86	0.91
Chile	0.50	0.50	0.59	0.47	0.48	0.57	0.49
China	0.90	0.77	1.40	0.72	0.63	1.12	0.68
Ecuador	0.44			0.41			
France	0.61	0.61	0.62	0.68	0.68	0.68	0.69
Germany	0.87	0.87	0.96	0.92	0.93	1.03	1.09
India	0.49	0.47	0.60	0.43	0.43	0.55	0.46
Indonesia	0.50			0.45			
Italy	0.90	0.91	0.93	0.74	0.75	0.77	0.83
Jamaica	0.56	0.53	0.91	0.51	0.48	0.87	0.51
Korea, Rep.	0.63	0.60	0.76	0.58	0.56	0.71	0.54
Mexico	0.48	0.48	0.45	0.45	0.45	0.42	0.48
Nicaragua	0.45	0.44	0.50	0.44	0.44	0.50	0.46
Panama	0.59	0.54	0.47	0.55	0.52	0.46	0.55
Peru	0.57	0.57	0.65	0.52	0.53	0.60	0.53
Puerto Rico	1.13	1.12	1.15	1.03	1.03	1.05	0.96
Russian Federation	0.38	0.39	0.83	0.35	0.36	0.77	0.41
Switzerland	1.15	1.12	1.03	1.36	1.36	1.19	1.32
Taiwan	0.57	0.58	0.59	0.51	0.52	0.53	0.56
Thailand	0.86	0.83	1.05	0.77	0.75	0.95	0.93
United Kingdom	0.70	0.69	0.88	0.55	0.55	0.72	0.62
Uruguay	0.64			0.57			
Vietnam	0.41	0.40	0.49	0.39	0.39	0.47	0.37

Notes: The aggregate human capital estimates in columns (1)-(3) are based on returns to experience estimates from fully flexible specifications (e.g., years of experience dummies). Those in columns (4)-(7) are based on a quintic specification. In columns (2) and (5), we include controls for calendar year dummy variables. In columns (3) and (6), we include categorical controls for birth cohorts (e.g., dummy variables indicating ten-year intervals for birth year). In column (7) we include both birth cohort and calendar year dummies.

Table A.2: Aggregate Total Human Capital

	Total Human Capital (Schooling + Experience)				
	No Experience	Cross-Section	Time Controls	Cohort Controls	Both
Country	(1)	(2)	(3)	(4)	(5)
	Human Capital Relative to US				
Argentina	0.84	0.40	0.37	0.42	0.38
Australia	0.83	0.52	0.48	0.63	0.56
Bangladesh	0.38	0.18			
Bolivia	1.11	0.59			
Brazil	0.95	0.51	0.47	0.56	0.46
Canada	0.85	0.73	0.71	0.71	0.76
Chile	0.95	0.46	0.42	0.56	0.45
China	0.78	0.49	0.50	0.49	0.54
Colombia	0.69	0.36			
Ecuador	0.52	0.22			
Egypt	0.52	0.28			
France	0.68	0.47	0.45	0.46	0.46
Germany	0.79	0.74	0.70	0.81	0.86
Guatemala	0.72	0.32	0.31	0.40	0.33
Honduras	0.95	0.47			
India	0.61	0.27	0.25	0.34	0.28
Indonesia	0.76	0.35			
Italy	0.66	0.50	0.48	0.50	0.54
Jamaica	0.89	0.46	0.32	0.74	0.34
Mexico	0.72	0.32	0.31	0.29	0.34
Nicaragua	0.46	0.20	0.19	0.22	0.20
Panama	0.72	0.41	0.41	0.34	0.44
Paraguay	1.19	0.53			
Peru	1.30	0.68	0.63	0.79	0.61
Puerto Rico	1.24	1.27	1.20	1.27	1.09
Korea, Rep.	0.92	0.51	0.43	0.64	0.41
Russian Federation	0.87	0.31	0.26	0.92	0.31
SouthAfrica	1.47	0.69			
Switzerland	1.03	1.40	1.33	1.15	1.33
Taiwan	0.92	0.47	0.46	0.48	0.51
Thailand	2.01	1.48	1.35	1.87	1.77
United Kingdom	1.34	0.75	0.65	1.02	0.74
Uruguay	0.53	0.31			
Vietnam	0.40	0.16	0.14	0.19	0.13

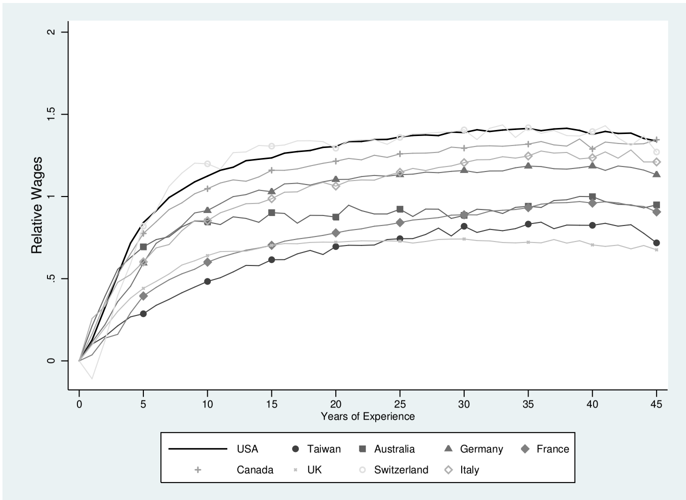
Notes: The aggregate human capital estimates in columns (1)-(5) are based on a quintic specification. In columns (3), we include controls for calendar year dummy variables. In columns (4), we include categorical controls for birth cohorts (e.g., dummy variables indicating ten-year intervals for birth year). In columns (5) we include both birth cohort and calendar year dummies.

Table A.3: Development Accounting

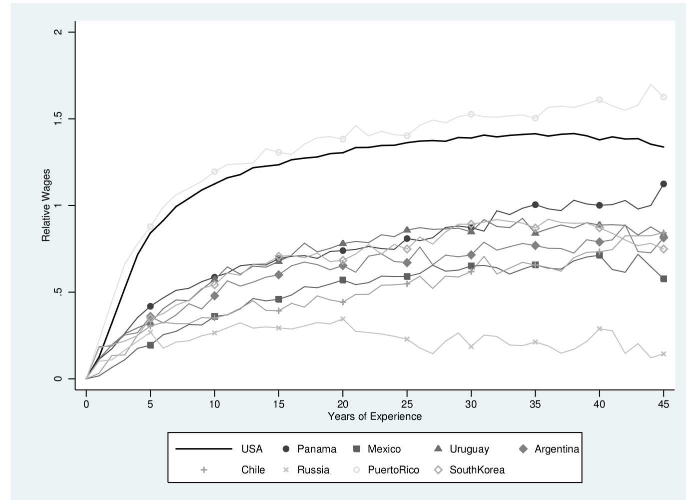
	Data from Caselli (2005)		Success2 as defined in Caselli (2005), Relative to US				
	Y	K	No Experience	Cross-Section	Time Controls	Cohort Controls	Both
Country	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Argentina	0.45	0.39	0.69	1.13	1.18	1.08	1.16
Australia	0.81	0.95	0.94	1.28	1.35	1.12	1.21
Bangladesh	0.11	0.05	0.57	0.95			
Bolivia	0.12	0.06	0.28	0.43			
Brazil	0.33	0.31	0.50	0.76	0.81	0.72	0.81
Canada	0.79	0.98	0.89	0.98	1.00	1.00	0.95
Chile	0.41	0.29	0.63	1.03	1.08	0.90	1.05
China	0.09	0.06	0.26	0.35	0.35	0.36	0.33
Colombia	0.21	0.12	0.55	0.84			
Ecuador	0.22	0.20	0.58	1.05			
Egypt	0.22	0.06	0.86	1.28			
France	0.79	1.08	0.99	1.27	1.32	1.29	1.30
Germany							
Guatemala	0.23	0.09	0.66	1.13	1.16	0.97	1.10
Honduras	0.12	0.08	0.29	0.46			
India	0.09	0.04	0.37	0.64	0.68	0.55	0.63
Indonesia	0.17	0.11	0.43	0.72			
Italy	0.89	1.11	1.14	1.37	1.40	1.37	1.29
Jamaica	0.13	0.14	0.28	0.43	0.56	0.31	0.52
Mexico	0.37	0.35	0.66	1.13	1.16	1.20	1.09
Nicaragua	0.10	0.08	0.39	0.68	0.71	0.63	0.68
Panama	0.27	0.25	0.53	0.77	0.77	0.87	0.73
Paraguay	0.21	0.11	0.39	0.67			
Peru	0.18	0.18	0.26	0.41	0.43	0.37	0.44
Puerto Rico							
Korea, Rep.	0.60	0.78	0.69	1.03	1.14	0.88	1.17
Russian Federatior							
SouthAfrica							
Switzerland	0.77	1.27	0.70	0.57	0.59	0.65	0.59
Taiwan	0.62	0.44	0.87	1.34	1.38	1.34	1.28
Thailand	0.23	0.30	0.22	0.27	0.29	0.23	0.24
United Kingdom	0.71	0.70	0.66	0.97	1.06	0.79	0.97
Uruguay	0.36	0.24	0.90	1.29			
Vietnam							

Notes: Columns (1) and (2) report GDP per worker and physical capital stocks from Caselli (2005), that we use as inputs into our accounting exercise. Columns (3)-(7) report Caselli's "success2" measure which is the fraction of a given country's income gap to the US that can be explained by physical and human capital. In column (5), we include controls for calendar year dummy variables. In columns (6), we include categorical controls for birth cohorts (e.g., dummy variables indicating ten-year intervals for birth year). In columns (7) we include both birth cohort and calendar year dummies.

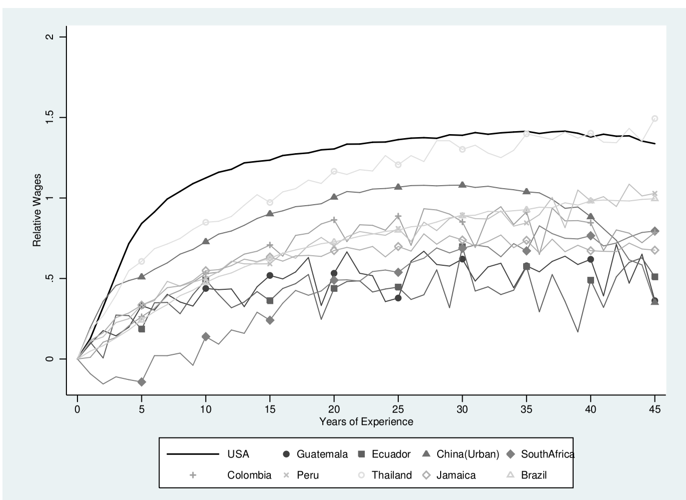
Figure A.1: Fully Flexible Experience-Earnings Profiles by Income Quartile (Relative to the USA)



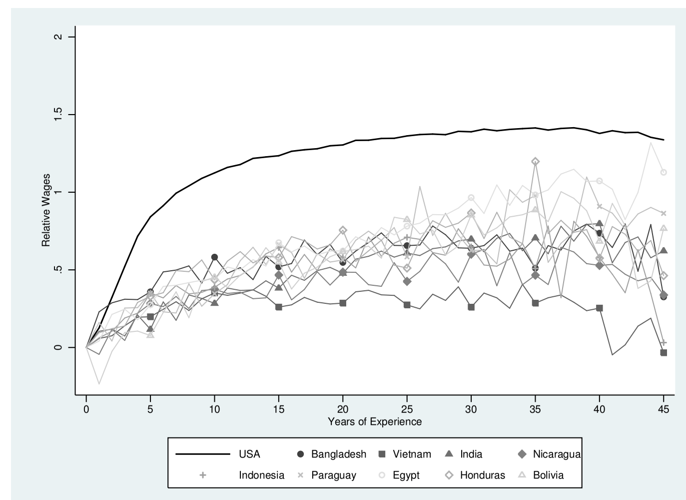
(a) Top Quartile



(b) Second Quartile

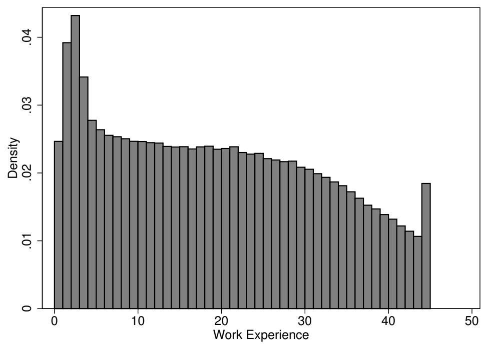


(c) Third Quartile

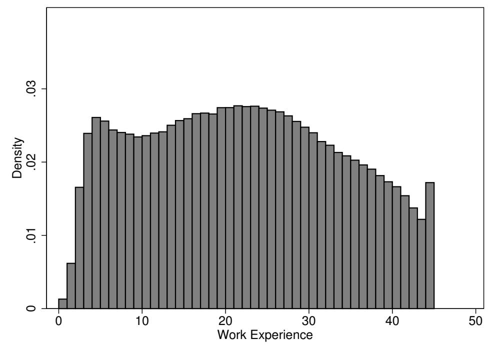


(d) Poorest Quartile

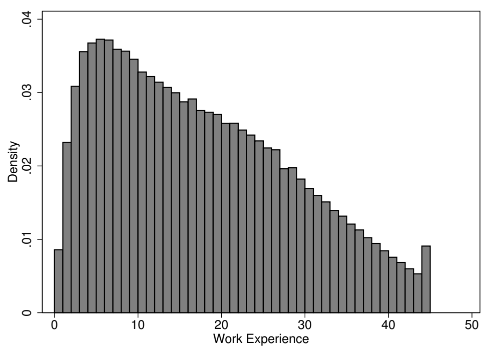
Figure A.2: Experience Histograms (for Six Select Economies)



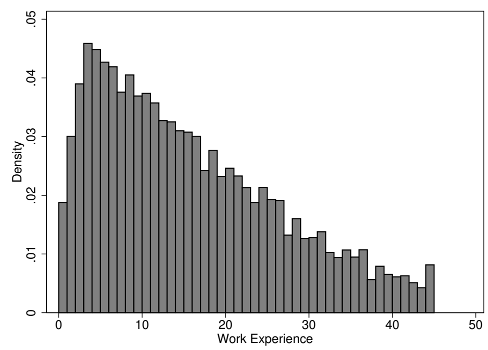
(a) USA



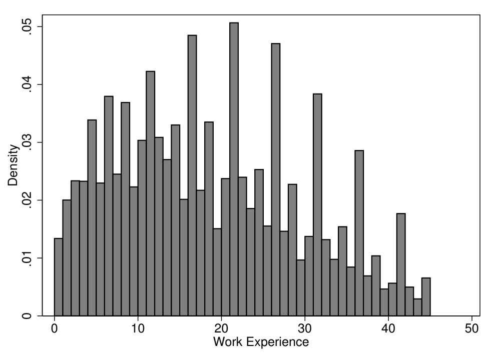
(b) Germany



(c) Brazil



(d) Mexico



(e) India

(f) China

Figure A.3: Average Experience versus Income

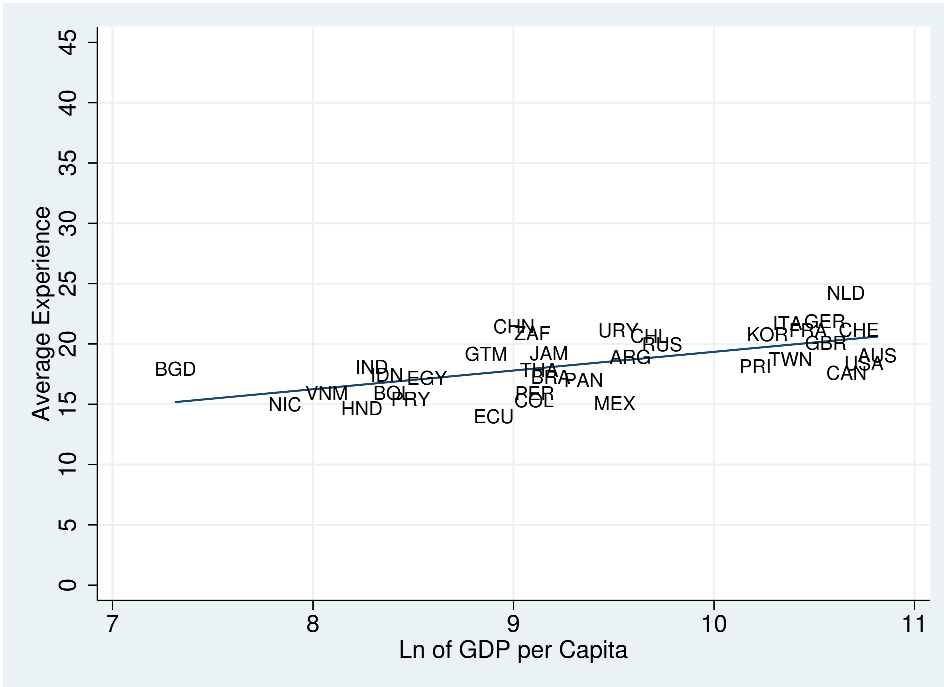


Figure A.4: Fraction of Individuals with Positive Wage Earnings by Age

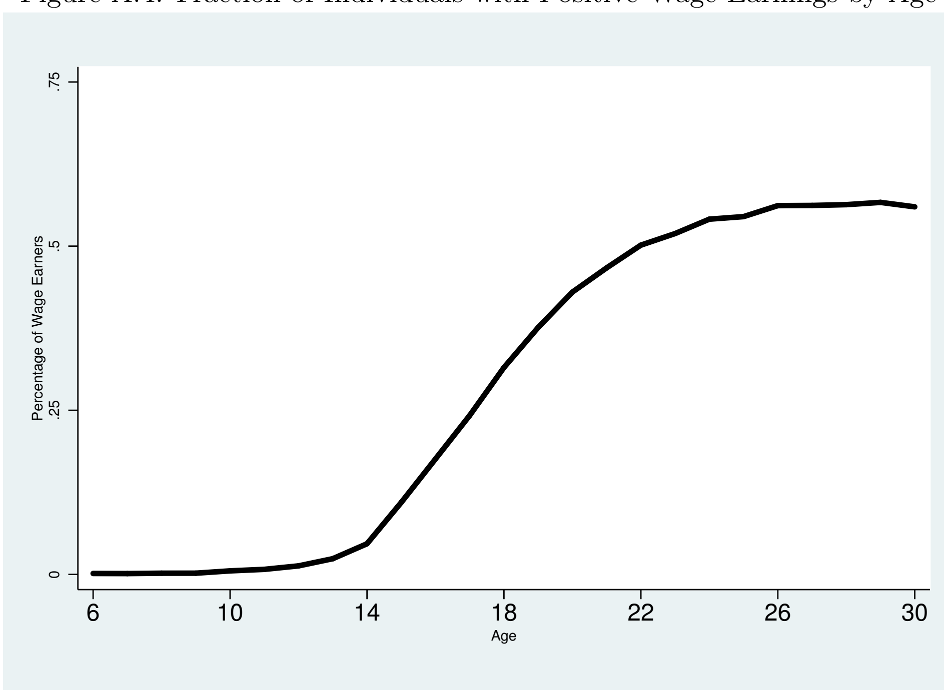
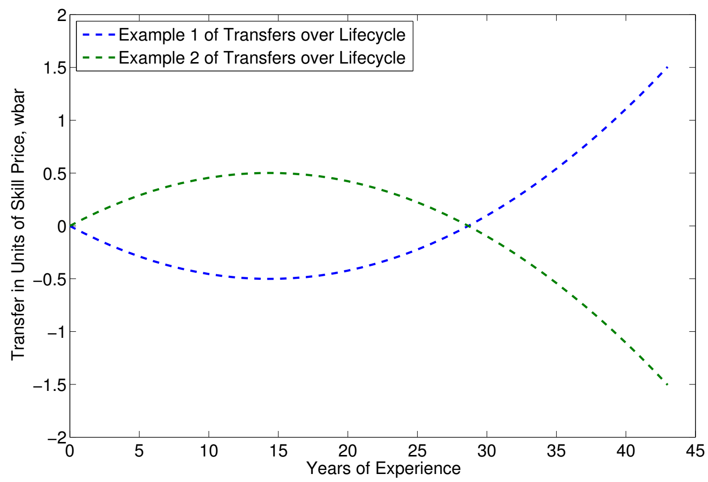


Figure A.5: Acceptable Violations of $w = MPL$

(a) Transfers over the Life Cycle



(b) Implied Experience-Earnings Profiles with Transfers

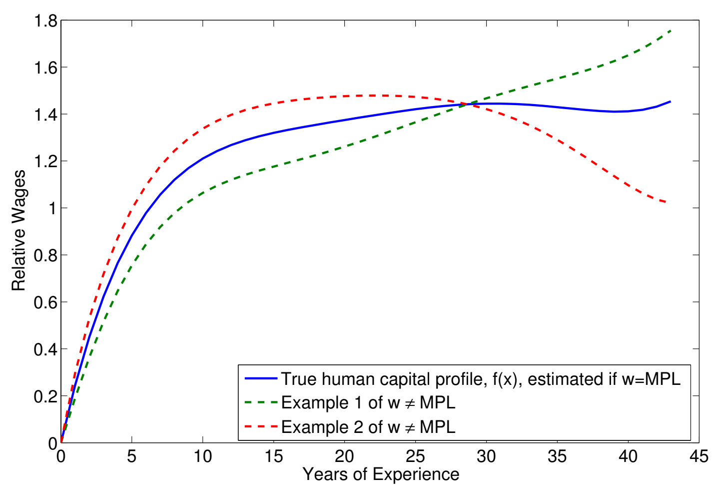
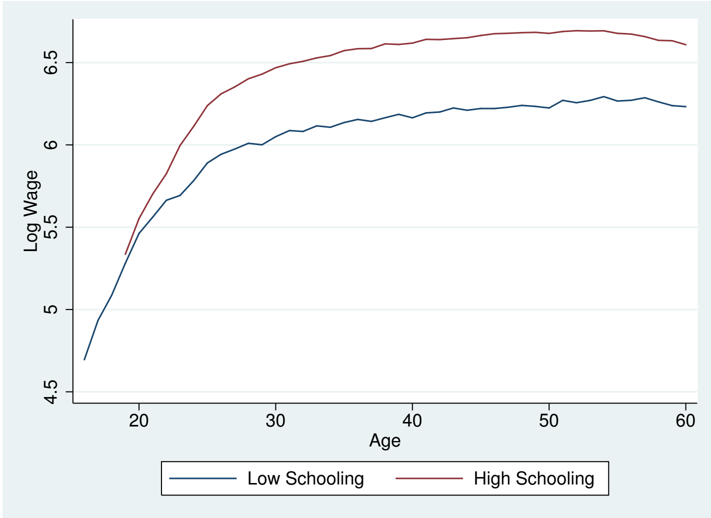
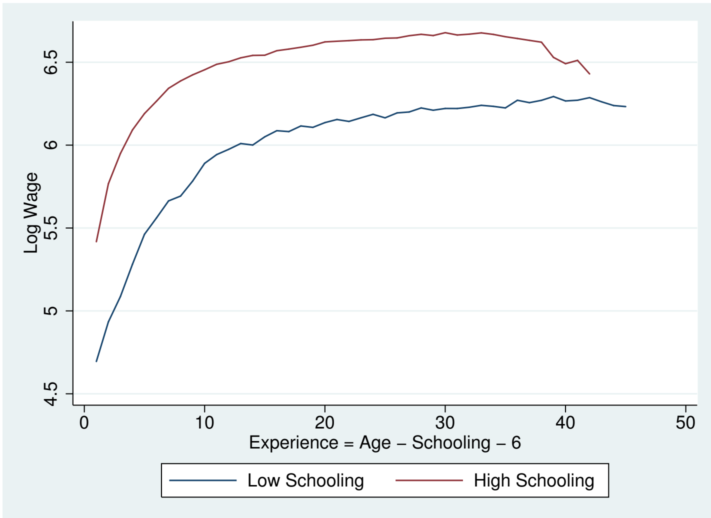


Figure A.6: Age- versus Experience-Earnings Profiles

(a) Age-Earnings Profiles (Levels)



(b) Experience-Earnings Profiles (Levels)



(c) Experience-Earnings Profiles (Relative)