

# Life Cycle Wage Growth across Countries

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This paper documents how life cycle wage growth varies across countries. We harmonize repeated cross-sectional surveys from a set of countries of all income levels and then measure how wages rise with potential experience. Our main finding is that experience-wage profiles are on average twice as steep in rich countries as in poor countries. In addition, more educated workers have steeper profiles than the less edu-

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cated; this accounts for around one-third of cross-country differences in aggregate profiles. Our findings are consistent with theories in which workers in poor countries accumulate less human capital or face greater search frictions over the life cycle.

## I. Introduction

This paper documents how life cycle wage growth varies across countries. It is well known that wages grow substantially over the life cycle in the United States and other advanced economies. However, there is little comparable evidence from less developed countries. This is unfortunate, as cross-country differences in life cycle wage growth are key for addressing questions such as the importance of human capital and labor market frictions for explaining cross-country income differences (Burdett 1978; Jovanovic 1984; Klenow and Rodriguez-Clare 1997; Bils and Klenow 2000; Caselli 2005; Manuelli and Seshadri 2014).

We fill this gap by measuring life cycle wage growth in both low- and high-income countries. We use representative large-sample household surveys from 18 countries with individual-level data on educational attainment, labor earnings, and the number of hours worked. These data allow us to construct comparable measures of hourly wages and potential experience for all countries in our sample.

Our main finding is that wages increase substantially more over the life cycle in rich countries than in poor countries. We take three alternative approaches to measuring life cycle wage growth. The first and simplest approach is to construct cross-sectional experience-wage profiles in which experience is measured as years of potential experience, that is, years elapsed since finishing school. To do this, we compute mean wages for each 5-year experience bin relative to the bin with the least experience. We show that profiles are steeper in rich countries than in poor countries, with differences that are statistically and economically significant: wages almost double over the life cycle in rich countries whereas

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they increase by only around 50 percent in poor countries. Put differently, wages rise almost twice as much in rich countries as in poor ones.

Our second approach follows Mincer (1974), which allows us to control for years of schooling in the standard way. It also provides a framework for addressing the well-known challenge to estimating life cycle profiles in age (or potential experience), which is that age is collinear with time and birth cohort (i.e., calendar year and birth year). This means that one cannot separately identify the effect of age from the effect of time or birth cohort without further restrictions, a point that has not been addressed in the existing cross-country literature. We begin by following the standard approach outlined by Hall (1968) and Deaton (1997). They show that experience or age profiles can be estimated if one assumption about the source of aggregate income growth is imposed. We find that if time effects explain half or more of growth, then wages rise more over the life cycle in rich countries. However, there are two challenges: one does not know in general what fraction of growth is due to time effects, and this fraction could differ across countries.

Our third and preferred approach draws on economic theory to address this challenge. We draw on a common prediction of theories of life cycle wage growth that there should be little or no effect of experience on wages near the end of the life cycle.<sup>1</sup> For example, human capital theory predicts that the incentive to invest in human capital formation declines at the end of the life cycle, while search and matching theory predicts that the incentive to search for better matches declines similarly. Our insight, based on the work of Heckman, Lochner, and Taber (1998), is that this theoretical prediction is sufficient to disentangle experience, time, and cohort effects. Intuitively, if we follow a fixed cohort across multiple cross sections for the last years of their working life, then we rule out both cohort effects (by construction) and experience effects (by the theoretical result above), allowing us to attribute any wage changes to time effects. Once we have recovered the aggregate time effects, it is straightforward to estimate the experience and cohort effects of workers who are not near the end of the life cycle. Applying this method, we again find that estimated experience-wage profiles are substantially steeper in rich countries than in poor countries. We also experiment with variants of this idea in which wage profiles are assumed to decrease at the end of the life cycle, for example, because of human capital depreciation, and find similar results.

We provide evidence that our findings are robust to a number of alternative measurement assumptions and sample restrictions. While our

<sup>1</sup> For example, Rubinstein and Weiss (2006) review the literature on life cycle wage growth and explain in detail the three main mechanisms emphasized in this literature (human capital investment, search, and learning), noting that all three have “similar implications with respect to the behavior of mean wages, implying rising and concave wage profiles” (4).

benchmark results focus on full-time male wage workers, we show that experience-wage profiles are steeper in rich countries when we include women, part-time workers, and the self-employed. To address concerns that our findings are driven by mismeasurement of experience, we show that our results are similar when using an alternative measure of experience based on age- and education-specific employment rates. Furthermore, adding plausible amounts of measurement error to the age and education variables in rich countries does not cause the profiles of rich countries to look like those of poor ones. Finally, we show that our cross-sectional experience profiles from the United States and Mexico are similar to those computed using panel data.

We next explore one natural hypothesis for why experience-wage profiles are steeper in richer countries, which is that richer countries have a greater fraction of educated workers. While Mincer (1974) found that US experience-wage profiles were similar for different education groups, more recent work has tended to find that more educated workers have steeper experience-wage profiles (Lemieux 2006). Overall, we find that across our 18 countries, more educated workers have steeper experience-wage profiles on average than less educated workers and that cross-country differences in the distribution of educational attainment account for around one-third of the flatter aggregate experience profiles in poor countries. This implies that education is likely to be an important factor for explaining cross-country differences in life cycle wage growth but also suggests that other factors play important roles.

We conclude by returning to the interpretation and broader implications of our findings. Three popular theories of life cycle earnings patterns and wage dynamics are human capital accumulation, on-the-job search, and long-term contracts. While it is hard to provide definitive conclusions about which theory best explains our findings, several pieces of evidence point to human capital and search frictions as playing important roles. First, when we look at profiles by broad occupation category, we find robust evidence that manual occupations have flatter profiles than cognitive occupations. Since manual occupations likely have less scope for lifetime learning and since around half of workers in poor countries are in manual occupations, this suggests a human capital interpretation. Second, we find that wage variances generally increase over the life cycle, with some evidence of a dip for early experience levels in rich countries. We note that this is predicted by several classes of theories of human capital and search and matching frictions. Finally, we look at wage profiles for day laborers, who are not engaged in long-term wage contracts, and find that, in the poor countries for which we have data, these are again flatter than in rich countries.

Both human capital and search theories suggest that our findings may help explain cross-country income differences. Through the lens of hu-

man capital theory, our findings point to a much greater role for human capital in accounting for cross-country income differences than suggested by previous studies, in particular those of Klenow and Rodriguez-Clare (1997), Bils and Klenow (2000), and Caselli (2005). Specifically, our findings are consistent with workers in rich countries accumulating more human capital over the life cycle than workers in poor countries. This is exactly the theoretical prediction of Manuelli and Seshadri (2014). Through the lens of search and matching theory, our findings suggest less labor market fluidity in poor countries, which prevents workers from climbing the job ladder and may act as a form of misallocation: workers are less able to move to better jobs that fit their skills in poor countries. This misallocation could once again be an important contributor to cross-country income differences, in the spirit of Hsieh et al. (2013).

We are not the first to examine the relationship between wages and experience across countries. Our findings contrast with those of earlier work, in particular, Psacharopoulos (1994) and Bils and Klenow (2000), who found no relationship between returns to experience and GDP per capita. Our conclusion differs for three main reasons. First, previous studies focus on earnings, which conflates growth in hourly wages and growth in hours worked. Second, some of the earlier estimates draw on small, nonrepresentative samples and the cross-country comparisons combine estimates from underlying studies with different specifications and sampling frames. In contrast, we restrict our attention to comparable nationally representative samples of 5,000 or more full-time, male, private-sector workers. Third, the previous literature focuses exclusively on cross-sectional estimates—often a single cross section—and does not address the potentially confounding influences of cohort and time effects.

This paper is organized as follows. Section II describes our household survey data. Section III documents that simple cross-sectional experience-wage profiles are flatter in poorer countries. Section IV measures experience-wage profiles using the Deaton-Hall and Heckman-Lochner-Taber methods. Section V investigates the robustness of our estimated experience-wage profiles. Section VI considers interactions between schooling and experience and the role of schooling in accounting for aggregate experience profiles. Section VII discusses broader implications and interpretations of our findings. Section VIII concludes the paper.

## II. Data

Our analysis uses large-sample household survey data from 18 countries. The surveys we use satisfy three criteria: (i) they are nationally representative and have at least 5,000 observations on full-time males in the private sector; (ii) they contain individual labor earnings; and (iii) they contain

individual data on the number of hours worked. The large sample size in restriction i is important for estimates that require us to cut the sample into multiple groups, such as our estimates of life cycle wage growth by educational attainment later in the paper. Restrictions ii and iii are important because they allow us to compute individual-level wages. Note that all of our data have demographic as well as educational attainment information on all individuals. We focus much of our analysis on a sample of eight core countries that satisfy restrictions i–iii and additionally have repeated cross sections spanning 15 or more years. This additional restriction is necessary for our method to disentangle experience, time, and cohort effects in Section IV.<sup>2</sup>

Table 1 lists the countries in our sample, the income level of each country, the data source, the years of coverage, and whether each country is in the core sample. The countries in both the full and core samples comprise a wide range of income levels, from the United States and Germany to Bangladesh (in the extended sample) or Jamaica (in the core sample). Please see table 1 and online appendix A.1 for the source of each survey. The main limitation in terms of data coverage is that we do not observe the poorest countries in the world, such as those in sub-Saharan Africa, since data from these countries do not satisfy the criteria described earlier. We define the rich countries to be the United States, Germany, Australia, Canada, France, and South Korea, and we define the poor countries to be all the rest.

The main outcome variable is an individual's wage, which we define to be his labor earnings divided by the number of hours that he worked. In most countries, we observe earnings during the month prior to the survey and hours worked during the week prior to the survey. For the United States, Canada, Brazil, and Jamaica, we observe labor income and hours worked at an annual frequency. We restrict attention to individuals with 0–40 years of experience who have positive labor income and nonmissing age and schooling information. In all surveys, we impute the years of schooling using educational attainment data. For all countries, we examine earnings and wages in local currency units of the most recent year for which we have a survey, using the price deflators provided by the International Monetary Fund's International Financial Statistics.

In our main analysis we use sample selection criteria that are standard in the labor and development literature on returns to education and ex-

<sup>2</sup> A number of survey results are freely downloadable from IPUMS (Minnesota Population Center 2011), and all are publicly available. An earlier version of our paper (Lagakos et al. 2012) used data from 35 countries. For 14 of these countries, the data did not satisfy all of the criteria i–iii listed above. An additional three countries were removed because they reported income in a way that was inconsistent with all of the other countries. Details are available on request. However, note that our main finding that experience-wage profiles are steeper in rich countries is still present in this expanded set of countries.

TABLE 1  
SUMMARY OF DATA

	GDP per Capita (2011) (1)	Data Source (2)	Years Covered (3)
United States*	49,781	Census, American Community Survey	1960–2013
Germany*	42,143	German Socioeconomic Panel (SOEP)	1991–2009
Australia	41,763	Household Income and Labour Dynamics	2001–9
Canada*	41,567	Census of Canada	1971–2001
France	37,325	Survey of Employment	1993–2001
United Kingdom*	36,590	British Household Panel Survey (BHPS)	1994–2008
South Korea	31,327	Korea Labor and Income Panel Study	1999–2008
Chile*	20,266	National Socioeconomic Survey (CASEN)	1990–2011
Uruguay	17,905	Extended National Survey of Households	2006
Mexico*	15,730	General Population and Housing Census	1990–2010
Brazil*	14,831	General Census of Brazil	1991–2010
Peru	10,379	National Household Survey	2004, 2010
Indonesia	8,870	National Labor Force Survey	2001–10
Jamaica*	8,481	Population Census	1982–2001
Guatemala	6,799	National Living Standards Survey	2000, 2006
Vietnam	4,717	Living Standards Survey	1998, 2002
India	4,686	Human Development Survey	2012
Bangladesh	2,579	Household Income and Expenditure Survey	2005, 2010

NOTE.—Core countries are denoted by an asterisk. GDP data are from the World Bank's World Development Indicators (2016), and the measure used is 2011 GDP per capita (PPP) in constant 2011 international dollars. For exact years of each survey, see online app. sec. A.1.

perience (Murphy and Welch 1990; Duflo 2001; Lemieux 2006). We restrict our attention to male, full-time workers who earn wages. These restrictions are motivated by the fact that potential experience is a better proxy of actual experience for male and full-time workers than for female and part-time workers. The restriction to wage workers is motivated by the observation that earnings of self-employed workers can reflect payments to both capital and labor, making it difficult to accurately measure wages of the self-employed (see, e.g., Deaton 1997; Gollin 2002; Hurst, Li, and Pugsley 2014). In addition to these standard restrictions, we focus our analysis on private-sector workers, which is motivated by the concern that public-sector workers may receive nonwage compensation such that their wages do not reflect the full payment for their labor. In the main analysis, we follow the literature and define potential experience as  $\text{experience} = \text{age} - \text{schooling} - 6$  for individuals with 12 or more years of schooling and as  $\text{experience} = \text{age} - 18$  for individuals with fewer than 12 years of schooling. This definition implies that individuals begin to work at age 18

or after they finish school, whichever comes later. The cutoff at age 18 is motivated by the fact that few individuals have positive wage income before the age of 18 in the data. Although each of these sample restrictions and the definition of potential experience are fairly standard in the literature, we reconsider each of them in Section V.

### III. Life Cycle Wage Growth: Cross-Sectional Evidence

In this section, we present cross-sectional evidence on life cycle wage growth. We focus first on our core eight countries, where we have the most data, and compute experience-wage profiles, a simple measure of life cycle wage growth that has been studied in the literature. We find that profiles are steeper in the rich countries than in the poor countries. We then turn to our full set of countries and document the same pattern.

#### A. *Experience-Wage Profiles for Core Countries*

We begin by presenting experience-wage profiles for our eight core countries. We focus on experience-wage profiles as our measure of life cycle wage growth rather than age-wage profiles. The reason is that experience-wage profiles allow us to summarize the evolution of wages over the life cycle for groups with different educational attainment and hence different ages of entry into the labor market. Relatedly, age-wage profiles typically differ by education groups, while experience profiles tend to be much more parallel. We discuss these issues in detail in Section VI.A, where we present age- and experience-wage profiles separately by educational attainment.

For each country, we calculate an experience-wage profile for each survey year by computing the average wage by 5-year experience bin and expressing it as a percent difference from the average wage of the lowest experience bin (0–4 years of experience). We then compute each country's experience-wage profile as the average profile across calendar years. Note that this is conceptually similar to estimating experience-wage profiles with repeated cross sections while controlling for time (i.e., the year of each survey) fixed effects. The reason is that, by normalizing the average wages of workers in each experience group by the average wage of the lowest experience bin in each year, the profiles are made comparable over time for countries with different time trends.

Figure 1 plots experience-wage profiles for our core countries.<sup>3</sup> For expositional purposes we plot the profiles for rich countries on the left-

<sup>3</sup> See app. fig. A.1 (all app. figures and tables are available online) for the same figure with the 95 percent confidence intervals.



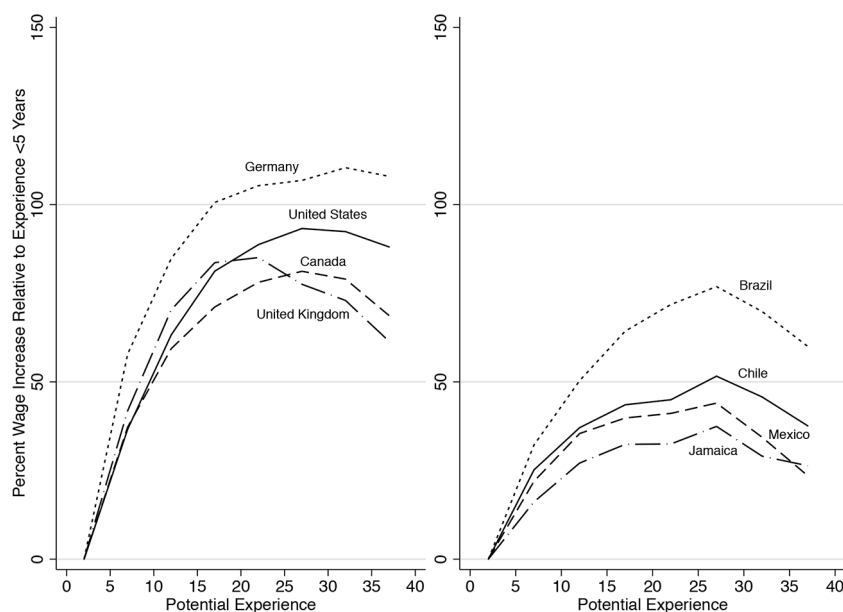


FIG. 1.—Cross-sectional experience-wage profiles, core countries. Experience-wage profiles are for full-time males working in the private sector and are calculated using all available years of data for each country. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. For each country and year, we compute the ratio of average wages for workers in each 5-year experience bin relative to the average wages of workers with less than 5 years of experience. The experience-wage profiles in the figure are the unweighted average wage ratios by experience across all years. The left-hand panel shows the rich core countries, and the right-hand panel shows the poor core countries.

hand panel and for poor countries on the right-hand panel. In all countries, profiles are increasing until at least 20 years of potential experience and then flatten or decline afterward. Among the rich countries, Germany has the steepest profile, at above 100 percent higher wages by 20 years of experience. The profiles for the United States, Canada, and the United Kingdom are similar and somewhat flatter than that of Germany, with around 75 percent higher wages by 20 years of experience. Among the poor countries, Brazil is the steepest, reaching a height of just above 70 percent, followed by Chile, Mexico, and then Jamaica.

To summarize these findings and more formally compare experience-wage profiles across countries, we compute five summary statistics for each country. The first is the height of the profile at 5–9 years of experience, or 5 years more experienced (on average) than the least experience bin. The second and third are the heights at 20–24 and 35–39 years of experience. The fourth is the average height of the profile, computed

as the average across all experience bins other than the lowest. The fifth is the average height when discounting each year at 4 percent per year, which is meant to be a simple measure of the discounted value of lifetime income gains.<sup>4</sup>

Panel A of table 2 reports the summary statistics for each country. The reported heights are relative to the least experienced group, which comprises workers with 0–4 four years of experience. Germany's profile is the steepest, reaching 105 percent by 20–24 years of experience. This is followed by the United States (90 percent), the United Kingdom (85 percent), and Canada (80 percent).<sup>5</sup> Brazil's profile is the steepest among poor countries, at approximately 70 percent. This is followed by Chile (45 percent), Mexico (40 percent), and Jamaica (33 percent). The heights at 35–39 years of experience paint a similar picture, as do the average and discounted heights.

Panel B of table 2 presents permutation tests of the null hypothesis that experience-wage profiles are the same in the rich and poor countries. The logic of the permutation test is that under the null, one can resample the data many times to compute the probability that one would observe a difference as extreme as the actual difference in the data by chance. Permutation tests have better properties for small samples than other commonly used tests, such as *t*-tests (Lehmann and Romano 2005).

The differences between the means for rich countries and poor countries are large and statistically significant for all four of the summary statistics. In the rich countries, the wages of workers with 20–24 years of experience are 89.3 percent higher than those with less than 5 years of experience. In contrast, in the poor countries, the wages of workers with 20–24 years of potential experience are just 47.6 percent higher than those with less than 5 years of experience. The difference is 41.7 percentage points, which means that experience-wage profiles are roughly twice as steep on average in rich countries by 20 years of experience.

The profiles are also roughly twice as steep in rich countries according to the other summary statistics. At the lowest experience level, 5–9 years

<sup>4</sup> A convenient property of the discounted average height is that it appropriately trades off wage gains that occur early vs. late in life, and it therefore can be used, e.g., to compare the profiles of two countries that cross. This summary statistic is also related to a statistic commonly used to compute returns to education: the difference in the present discounted value of lifetime earnings across different education groups (see, e.g., Todaro and Smith [2012], sec. 8.2, and references cited there).

<sup>5</sup> Our estimated experience-wage profiles for the rich countries are largely in line with previous estimates in the literature. In the United States, e.g., Lemieux (2006) uses Current Population Survey data to estimate an increase in wages of 0.7 log points, or roughly 100 percent, between 0 and 20 years of experience. Our estimates of other measures of life cycle income growth, e.g., age-earnings profiles, also line up well with previous estimates in the literature. Guvenen et al. (2014) use administrative data to estimate 127 percent higher average earnings for those aged 51 than those aged 25. Using our data, we calculate 116 percent higher average earnings for those aged 51 than those aged 25.

TABLE 2  
CROSS-SECTIONAL EXPERIENCE-WAGE PROFILES

	Height at Experience 5–9 (1)	Height at Experience 20–24 (2)	Height at Experience 35–39 (3)	Average Height (4)	Discounted Average Height (5)
A. Summary Statistics by Country					
United States	36.6	88.7	88.1	67.9	30.5
Germany	57.8	105.3	108.0	84.2	38.8
Canada	37.3	78.1	68.7	59.3	27.3
United Kingdom	41.8	85.1	61.5	61.6	29.3
Chile	25.2	45.0	37.6	35.7	16.7
Brazil	32.2	71.8	60.0	53.2	24.3
Mexico	21.9	41.1	23.5	30.0	14.5
Jamaica	16.1	32.5	26.4	25.1	11.8
B. Test of Differences in Means, Rich and Poor Groups					
Rich mean	43.4	89.3	81.6	68.3	31.5
Poor mean	23.9	47.6	36.9	36.0	16.8
Rich – poor	19.5** (.013)	41.7** (.012)	44.7** (.014)	32.3** (.014)	14.7** (.015)

NOTE.—Column 1 of panel A is the average height of the experience-wage profile at potential experience of 5–9 years, defined as the ratio of average wages for workers with 5–9 years of potential experience to average wages for workers with 0–4 years of potential experience. Column 2 is the average height of the experience-wage profile at experience 20–24 years. Column 3 is the average height of the experience-wage profile at experience 35–39 years. Column 4 is the average height of the profile relative to workers with 0–4 years of potential experience. Column 5 is the discounted average height of the profile relative to workers with 0–4 years of potential experience, where wages are discounted at a rate of 4 percent per year. The sample is restricted to full-time males in the private sector. Panel B shows the results of permutation tests of the null hypothesis that the experience-wage profiles are the same in rich and poor countries.

\*  $p$ -value < .10.

\*\*  $p$ -value < .05.

\*\*\*  $p$ -value < .01.

of experience, differences are already significant, at 43.4 percent higher in the rich countries, versus 23.9 percent higher in the poor countries. By the highest experience level, 35–39 years of experience, wages in the rich countries are 81.6 percent higher on average than for the least experienced workers, compared to 36.9 percent in the poor countries. The average height of the profile is 68.3 percent in the rich countries and 36.0 percent in the poor countries, for a difference of 32.3 percentage points. The discounted average height is 31.5 percent in the rich countries and 16.8 percent in the poor countries, for a difference of 14.7 percentage points. The  $p$ -values for these differences are below 5 percent in all cases, meaning that these differences are unlikely to have occurred by coincidence. Thus, experience-wage profiles are on average steeper in the rich countries.

Finally, a point worth emphasizing is that virtually the entire difference in steepness between rich and poor countries occurs over the first 20 years of workers' potential experience. For instance, panel B of table 2 shows that 41.7 of the 44.7 percentage point mean difference between rich and poor countries in the height of the experience profiles is due to potential experience increasing from 0–4 to 20–24 years, and only an additional 3 percentage points are due to potential experience increasing further to 35–39 years. This fact is also apparent visually from figure 1. In online appendix A.3, we explore in more detail at what point of the life cycle the differences in returns to experience between rich and poor countries occur and show that about half of the difference in profiles at 20–24 years of experience is realized after only 5 years.

### *B. Experience-Wage Profiles for All Countries*

We now turn to a broader set of countries for which cross-sectional wage profiles can be constructed. This offers a more comprehensive examination of life cycle wage growth across countries, simply by way of covering more countries, though the noncore countries cover fewer individuals and years than the core countries.

Figure 2 presents experience-wage profiles for all 18 countries in our sample. Countries are sorted in descending order of GDP per capita from the top-left to the bottom-right panel. The top-left panel adds the profile for Australia and France to the core countries of the United States, Germany, and Canada. The top-right panel includes the second-richest group of countries: the United Kingdom (which has slightly lower GDP per capita than France), South Korea, Uruguay, and Chile; the bottom-left panel includes the second-poorest group of countries: Indonesia, Brazil, Peru, and Mexico; and the bottom-right panel includes the poorest countries in our sample: Bangladesh, Guatemala, India, Jamaica, and Vietnam.

A comparison of the profiles across panels shows clearly that experience-wage profiles become flatter as the country's income falls. The difference between the richest countries (upper-left) and poorest (lower-right) is readily apparent, with all of the richest countries having 75–100 percent higher wages by 20 years of experience and all of the poorest countries having less than 50 percent higher wages. Life cycle wage growth in countries with more intermediate income levels (in the upper-right and lower-left panels) is roughly in between that of the richest and poorest countries. While figure 2 confirms that experience-wage profiles are steeper in richer countries, it also highlights that there is a fair amount of dispersion in steepness particularly in the intermediate income groups (upper-right and lower-left panels). For example, the experience-wage profile for Indonesia ultimately rises as much as that for some of the richest coun-

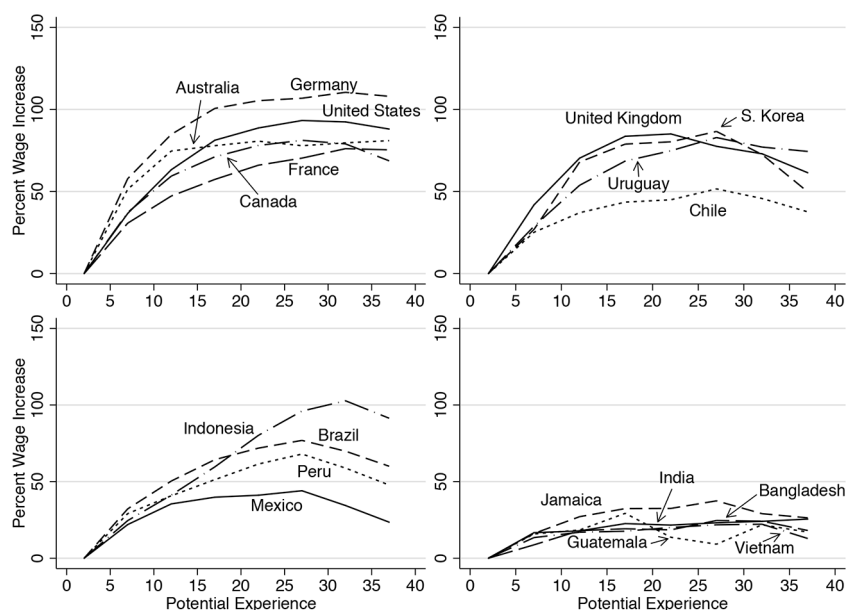


FIG. 2.—Cross-sectional experience-wage profiles, all countries. Experience-wage profiles are for full-time males working in the private sector and are calculated using all available years of data for each country. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. For each country and year, we compute the ratio of average wages for workers in each 5-year experience bin relative to the average wages of workers with less than 5 years of experience. The experience-wage profiles in the figure are the unweighted average wage ratios by experience across all years. Countries are sorted in order of 2011 PPP GDP per capita from the top-left to the bottom-right panel.

tries. Nevertheless, on average, the overall pattern that experience-wage profiles are steeper in richer countries remains: taking an average across all rich countries (in the core and full samples), the average height at 20–24 years of experience is 83.5 percent. For the poor countries, the average is 45.9 percent, which results in a difference between rich and poor countries of 37.5 percentage points. This difference is statistically significant at the 1 percent level and comparable in magnitude to the difference in the core sample. Thus, figure 2 shows that the finding that experience-wage profiles are steeper in richer countries is true in the full sample as well as in the sample of core countries. Finally, as already noted in the previous section, the majority of the differences in profiles between rich and poor countries occur over the first 20 years of workers' life cycle.

A complementary way to present the data is to look at the height of the profiles at one particular experience level by GDP per capita. Figure 3 plots the heights of the profiles after 20–24 years of potential experience

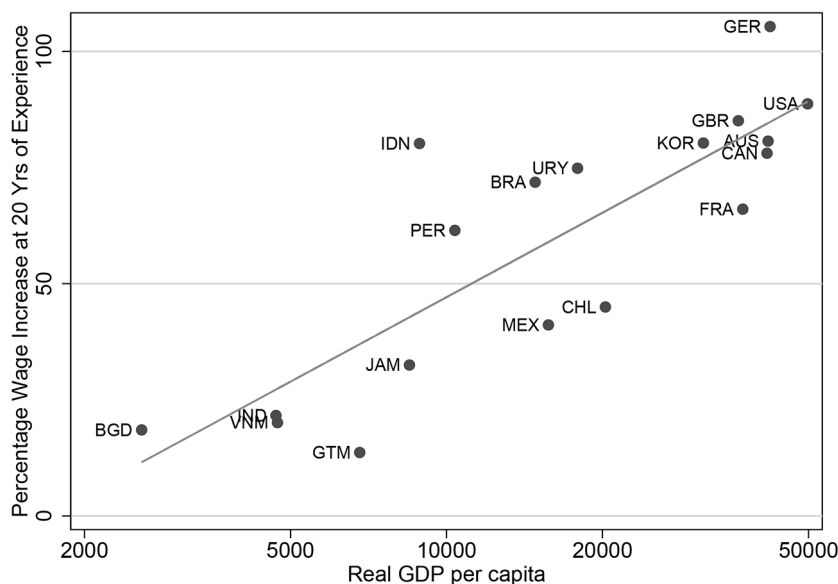


FIG. 3.—Percentage wage increase at 20–24 years of experience by GDP per capita. This figure plots the heights of the cross-sectional experience-wage profiles by 20–24 years of potential experience relative to 0–4 years of potential experience against GDP per capita at PPP in 2011. Experience-wage profiles are for full-time males working in the private sector and are calculated using all available years of data for each country. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. For each country and year, we compute the ratio of average wages for workers in each 5-year experience bin relative to the average wages of workers with less than 5 years of experience. The experience-wage profiles used in the figure are the unweighted average wage ratios by experience across all years.

against GDP per capita in 2011. We choose 20–24 years of experience because, as argued above, most of the life cycle wage gains occur by then. The coefficient of a regression on profile heights at 20–24 years of experience on log GDP per capita is 26.2, and it is statistically significant at well below the 1 percent level. The  $R^2$  from this regression is .70. Thus, as the figure shows, the profile heights are clearly increasing in GDP per capita through the entire range of income.

#### IV. Life Cycle Wage Growth: Controlling for Education, Time, and Cohort

In the previous section, we presented cross-country evidence on experience-wage profiles by simply plotting average wages within age or experience bins in the cross section of individuals. While we view this as a useful start-

ing point because it imposes minimal structure and assumptions on the data, there are a number of important issues that such a simple exercise does not address. First, our cross-sectional profiles ignore the role of schooling. Second, cross-sectional estimates leave open the possibility that experience-wage profiles are driven by cohort effects, such as improvements in the health of subsequent birth cohorts. In this section we address both of these issues.

Throughout this section, we estimate flexible versions of Mincer regressions of individuals' wages on their years of schooling and potential experience. That is, we estimate equations of the form

$$\log w_{ict} = \alpha + \theta s_{ict} + f(x_{ict}) + \gamma_t + \psi_c + \varepsilon_{ict}, \quad (1)$$

where  $w_{ict}$  is the wage of individual  $i$ , who is a member of birth cohort  $c$  and is observed at time  $t$ ;  $s_{ict}$  and  $x_{ict}$  are her years of schooling and experience;  $\gamma_t$  is a vector of time period dummy variables;  $\psi_c$  is a vector of cohort dummy variables; and  $\varepsilon_{ict}$  is a mean zero error term. We follow the textbook specification and assume that schooling and experience enter in an additively separable fashion. This assumption is relaxed in Section VI.A, where we allow the returns to experience to differ between more and less educated workers. In what follows, we estimate equation (1) separately for each country under various assumptions on cohort and time effects and then assess how the function  $f(\cdot)$  varies across countries. Equation (1) differs from the traditional Mincer regression in two ways. First, we allow the relationship between experience and wages to be flexible and do not restrict the functional form to be linear. Second, we allow for cohort and time effects, as we describe below.

#### A. *Deaton-Hall Approach*

The main challenge to estimating returns to experience (or age) is that one cannot separately identify the effects of experience, birth cohort, and time because of collinearity. In this section, we consider the effects of cohort and time controls following the approach proposed by Hall (1968) and Deaton (1997) for estimating returns to experience using repeated cross sections. The main purpose of the Deaton-Hall approach is to illustrate the mechanics of the econometric difficulty. The next section then provides a theoretically motivated method for disciplining time and cohort effects. Before proceeding, we note that panel data would not solve this identification problem. The reason is that even when following specific individuals (rather than cohorts) over time, one cannot separate how much of their wage growth is due to aging or the passing of time. In either cross-sectional or panel data these effects can be identified only

with additional assumptions, which, as is well known in the literature, are identical for both types of data.<sup>6</sup>

To implement (1), we regress the logarithm of wages on schooling and a set of dummy variables for 5-year experience groups,

$$\log w_{ict} = \alpha + \theta s_{ict} + \sum_{x \in X} \phi_x D_{ict}^x + \gamma_t + \chi_c + \varepsilon_{ict}, \quad (2)$$

in combination with one additional linear restriction on the set of cohort and time effects corresponding to different versions of the Deaton-Hall approach. The term  $D_{ict}^x$  is a dummy variable that takes the value of one if a worker is in experience group  $x \in X = \{5-9, 10-14, \dots\}$ ; the omitted category is experience less than 5 years. This specification allows us to capture nonlinearities in a flexible way. The coefficient  $\phi_x$  estimates the average wage of workers in experience group  $x$  relative to the average wage of workers with less than 5 years of experience. In terms of our notation of equation (1), the  $\phi_x$  terms represent  $f(x)$  such that the coefficient estimate corresponding to each experience level,  $x$ , identifies the experience-wage profile evaluated at point  $x$ .

To resolve the difficulty of collinearity, Hall (1968) and Deaton (1997) impose one additional linear restriction on the set of cohort and time effects in equation (2). We consider three different versions of the Deaton-Hall approach. The first version attributes all labor productivity growth to cohort effects and uses year dummies to capture only cyclical fluctuations. This is the assumption made in Deaton's (1997) original analysis and more recently by Aguiar and Hurst (2013). We implement this by estimating equation (2) with birth cohort dummies and time dummies, with the restriction that the time dummies are orthogonal to a time trend. See online appendix A.2 for a more formal description of our methodology. The second version takes the opposite extreme and attributes all labor productivity growth to time effects. We implement this by estimating equation (2) with cohort and time dummies, but now we restrict the cohort effects to be orthogonal to a time trend. The third takes the intermediate view that productivity growth is attributed in equal parts to cohort and time effects. While we are agnostic on the most natural split between time and cohort effects, the case of an equal split is nonetheless useful for illustrating how the estimated returns to experience across countries depend on the relative importance of the two effects.

Figure 4A plots the estimates from the first version, in which all income growth is attributed to cohort effects.<sup>7</sup> The left-hand panel shows

<sup>6</sup> For example, Heckman and Robb (1985, 140) note that "it is by now well known (Cagan 1973) that [panel] data do not solve the identification problem" and that "panel data and a time series of cross sections of unrelated individuals are equally informative."

<sup>7</sup> The confidence intervals tend to be narrow for most countries, so we omit them for brevity.



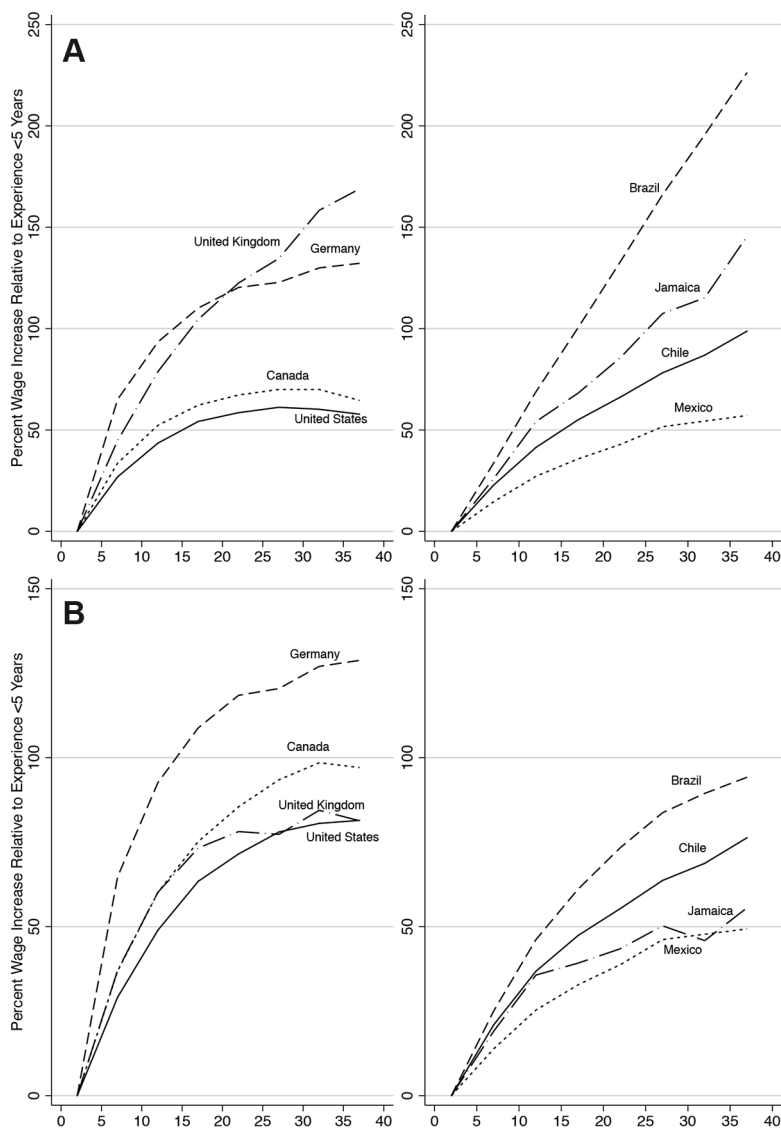


FIG. 4.—Deaton-Hall experience-wage profiles. Experience-wage profiles are for full-time males working in the private sector. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. Panel A shows the experience-wage profiles estimated using equation (2), with time controls as well as cohort controls, assuming that all growth is driven by cohort effects. Panel B shows the experience-wage profiles estimated using equation (2), with time controls as well as cohort controls, assuming that all growth is driven by time effects. See Section IV.A and online appendix A.3 for a detailed description of our methodology.

that Germany and the United Kingdom have the steepest profiles, with more than 100 percent growth by 20 years of experience, while the United States and Canada have around 60 percent growth by 20 years of experience. The right-hand panel shows that all of the poor countries have steep and linear (or close to linear) experience profiles, with Brazil being the steepest, followed by Jamaica, Chile, and then Mexico. The reason that this version has such steep profiles is that, with time effects shut down, all wage growth by individual cohorts over their lifetimes is attributed to their increased experience. In countries such as Brazil and Jamaica that have experienced high rates of aggregate growth over this period, the size of the effects attributed to experience is large.<sup>8</sup>

Figure 4*B* plots the estimates from the second version, in which all labor productivity growth is attributed to time effects. The left-hand panel shows that Germany is still the highest, at more than 100 percent growth, while Canada, the United Kingdom, and the United States are close behind at between 75 percent and 90 percent growth. The right-hand panel shows that the poor countries have flatter profiles than the rich countries, with Brazil still highest at around 70 percent growth, followed by Chile at 65 percent growth and Mexico and Jamaica at just under 50 percent growth. These profiles are very similar to the cross-sectional profiles in Section III because both sets of profiles attribute wage growth over time to changes in aggregate economic conditions rather than to improvements across cohorts.

Panel A of table 3 reports the five summary statistics when all growth is explained by cohort effects. By 5–9 years of experience, profiles are 18.3 percentage points higher in the rich than in the poor countries (and statistically significant). By 20–24 years of experience, profiles are, on average, 10.8 percentage points higher in the rich countries, and by 35–39 years the difference is 38.8 percentage points (though neither difference is statistically significant). The average and discounted heights are slightly higher in the rich countries, but the magnitudes are small and statistically insignificant.

Panel B of table 3 shows the intermediate case in which growth is explained equally by cohort and time effects. By 5–9 years of experience, the difference is 20.2 percentage points and is statistically significant at the 5 percent level. By 20–24 years of experience, the rich mean is 27.4 percentage points higher than the poor country mean, which is significant at the 10 percent level. By 35–39 years of experience, rich and poor countries have similar means. The average height is 16.1 percentage points higher among the rich, while the discounted height is 9.0 percentage points higher

<sup>8</sup> Brazil and Jamaica had wage growth of 3.5 percent per year and 2.1 percent per year on average, while Chile and Mexico had growth of 1.6 percent and 1.1 percent. Among the rich countries, the United Kingdom and Germany had wage growth of 2.0 and 1.9 percent, while Canada and the United States had average wage growth of 0.5 percent.

TABLE 3  
DEATON-HALL EXPERIENCE-WAGE PROFILES

	Height at Experience 5–9 (1)	Height at Experience 20–24 (2)	Height at Experience 35–39 (3)	Average Height (4)	Discounted Average Height (5)
A. All Growth Explained by Cohort Effects					
Rich mean	42.6	90.9	94.1	70.9	32.0
Poor mean	24.3	80.1	132.7	70.5	28.9
Rich – poor	18.3** (.04)	10.8 (.352)	–38.7 (.839)	.4 (.489)	3.1 (.365)
B. Growth Explained Equally by Cohort and Time Effects					
Rich mean	42.4	93.2	96.7	72.7	32.7
Poor mean	22.2	65.8	99.5	56.6	23.7
Rich – poor	20.2** (.030)	27.4* (.082)	–2.8 (.562)	16.1 (.106)	9.0* (.089)
C. All Growth Explained by Time Effects					
Rich mean	41.9	95.8	101.1	75.0	33.6
Poor mean	19.7	51.4	69.9	43.4	18.6
Rich – poor	22.2** (.016)	44.4** (.029)	31.1 (.117)	31.6** (.042)	15.0** (.024)

NOTE.—This table reports summary statistics of experience-wage profiles estimated using the Deaton-Hall method under the assumptions that all growth is driven by cohort effects (panel A), growth is equally explained by cohort and time effects (panel B), and all growth is driven by time effects (panel C). The rows present the average of the rich countries, the average of the poor countries, and the difference between the rich and poor means, plus the results of permutation tests of the null hypothesis that the experience-wage profiles for rich and poor are the same. Column 1 is the average height of the experience-wage profile at potential experience of 5–9 years, defined as the ratio of average wages for workers with 5–9 years of potential experience to average wages for workers with 0–4 years of potential experience. Column 2 is the average height of the experience-wage profile at experience 20–24 years. Column 3 is the average height of the experience-wage profile at experience 35–39 years. Column 4 is the average height of the profile relative to workers with 0–4 years of potential experience. Column 5 is the discounted average height of the profile relative to workers with 0–4 years of potential experience, where wages are discounted at a rate of 4 percent per year.

\*  $p$ -value < .10.

\*\*  $p$ -value < .05.

\*\*\*  $p$ -value < .01.

among the rich, with the latter being statistically significant at the 10 percent level.

Panel C of table 3 reports the results when all growth is explained by time effects. The mean for rich countries is 22.2 percentage points higher by 5–9 years, 44.4 percentage points higher by 20–24 years, and 31.1 percentage points higher by 35–39 years. The average height is 31.6 percentage points higher for the rich countries, while the discounted height is 15.0 percentage points higher. All differences are statistically significant at the 5 percent level except for the height at 35–39 years.

We conclude that if cohort effects explain all of growth, the profiles of the rich countries are marginally steeper than those of the poor countries we observe. If, however, time effects explain half or more of growth, then experience-wage profiles are steeper in rich countries than in poor countries, with differences that are statistically and economically significant. Thus, we next ask whether economic theory can help us further discipline these profiles.

*B. Heckman-Lochner-Taber Approach: No Growth at the End of the Life Cycle*

The insight from the previous illustration is that the interpretation of the cross-sectional results depends on the extent to which aggregate growth is attributable to time or cohort effects. In this section, we propose a theoretically motivated method for disentangling the relative importance of time and cohort effects. In particular, we draw on the basic prediction of a large number of theories of life cycle wage growth that there should be little or no growth in the final years of a worker's career. This prediction is shared by the three basic mechanisms for explaining life cycle wage profiles emphasized in the literature, namely, human capital investment, search, and learning.<sup>9</sup> The basic idea of our approach is to use the assumption that there are no experience effects in the final working years as a restriction to identify time effects and cohort effects. A similar reasoning has been used by Heckman, Lochner, and Taber (1998), so we refer to this as the Heckman-Lochner-Taber (HLT) approach, though credit is due more broadly, as variants of this idea have appeared in the works of McKenzie (2006), Huggett, Ventura, and Yaron (2011), Bowlus and Robinson (2012), and Schulhofer-Wohl (2013).<sup>10</sup>

A simple example helps motivate how this method identifies the effect of wages due to experience (or age) rather than time or cohort. Imagine that we follow the wages of two cohorts: a "young cohort" that has 0–4 years of experience in the year 2000 and an "old cohort" that has 30–34 years of experience in the year 2000. Say we observe that the young cohort has wage growth of 5 percent between 2000 and 2005, while the old cohort has growth of only 1 percent over the same period. Under the assumption that

<sup>9</sup> See, e.g., the review by Rubinstein and Weiss (2006).

<sup>10</sup> Heckman et al. (1998) and Bowlus and Robinson (2012) have used a similar insight in models of human capital to separate prices and quantities of human capital, and Huggett et al. (2011) have used the assumption of no human capital investment at the end of the life cycle to identify shocks to human capital. McKenzie (2006) shows that when using repeated cross-sectional data, second differences of age, cohort, and time effects are identified without any assumptions and that first differences can be identified as well with a restriction on one first difference. Our method selects one such restriction using economic theory. Similarly, Schulhofer-Wohl (2013) argues that one should use the curvature of wage profiles to identify parameters of structural models.

the old cohort has no wage growth coming through experience, the difference in the time effects between 2000 and 2005 must be 1 percent. Thus, we infer that the young cohort had wage increases of 4 percent ( $5 - 1$ ) coming from their increased experience. Repeating this idea for many cohorts, we can build up a full series of time effects. Given time effects, we can then estimate the remaining cohort and life cycle age or experience effects. This method is easily extended to allow for depreciation of skills or of match quality at the end of life. In this case, we replace the assumption that age/experience effects are zero with the assumption that they are  $-d$  percent, where  $d$  is the depreciation rate. The rest of the method proceeds as above.

This approach requires assumptions about two main parameters: first, the number of years at the end of the life cycle for which there are no experience effects and, second, a number for the depreciation rate. We follow Huggett et al. (2011) and consider either 5 or 10 years with no experience effects. We consider two alternative depreciation rates of either 0 or 1 percent per year. Given the assumptions about the number of years without experience effects,  $y$ , and a depreciation rate,  $d$ , this approach to estimating the experience-wage profile in a particular country works as follows. First, we guess an initial trend in the time effects. We then deflate wages for each individual in each year by the wage growth rate implied by the time effect. Next, we estimate equation (1) with experience effects and cohort effects, and we check whether the estimated experience effects have declined, on average, by  $d$  percent in the last  $y$  years. If they have, we stop. Otherwise we adjust the trend in the time effects and repeat. Once the process has converged, it produces separate estimates of cohort effects, time effects, and experience effects for a given country and for given values of  $y$  and  $d$ .

For the purposes of our paper, there are two main benefits to this HLT approach. First, it uses economic theory to motivate restrictions on time and cohort effects. Second, it allows the sources of growth to be country specific, which is useful when comparing countries with very different income levels and growth rates.<sup>11</sup>

Figure 5 plots the experience-wage profiles estimated using the HLT method under the assumption that there are no experience effects in the last 10 years of the life cycle and no depreciation. In the rich countries, the experience-wage profiles are concave and grow by 70–100 percent by 20 years of experience. Profiles for the poor countries are also

<sup>11</sup> The most widely applied alternative theoretical restriction, proposed by Deaton (1997), restricts time effects to sum to zero, as in fig. 4A above. The theoretical rationale for this was “to use the year effects to capture cyclical fluctuations or business-cycle effects that average to zero over the long run” (126). This restriction is less relevant for our analysis given that our sample includes many fast-growing countries.

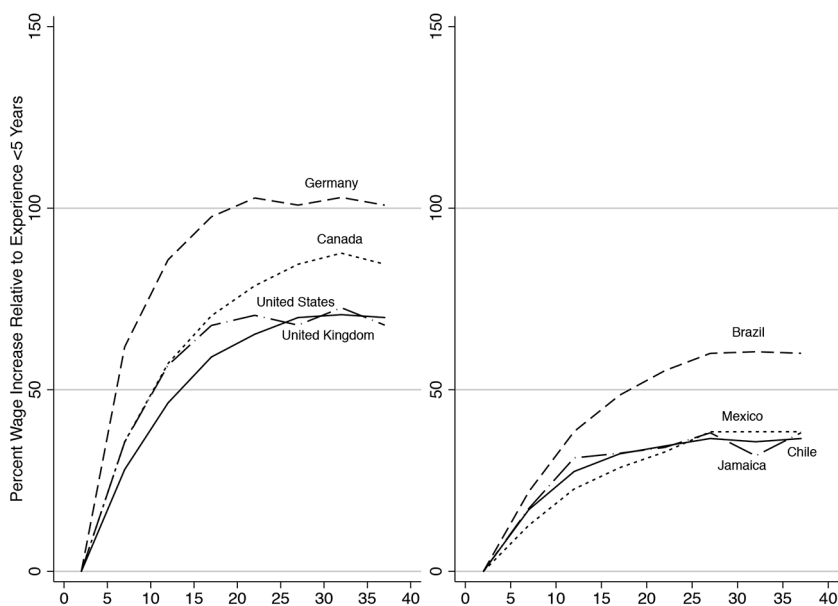


FIG. 5.—Heckman-Lochner-Taber (HLT) experience-wage profiles. Experience-wage profiles are for full-time males working in the private sector. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. The experience-wage profiles are estimated using equation (2) with time controls as well as cohort controls, assuming that the last 10 years of potential experience have 0 percent growth. See Section IV.B for a detailed description of our methodology.

concave, but are flatter, and wage growth ranges between 40 and 60 percent.<sup>12</sup>

Table 4 reports summary statistics of the profiles in rich and poor countries for the experience-wage profiles estimated using the HLT approach. Panel A summarizes estimates for the case with no experience effects over the last 10 years and zero depreciation (as in fig. 5), panel B summarizes the case with no experience effects over the last 5 years and zero depreciation, panel C summarizes the case with no experience effects over the last 10 years and 1 percent depreciation, and panel D summarizes the case with no experience effects in the last 5 years and 1 percent depreciation.<sup>13</sup>

<sup>12</sup> Appendix fig. A.2 presents the same profiles with their 95 percent confidence intervals.

<sup>13</sup> Note that assuming a depreciation rate of 1 percent is rather extreme as it causes poor countries to experience almost no growth over the life cycle. The reason is that assuming that there is no growth over the last few years of the life cycle mechanically rotates the experience-wage profiles clockwise and adding depreciation further rotates the tail end of the life cycle in the same direction.

TABLE 4  
HECKMAN-LOCHNER-TABER (HLT) EXPERIENCE-WAGE PROFILES

	Height at Experience 5–9 (1)	Height at Experience 20–24 (2)	Height at Experience 35–39 (3)	Average Height (4)	Discounted Average Height (5)
A. No Experience Effects in Last 10 Years, 0% Depreciation					
Rich mean	40.3	79.3	80.8	62.5	28.5
Poor mean	17.2	39.2	43.3	31.3	14.0
Rich – poor	23.1** (.014)	40.1** (.013)	37.5** (.013)	31.2** (.013)	14.5** (.013)
B. No Experience Effects in Last 5 Years, 0% Depreciation					
Rich mean	42.3	90.3	100.7	72.1	32.3
Poor mean	16.0	33.2	33.1	26.2	12.0
Rich – poor	26.3** (.015)	57.0** (.013)	67.6** (.013)	45.9** (.016)	20.3** (.015)
C. No Experience Effects in Last 10 Years, 1% Depreciation					
Rich mean	33.9	47.1	27.5	35.2	17.7
Poor mean	12.1	14.3	1.3	10.0	5.6
Rich – poor	21.8** (.015)	32.7** (.015)	26.2** (.017)	25.3** (.015)	12.2** (.014)
D. No Experience Effects in Last 5 Years, 1% Depreciation					
Rich mean	35.8	55.9	41.3	42.6	20.7
Poor mean	10.9	9.4	–6.0	5.9	3.9
Rich – poor	24.9** (.013)	46.5** (.014)	47.3** (.013)	36.7** (.014)	16.8** (.015)

NOTE.—This table reports summary statistics of the estimated experience-wage profiles estimated under the assumption that there are no experience effects in the last 10 years of potential experience and no depreciation (panel A), no experience effects in the last 5 years and no depreciation (panel B), no experience effects in the last 10 years and 1 percent depreciation (panel C), and no experience effects in the last 5 years and 1 percent depreciation (panel D). The rows present the average of the rich and poor countries, plus permutation tests of the null hypothesis that rich and poor are the same. Column 1 is the average height of the experience-wage profile at potential experience of 5–9 years. Columns 2 and 3 are the same but for 20–24 and 35–39 years of potential experience. Column 4 is the average height of the profile relative to workers with 0–4 years of potential experience. Column 5 is the discounted average height of the profile, relative to 0–4 years of experience, where wages are discounted at a rate of 4 percent per year.

\*  $p$ -value < .10.

\*\*  $p$ -value < .05.

\*\*\*  $p$ -value < .01.

In all four panels the rich-poor country differences in heights at 5–9 years and 20–24 years of experience are large and statistically significant. The same is true for the heights at 35–39 years of experience, the average heights, and discounted average heights. The largest differences are estimated under the assumption that there are no experience effects in the last 5 years and no depreciation (panel B), while the differences

are smallest when depreciation is 1 percent and there are no experience effects in the last 10 years (panel C). The reason is that when there is depreciation, the profiles themselves are flatter in all countries; hence cross-country differences become smaller. In summary, the results in table 4 show that the heights of the profiles can be sensitive to the depreciation rate or the length of time with no gains from experience. However, our main result that there are more life cycle wage gains in rich countries is present in all cases.

Similarly to the cross-sectional profiles in Section III.A, most of the difference in steepness between rich and poor countries occurs over the first 20 years of workers' potential experience. For instance, panel A shows that with no experience effects over the last 10 years and zero depreciation, experience-wage profiles at 20–24 years are 40.1 higher in rich countries, and at 35–39 years they are 37.5 percent higher. That is, toward the end of the life cycle poor countries actually make up for a small part of the gap in the height of the profiles. Also see online appendix A.3, where we explore this point in greater detail and show that, similarly to our cross-sectional results, about half of the difference in profiles at 20–24 years of experience is realized after 5 years only.

Note that the HLT results in table 4 are quite similar to the cross-sectional estimates shown earlier in table 2. In light of the discussion in the previous section, this is consistent with most of the growth experienced by the countries in our core sample being attributable to time effects.

## V. Robustness

This section considers the robustness of our main finding that life cycle wage profiles are steeper in richer than in poorer countries. In particular, we demonstrate that our main result that experience-wage profiles are steeper in rich countries is unlikely to be an artifact of how we measure experience or restrict the sample. Unless otherwise stated, we focus on our preferred estimates that use the HLT method to decompose age, time, and cohort effects and restrict our attention to the core sample of countries.

Most of our results are summarized in table 5. Each row corresponds to an alternative sample selection criterion or variable construction. We focus on the heights of the profiles at 20–24 years of experience for brevity. The columns contain the average height across the four rich countries, the average height across the four poor countries, and the difference. We conducted similar analyses to verify that our cross-sectional results from Section III are also robust. See appendix table A.2, where we present the results for both the core sample of eight countries and the full sample of 18 countries.



TABLE 5  
HEIGHT AT 20–24 YEARS OF EXPERIENCE, HLT PROFILES

	Rich	Poor	Rich – Poor
1. Baseline	79.3	39.2	40.1**
2. Experience at 16	82.1	45.8	36.3**
3. Constructed experience	90	43.5	46.5**
4. Measurement error: age	81.1	39.2	41.9**
5. Measurement error: education	71.7	39.2	32.5**
6. Measurement error: age and education	74.4	39.2	35.2**
7. Include self-employed	80.3	36.6	43.6**
8. Include public-sector employees	80.4	42.2	38.2**
9. Include women	70	29.1	41.0**
10. Constructed experience, men and women	76.6	25.5	51.1**
11. Include part-time (20+ hours)	83	38.2	44.8**
12. Include part-time (>0 hours)	84.8	36.7	48.1**
13. Constructed experience, include part-time	100	42	58.0**
14. 1% depreciation for last 10 years in poor	79.3	14.3	64.9**
15. 2% depreciation for last 10 years in poor	79.3	–6.1	85.4***
16. 1% depreciation for last 5 years in poor	90.3	9.4	80.9***
17. 2% depreciation for last 5 years in poor	90.3	–10.2	100.5***

NOTE.—Row 1 uses the baseline sample and measures. Row 2 expands the sample to include individuals who are age 16 and 17. Row 3 uses constructed experience instead of potential experience (see Sec. V.A.1). Row 4 adds noise to the age variable in rich countries in order to match the same amount of age heaping observed in Chilean data (see Sec. V.A.2). Row 5 adds noise to the years of education variable in rich countries by assuming that the distribution in the years of education for a given level of educational attainment is the same as in Chile (see Sec. V.A.2). Row 6 adds noise to both the age and years of education variables in rich countries. Row 7 includes self-employed workers. Row 8 includes public-sector workers. Row 9 includes female workers. Row 10 includes female workers and uses constructed experience, constructed separately for male and female workers. Row 11 includes part-time workers who work at least 20 hours per week. Row 12 includes all part-time workers. Row 13 includes all part-time workers and uses constructed experience, where it is constructed separately for full-time and part-time workers. Row 14 assumes 1 percent depreciation in the last 10 years in the poor core countries and 0 percent depreciation in the last 10 years in the rich core countries. Row 15 assumes 2 percent depreciation in the last 10 years in the poor core countries and 0 percent depreciation in the last 10 years in the rich core countries. Row 16 assumes 1 percent depreciation in the last 5 years in the poor core countries and 0 percent depreciation in the last 5 years in the rich core countries. Row 17 assumes 2 percent depreciation in the last 5 years in the poor core countries and 0 percent depreciation in the last 5 years in the rich core countries.

\*  $p$ -value < .10.

\*\*  $p$ -value < .05.

\*\*\*  $p$ -value < .01.

### A. *Measurement of Experience*

Our benchmark measure of potential experience is constructed as years since the expected date of graduation or age 18, whichever comes last. This could introduce measurement error into our main explanatory variable for several reasons, which we discuss in detail in this section. Since measurement error (if classical) can cause attenuation bias, a natural concern is that there is more measurement error of experience in poor

countries, which biases the difference between the experience-wage profiles of rich and poor countries upward.

### 1. Alternative Measure of Experience

One potential concern with our main measure of experience is that we may misdate the start of work, either because we misdate graduation or because some less educated workers undertake meaningful work before graduation or age 18. We consider two alternatives. First, we simply allow experience to start at the expected date of graduation or age 16, which may be more appropriate for the poorer countries in our sample. Doing so raises poor country profiles modestly but does little to rich countries. Row 1 of table 5 contains our baseline results for comparison. Row 2 shows that lowering the age at which individuals start accumulating experience has little effect on our results.

Second, we can construct an alternative measure of experience, which we refer to as “constructed experience.”<sup>14</sup> The idea behind this measure is to use the cross-sectional relationship between employment and age by education group to infer the life cycle relationship between experience and age. Mechanically, we divide workers into three broad education groups (less than high school, high school, and more than high school) and calculate the percentage of individuals who are engaged in wage employment for each age and education group.<sup>15</sup> We then normalize this employment rate by dividing it by the employment rate of an arbitrary group, which we choose to be 40-year-olds. To calculate the years of experience for an individual, we sum the normalized employment rates over all prior ages. For example, if for high school graduates the employment rate was 70, 35, and 50 percent for 40-, 18-, and 19-year-olds, then we infer that the average high school graduate who is 20 years old has  $35/70 + 50/70 = 1.21$  of constructed experience.

We calculate constructed experience for each country. This allows us to test whether our results are sensitive, for example, to differences in postgraduation employment patterns between poor and rich countries. Row 3 of table 5 shows that the rich-poor differences in heights at 20–

<sup>14</sup> This follows an older labor literature that uses the cross-sectional relationship between age, school attendance, and school enrollment/work to estimate the age at graduation rather than simply equating it with years of schooling plus 6 (Hanoch 1967; Gould and Welch 1976). Smith and Welch (1978) and Welch (1979) estimate returns to experience that build on this alternative measured age at graduation, emphasizing as we do that it allows them to incorporate variation in age at graduation (in their case, by race and cohort within the United States).

<sup>15</sup> We use the three groups to be consistent with the exercises later in Sec. VI.A. The robustness results presented here are similar when we use more disaggregated groups (e.g., each year of education). These are available on request.

24 years of experience using constructed experience are, if anything, slightly larger than our baseline results.<sup>16</sup>

## 2. Measurement Error in Age or Education

Since potential experience is constructed using reported age and estimated years of schooling, mismeasurement of either variable that is more pronounced in poor countries could cause the experience-wage profiles of poor countries to attenuate more than that of rich countries. In particular, one may worry that survey respondents in poor countries are more likely to round their ages or provide a noisy estimate of their actual educational attainment. This could in principle lead to a spurious finding of flatter experience-wage profiles.

When looking at reported age distributions in the poor core countries, we do observe that there is some age heaping in Mexico and Chile, where there are small spikes in population frequency at every 10 years of age (see fig. A.6). To examine whether age heaping drives the difference between poor and rich country experience-wage profiles, we artificially distort the age distributions of rich countries to match the age heaping observed in the Chilean data.<sup>17</sup> We then reconstruct potential experience using the distorted age data in each country and reestimate the experience-wage profiles using our HLT approach. We find that with these distorted age data, the experience-wage profiles of the rich countries are very similar to the actual profiles. Row 4 in table 5 shows that with distorted ages, the rich countries have an average height of 81.1 compared to the 79.3 in the baseline. Artificially distorting the age distribution to replicate the same level of age heaping observed in Chile makes the profile of Germany slightly steeper and the profiles of the United States, Canada, and the United Kingdom marginally flatter (see app. fig. A.3). We conclude that it is unlikely that mismeasurement of age plays an important role in explaining our findings.

<sup>16</sup> Note that interpreting the results using constructed experience relies on the assumption that patterns of work are consistent over time within a country: that if the average high school graduate gains 0.5 year of experience at age 18 in 2001, the same was true for earlier cohorts. We do not expect this assumption to hold exactly but nevertheless find it a useful robustness check as it allows us to present results that do not depend on assumptions about the expected graduation date or the earliest possible age of work.

<sup>17</sup> We estimate a smooth version of the age distribution in Chile using a quintic regression and define *age heaping* as the difference between the actual age distribution and the smoothed one. Equipped with the estimated age heaping level for each age, we turn back to the microdata from the rich countries and artificially distort them. For example, if we observe that in Chile there are 5 percent fewer individuals aged 19 than expected according to the smoothed age distribution and 5 percent more individuals aged 20, then we randomly assign 5 percent of 19-year-olds to be 20 years old instead in each rich country. This exercise replicates, by construction, the same amount of age heaping as in Chile.

To address concerns about measurement error in education, we turn to the Chilean data, where respondents were asked to report both the number of years they attended school and the highest level of attainment.<sup>18</sup> The data show that there is indeed variation in the number of years of actual schooling for a given level of attainment (see app. table A.4). For example, in Chile, the years of schooling for someone who completed “some primary” range from 3 to 8 years. For those who complete “college,” the number of years varies only between 16 and 18 years. Thus, those who report having “some primary” range between 33 percent fewer and 100 percent more than the imputed number of years of schooling. And those who complete college range between 0 percent less and 12.5 percent more than the imputed number of years of schooling.

To investigate whether this variability drives the steeper profiles in rich countries, we impose the same dispersion onto the four rich countries in our core sample. Since the categories of educational attainment differ across surveys, we divide the data into three groups: less than high school, high school, and more than high school. For each group, we use the data from Chile to calculate the average percentage deviation from the imputed years of schooling for each percentile. We then distort the data for the rich countries such that the dispersion in the years of schooling for each attainment level follows the Chilean distribution of the group that the level belongs to, and we reestimate the experience-wage profiles with the distorted data.

We find that the data with distorted education levels yield experience-wage profiles that are modestly flatter than the actual profiles. Table 5, row 5, shows that the mean for rich countries is 71.7 compared to 79.3 in the benchmark. The difference with the poor countries is still large, at 32.5, and statistically significant at the 5 percent level. Therefore, at least with the measurement error in the Chilean data as a guide, mismeasurement of education is not likely to explain much of our findings.<sup>19</sup>

### *B. Sample Selection*

Our baseline analysis focused on a sample that is designed to maximize comparability between countries and minimize measurement concerns:

<sup>18</sup> We focus on the Chilean data from 2009 since it is the most recent year, though similar data are available in 2000, 2003, and 2006. The Jamaican data from 1991 and 2001 also asked these questions. However, the quality of the data for years of education is poor: there are many missing values and implausible responses (e.g., the number of years for those who report “no education” as their highest level of attainment ranges from 0 to 15 years). Thus, we do not use the data from Jamaica.

<sup>19</sup> Appendix fig. A.4 presents the experience-wage profiles using the distorted and actual education data. We also estimated the profiles using distorted age and education data, finding profiles that were again only modestly flatter than those of the baseline analysis; see app. fig. A.5 and row 6 of table 5 for the rich-poor differences in profile heights.

full-time, private-sector male wage workers. This raises two questions. The first and most important for our study is the concern that the main result that experience-wage profiles are steeper for the sample of interest in richer countries is driven by differential selection into the sample. For example, if less productive workers select out of wage employment in rich countries as they age while such workers select into wage employment in poor countries as they age, our finding of steeper profiles for wage workers could be driven by differential selection. The second question is whether the profiles will still be steeper once we relax the sample restrictions and include other types of workers.<sup>20</sup> In this section, we provide evidence against the concern that selection is the main driving force of our results and suggestive evidence that the profiles will still be steeper when we expand the sample. We explain our approach in detail for self-employed workers and then briefly overview the parallel results for public-sector workers, women, and part-time workers.

### 1. Self-Employed Workers

An important sample restriction is that we focus on wage earners because wage income is a direct payment for labor services that is generally considered to be accurately reported. In contrast, the income of the self-employed presents two challenges. First, it can represent payments for both labor and capital services, implying that it is less directly related to life cycle theories of human capital accumulation or search and matching. Second, it is well known that the reported income of the self-employed suffers from substantial underreporting (Hurst et al. 2014).

A concern with using only wage workers in repeated cross-sectional data is that there may be selection into or out of self-employment over time. We address this concern in several ways. One is to simply include these workers in our estimates. In row 7 of table 5, we show the result from including the self-employed, taking their reported income to be their wage and salary income. Doing so has little effect on our results.

The caveat for interpreting this result is that proxying for wages this way introduces measurement error for the reasons discussed earlier. To address this, we use panel data. Since panel data are not widely available, we choose one rich country, the United States (Panel Study of Income Dynamics [PSID], annually 1975–97, biannually 1999–2013), and one poor country, Mexico (Mexican Family Life Survey [FLS], 2002, 2005, and 2009). In the main analysis, US workers have very steep pro-

<sup>20</sup> Note that for the eight core countries, the size of our sample as a percentage of total male workers is 63 percent in the United States, 66 percent in the United Kingdom, 65 percent in Mexico, 45 percent in Jamaica, 67 percent in Germany, 70 percent in Chile, 67 percent in Canada, and 61 percent in Brazil.

files, while Mexican workers have flat profiles. Thus, they are useful for understanding whether selection into or out of self-employment causes profiles in rich countries to be steeper. Moreover, to the best of our knowledge, Mexico is the only poor country within our core sample to have panel data. As with the main exercise, we examine male full-time workers in the private sector.

*Experience-wage profiles following the same individuals.*—First, we show that the estimated experience-wage profiles from panel data are similar to those from repeated cross sections. To be transparent, we employ a non-parametric approach and simply follow individuals over time without controlling for time fixed effects. Since the Mexican FLS data are available only for the years 2002, 2005, and 2009, we use waves of the PSID from a comparable time period, 2003–13. The sample is restricted to individuals who were present during all of the specified waves for the surveys.

We divide the sample into cohorts based on the level of potential experience in the first year of the data (i.e., 2002 for the FLS and 2003 for the PSID). As with the main exercise, a cohort group comprises 5 years of experience levels (e.g., the youngest cohort in Mexico had 0–4 years of experience in 2002). We then calculate the average wage for each bin and normalize it by dividing it by the average wage of the youngest cohort that year.

Figure 6A shows that the US profile is higher than the Mexican profile. Each line segment in the figure is the normalized wage of a cohort over time. Figure 6B shows the analogous profiles from the repeated cross-sectional data (these are identical to those in fig. 1). A comparison of the two figures shows that the panel and repeated cross-sectional data are broadly similar.

*Selection into and out of wage employment.*—Another concern is that our results are driven by differential selection into (or out of) our sample across countries. In online appendix A.4 we use the panel data described above from the United States and Mexico to show that this is unlikely. Specifically, we show that selection into or out of wage employment, private-sector employment, and full-time employment has negligible effects on the estimated relationship between experience and wages in the United States and Mexico.

## 2. Other Sample Selection

In this section we quantify the importance of the remaining sample selection criteria, using many of the same techniques introduced at length in the previous section. We start with the restriction to private-sector workers. Row 8 of table 5 shows that our results are very similar if we include public-sector employees. We then repeat the same analysis using

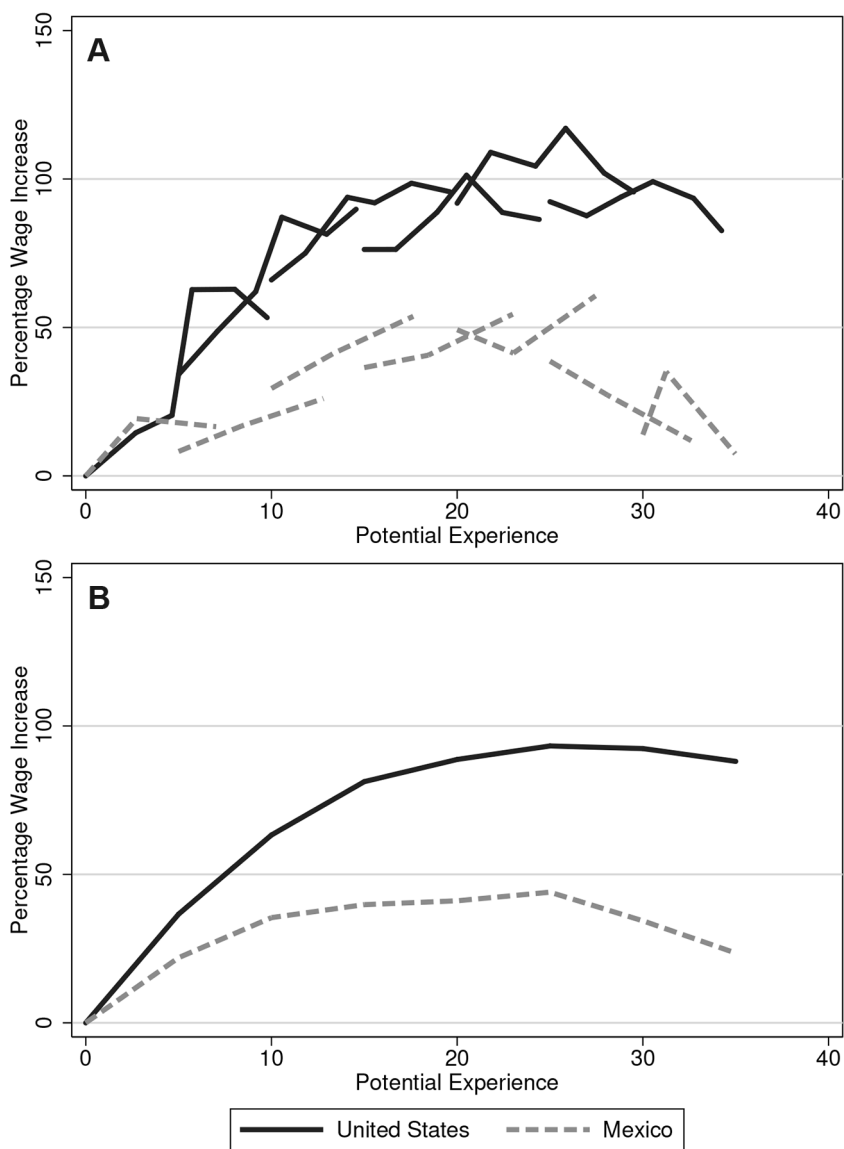


FIG. 6.—Experience-wage profiles using panel data. In panel A, a cohort group comprises 5 years of experience levels (e.g., the youngest cohort in Mexico had 0–4 years of experience in 2002). Each line segment in the figure is the normalized mean wage of a cohort over time. Panel B shows the analogous profiles from the repeated cross-sectional data (these are identical to those in fig. 1). The data are from the US PSID (biannually, 2003–13) and the Mexican FLS (2002, 2005, and 2009).

panel data to compare workers who remain private-sector workers to those who switch to or from public-sector employment. We find that there is no obvious pattern over the life cycle, and the flow of workers from one sector to the other is very low such that selection into and out of the private sector can have only negligible effects on our estimates; the details and figures are in online appendix A.5. Finally, we find that public-sector employment is unlikely to drive our results because very few workers are employed in the public sector: on average, 8 percent in the rich countries in our sample and 3 percent in the poor countries in our sample.

We next turn to female workers, who were excluded from the baseline analysis. Table 5, row 9, shows the results if we include female full-time workers in the private sector. The results are very similar to the baseline in row 1. We do not use the panel data approach employed elsewhere since gender is a fixed characteristic, and we therefore are not worried about women transitioning in and out of our sample as we are for the self-employed. Instead, we consider robustness to measuring women's experience using constructed experience as in Section V.A.1 rather than potential experience; this helps address the concern that potential experience may not accurately reflect the women's actual experience if they are more likely to experience career interruptions. The results in row 10 show that this actually increases the gap in the heights of experience profiles between rich and poor countries.

Finally, we investigate the importance of the exclusion of part-time workers (those who work less than 30 hours a week). Rows 11 and 12 of table 5 show that the estimates change little when we include workers who work at least 20 hours a week or all part-time workers (i.e., workers who report any wage income). Row 13 shows the results when we use constructed experience, where this measure is constructed for full-time and part-time workers separately. The results are very similar to the baseline. Finally, in online appendix A.5 we study the experience profiles of workers who switch between part-time and full-time work. We find that such switches are common but have little effect on the profiles, suggesting that they are unlikely to drive our results.

### *C. Alternative Assumptions about Depreciation at the End of the Life Cycle*

Our implementation of the HLT method relies on the assumption that wage movements near the end of the working life can be attributed to depreciation rates. We started with the natural assumption that the depreciation rate was common across countries. In this section we consider relaxing that assumption and allowing the depreciation rate of human capital to differ across countries. In order to discipline this analysis, we link possible variation in the depreciation rate to the type of jobs done.



As we will document below in Section VII, most workers in rich countries are engaged in occupations that use their learned knowledge, whereas around half of workers in poor countries are engaged in occupations that use physical strength and stamina. This leads us to discipline the analysis through the age-related decline in mental and physical performance.

For the former, we draw on a large literature that documents the life cycle performance of athletes who compete in track and field events on an age-adjusted basis (Tanaka and Seals 2008). Consistent with the model, we study the decline in record performance (measured as distance or time) between ages 60–64 and ages 65–69, downloaded from World Masters Athletics Current Records (<http://www.world-masters-athletics.org/records/current-records>). Peak performance declines in all categories, with the median and mean depreciation agreeing closely at 1.2 and 1.3 percent. For the depreciation of knowledge we turn to the corresponding psychological literature, which generally focuses on vocabulary knowledge or other forms of related, easy-to-measure knowledge. The stylized finding in this literature is that learned knowledge grows until roughly age 60, with no large changes for the subsequent 10 years, implying that knowledge depreciation is 0 percent at least through age 70 (Salthouse 2003, 2013).

We consider four additional robustness checks based on these findings. In each, we fix the depreciation rate in rich countries at 0 percent. We consider allowing the depreciation rate in poor countries to be 1 or 2 percent for 5 or 10 years, motivated by the depreciation of physical strength and stamina. The results are given in rows 14–17 of table 5. The main result is that these robustness checks flatten out experience profiles in poor countries, which serves only to increase the gap between poor and rich countries. We conclude that restricting depreciation rates to be the same in poor and rich countries is probably a conservative assumption.

## VI. Interactions between Schooling and Experience

In this section, we allow for interactions between schooling and age or experience and ask what fraction of cross-country differences in aggregate wage profiles is accounted for by cross-country differences in education levels.

### A. *Experience-Wage Profiles by Schooling Level*

We have so far presented experience-wage profiles under the standard assumption that returns to experience do not vary by educational attainment. We now relax this assumption. That is, we generalize equation (1) to allow schooling and experience to enter in a nonseparable fashion and estimate returns to experience separately for different education groups.

That age profiles typically differ across education groups, with more educated individuals having steeper age-earnings or age-wage profiles in developed countries, is well known from earlier studies such as Mincer (1974), Carroll and Summers (1991), Guvenen (2007), or Kambourov and Manovskii (2009). Thus, we first check whether these patterns also exist in our data. Figure 7 plots age-wage profiles separately for three education groups: “college” (more than 12 years of school), “high school” (9–12 years of school), and “less than high school” (less than 9 years of school). This choice of categories is motivated by a desire to have sufficiently many observations in each group, particularly for poor countries, but we show in appendix figure A.12 that similar results apply if we look at finer education categories. For each country, we keep only education groups for which there are at least 10 observations in each education-experience bin. We find that profiles are substantially steeper for more educated workers in every single country in our data. The similarity between the rich countries of our sample and the findings from the existing literature reassures us of the integrity of our sample. Interestingly, we find that similar patterns also exist in poor countries.<sup>21</sup>

Mincer (1974) observed that while age profiles typically differ by education groups, experience profiles tend to be much more parallel. In other words, one would expect age profiles to be mechanically steeper for more educated workers even if experience profiles do not in fact depend on educational attainment. This is the reason that Mincer controls for experience instead of age in the wage regression. To see this, assume that individuals’ wages satisfy the additively separable Mincer equation (1) and consider the relationship between wages and age  $a$  given schooling  $s$ ,  $\log w = \alpha + \theta s + f(a - s - 6) + \varepsilon$ . Then the returns to age are mechanically increasing in educational attainment if the experience-wage profile is concave: if  $f'' < 0$ , then

$$\frac{\partial^2 \log w}{\partial a \partial s} = -f''(a - s - 6) > 0.$$

Exploring interactions between schooling and experience and how these differ across countries is therefore also more meaningful than exploring interactions between schooling and age, because the latter exercise would pick up interactions mechanically even if the true experience profiles do not, in fact, depend on educational attainment. We therefore concentrate on interactions between schooling and experience in the remainder of the paper.

<sup>21</sup> For completeness, online app. A.6 presents the aggregate cross-sectional age-wage profiles (i.e., not disaggregated by education groups). Analogously to the experience-wage profiles in fig. 1 and table 2, age-wage profiles are flatter in poor countries.

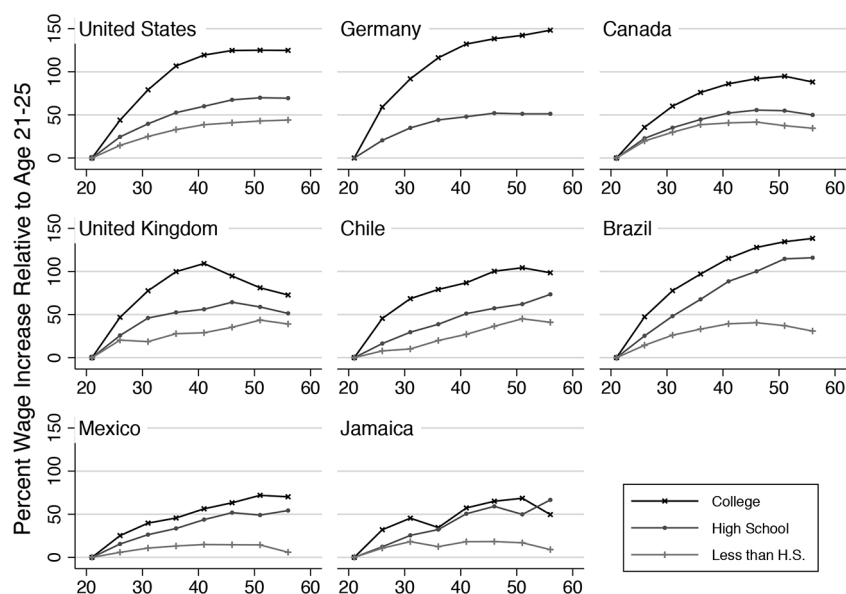


FIG. 7.—Age-wage profiles by education group. Age-wage profiles are for full-time males working in the private sector and are calculated for each educational attainment group. The wage is defined to be earnings divided by hours worked. College, high school, and less than high school mean that the individual (i) attended some college or graduated from college, (ii) attended some high school or graduated from high school, and (iii) did not attend high school. For each country, year, and education group, we compute the ratio of average wages for workers in each 5-year age bin relative to the average wages of workers in the same education group that are 20–24 years of age. The age-wage profiles in the figure are the unweighted average wage ratios by age group, for each education group, across all years. Countries are sorted in order of 2011 PPP GDP per capita from the top-left to the bottom-right panel.

Figure 8 plots experience-wage profiles separately for our three education groups.<sup>22</sup> As expected, we find that experience-wage profiles are much more similar across education groups than age-wage profiles. Nevertheless, experience-wage profiles are moderately steeper for more educated workers in some countries. Among poor countries, the differential returns to experience for different education groups are particularly pronounced in Mexico and Brazil.<sup>23</sup> This finding is not obvious a priori. In the next section, we explore its implications in more detail.

<sup>22</sup> Because the next section requires estimates by education groups for all our countries and not just our core countries, the figure presents simple cross-sectional profiles as in figs. 1 and 2. For our core countries, we have also computed profiles using our HLT methodology. These are similar and available on request.

<sup>23</sup> One caveat to interpreting these cross-sectional experience-wage profiles by education groups is that there may be differential selection into these education groups across cohorts, particularly in some of the poor countries that have seen a rapid rise in educational attainment across cohorts. For example, the group of workers in older cohorts who have ac-

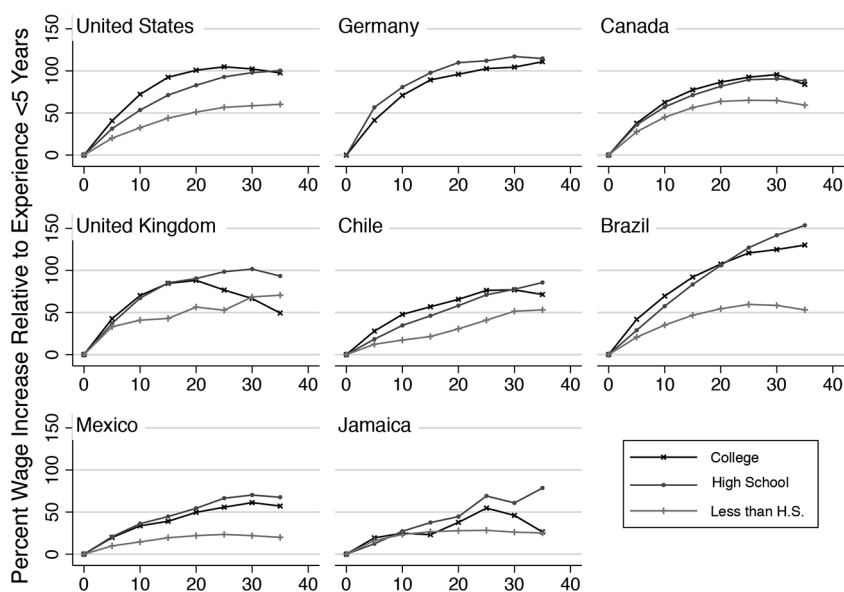


FIG. 8.—Experience-wage profiles by education group. Experience-wage profiles are for full-time males working in the private sector and are calculated for each educational attainment group. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. College, high school, and less than high school mean that the individual (i) attended some college or graduated from college, (ii) attended some high school or graduated from high school, and (iii) did not attend high school. For each country, year, and education group, we compute the ratio of average wages for workers in each 5-year experience bin relative to the average wages of workers in the same education group with less than 5 years of experience. The experience-wage profiles in the figure are the unweighted average wage ratios by experience, for each education group, across all years. Countries are sorted in order of 2011 PPP GDP per capita from the top-left to the bottom-right panel.

### B. Accounting for Experience-Wage Profiles: The Role of Schooling

The finding that experience-wage profiles are steeper for more educated workers in some countries suggests that part of the cross-country differences in average experience-wage profiles may be due to a simple composition effect: in rich countries, a larger share of the workforce is educated, and since more educated workers have steeper profiles, this mechanically

quired a college education may be more positively selected than those in younger cohorts. This would result in mechanically steep cross-sectional experience-wage profiles of college-educated workers and mechanically flat cross-sectional profiles of less educated workers. This logic may partly explain the stark differences in profiles across education groups in Mexico and Brazil. Note that this issue concerns the experience-wage profiles by education group in the present section but not our baseline results that aggregate across these education groups.

results in a steeper average profile. To assess the quantitative importance of the cross-country differences in the distribution of educational attainment, we conduct a counterfactual exercise in which we ask, What would a country's experience-wage profile look like if that country had the United States' distribution of educational attainment as measured by the number of workers in our three education groups?<sup>24</sup> If all of the cross-country differences in experience-wage profiles were due to differences in educational attainment, then this counterfactual would eliminate all such differences.

Figure 9 plots the average height (the integral under the profiles) of the counterfactual profile against the average height of the actual profile for each country in our sample. If composition effects explained all cross-country differences in the returns to experience, the counterfactual heights for all countries would lie on a straight horizontal line, marked 100 percent, at the level of the United States. If they explained none of the differences, all countries would lie on the 45-degree line marked 0 percent. For exposition we also added lines at 25 percent and 50 percent. We find that most of our countries lie between the 0 and the 50 percent lines. For example, for Chile, Mexico, and Jamaica, differences in the distribution of educational attainment account for around 30–40 percent of the difference of each country's profile relative to the United States. A few countries lie close to or even above the horizontal line, which means that composition effects explain more than the entire gap. However, for all of these countries, the actual profiles are quite similar to that for the United States to begin with, which means that the gap is small in the first place.

Overall, we find that for countries with experience-wage profiles substantially different from that of the United States, differences in the composition of educational attainment account for 25–40 percent of the difference in experience-wage profiles with the United States. It is important to emphasize that this is an accounting result and not a causal relationship. For example, it could well be that an omitted factor jointly causes low educational attainment and low returns to schooling. On the other hand, it is possible that we have understated the role for education in explaining the patterns in experience profiles because the differences in human capital from education may exceed the differences in years of schooling given the large cross-country differences in education quality (Schoellman 2012).<sup>25</sup>

<sup>24</sup> We also conduct a similar exercise for age-wage profiles and find modestly higher explanatory power of education composition. However, given the mechanical composition effect for age profiles discussed in the preceding subsection, we view this exercise as less informative and therefore did not include it in the paper. They are available on request.

<sup>25</sup> It is useful to note that the returns to experience for college-educated workers in our poor countries are similar to the returns to experience for entirely uneducated workers in rich countries (see app. fig. A.12). Hence, education quality can entirely explain cross-country differences in life cycle wage profiles if the education quality is so low in poor countries that students learn essentially nothing.

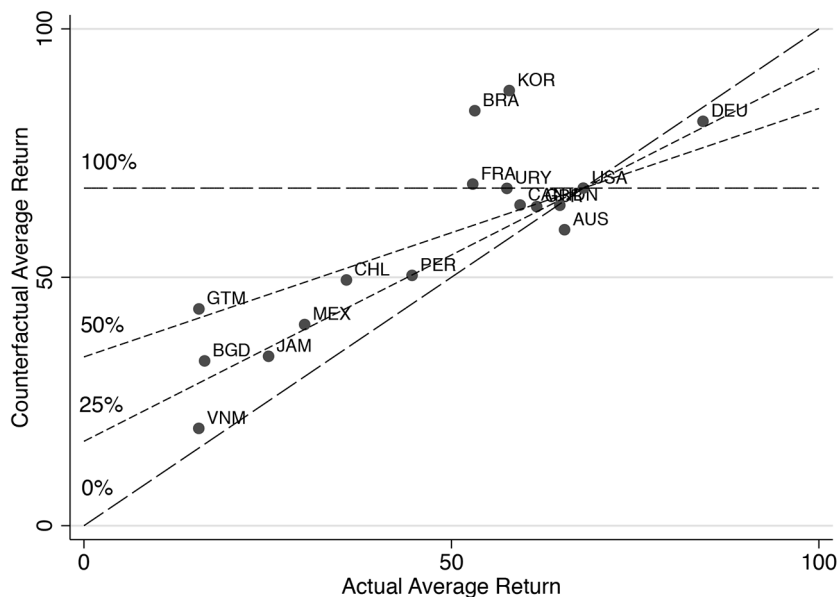


FIG. 9.—Contribution of education to cross-country differences in experience-wage profiles. Each point on the graph represents the actual and counterfactual average height of the experience-wage profile for one country. The average height of the experience-wage profile is the height of the profile for experience bins other than the smallest relative to the smallest experience bin. The counterfactual average height is the same statistic calculated under the assumption that the fraction of workers in each education bin—college, high school, and less than high school—is the same as in the United States. See Section VI for a more detailed description of our methodology.

Nonetheless, we view this finding as progress because it implies that education is likely an important factor for explaining cross-country differences in life cycle wage growth. At the same time, the finding suggests that other factors also play important roles.<sup>26</sup>

<sup>26</sup> We also explored the importance of cross-country differences along dimensions other than education in accounting for age-wage and experience-wage profiles (e.g., share of agriculture, manufacturing, services, public-sector employment). In Sec. VII.B.1 below we find that manual occupations have flatter profiles than cognitive occupations. Another key difference between rich and poor countries is that poor countries tend to have a much larger share of workers who work in agriculture than rich countries. This could affect our estimates of average experience-wage profiles for each country if profiles are flatter for agricultural workers, which has been found to be true in the United States (Herrendorf and Schoellman 2015). We therefore conducted an exercise analogous to the one discussed in the text, except that we estimate profiles separately for agriculture and nonagriculture rather than for different education groups. We found that such sectoral differences account for a relatively small fraction of differences in age-wage and experience-wage profiles. These and other results on compositional effects are available on request.

## VII. Potential Explanations

In this section, we discuss several potential explanations of lower life cycle wage growth in poor countries. We focus on three main candidate theories suggested by the literature: human capital accumulation, search and matching frictions, and long-term wage contracts. It is beyond the scope of this paper to conclusively rule in or rule out any particular theory. However, we can shed light on the likely relevance of theories by computing additional moments with our data. First, we compute life cycle wage profiles by broad occupation groups and find that manual occupations have substantially flatter profiles than cognitive occupations. Second, we compute life cycle wage variance profiles, finding some evidence of U-shaped profiles, at least in the rich countries. Third, we look at wage profiles for day laborers, who are not engaged in long-term wage contracts, and find that, in the poor countries for which we have data, these are again flatter than in rich countries. Finally, we discuss the evidence from a companion study to this one that looks at experience-wage profiles for immigrants to the United States. We find that these moments are consistent with theories based on human capital or search frictions and less supportive of models based on long-term contracts.

### A. Candidate Mechanisms

#### 1. Human Capital

There is a long tradition in economics that interprets experience-wage profiles as reflecting human capital accumulation (Becker 1964). Under this interpretation, our findings imply lower human capital accumulation over the life cycle in poor countries. The simplest version of this theory is that workers in poor countries use simpler technologies or engage in simpler tasks at work, for which there is less scope for learning. One may imagine that manual occupations, such as agricultural tasks, for example, have fewer possibilities for learning over the life cycle.<sup>27</sup> It is well known that manual occupations are more common in poor countries than in rich countries.

Another possibility is that workers in poor countries have fewer incentives to accumulate human capital over their lifetimes. Manuelli and Seshadri (2014) propose a model of this type in which human capital accumulation requires inputs of both goods and time, as in Ben-Porath

<sup>27</sup> One way of capturing the idea that simpler technologies result in fewer learning opportunities is as follows. Assume that the output of a firm is Leontief in the firm's technology and the human capital of each of the workers it employs:  $y = \sum_{i=1}^N \min\{A, h_i\}$ , where  $y$  denotes the firm's output,  $A$  denotes its technology, and  $h_i$  is the human capital of each of its workers indexed by  $i = 1, \dots, N$ . Since the human capital of a worker equals zero once her human capital reaches  $A$ , no worker has an incentive to invest past this point.

(1967). In their model, low total factor productivity depresses the returns to the accumulation of human capital by raising the price of physical inputs to human capital production, thereby resulting in flat experience-wage profiles. Alternatively, extractive institutions in poor countries may discourage workers from investing in human capital, since their returns can be arbitrarily expropriated (Bhattacharya, Guner, and Ventura 2013). This logic is consistent with recent evidence that higher taxation of labor income in Europe can explain a substantial fraction of European-US differences in wage inequality and life cycle wage growth (Guvenen, Kuruscu, and Ozkan 2014).

Another class of theories based on human capital accumulation focuses on learning through interactions with other individuals. For example, the models of Lucas (2009), Lucas and Moll (2014), and Perla and Tonetti (2014) posit that human capital is accumulated through social interactions with others; all determinants of the frequency or quality of such interactions are potential determinants of cross-country differences in life cycle wage growth. As one example, de la Croix, Doepke, and Mokyr (2016) argue that in the industrial revolution, the emergence of institutions such as guilds allowed skills to be disseminated faster, which led to increased lifetime human capital accumulation and, hence, economic growth.

## 2. Search and Matching Frictions

Another candidate explanation for slow life cycle wage growth in poor countries is search and matching frictions. If the labor market features search frictions and match-specific productivity, slow life cycle wage growth in poor countries may partly reflect low labor market turnover. This could work through several mechanisms. Burdett (1978), Jovanovic (1984), Burdett and Mortensen (1998), and Bagger et al. (2014) emphasize on-the-job search as a theory of job shopping. If frictions to search and matching lower the incentives or ability of workers to shop for jobs, they are less likely to climb the job ladder and will forgo some of the potential increase in labor productivity over the life cycle.<sup>28</sup> Empirically, one would then expect to see workers in poor countries experiencing fewer job-to-job transitions and receiving smaller wage gains during such transitions.<sup>29</sup>

<sup>28</sup> Burdett (1978, 219) puts it succinctly: "In the present study it has been assumed workers do not accumulate human capital while working. Older workers in the present study receive higher wage rates, on average, because they have obtained more job offers. And the more job offers a worker receives, the greater the probability a 'high' wage rate job will be found."

<sup>29</sup> There is little work comparing such moments between rich and poor countries or regions. One exception is the study by Heise and Porzio (2015), who use matched employer-



Although these ideas have been applied to studying aggregate labor productivity over the business cycle or across developed countries (Lise and Robin 2013; Postel-Vinay and Turon 2014), the large cross-country differences in life cycle wage profiles suggest a new exploration. Alternatively, long-lasting frictions may prevent workers from sorting to the jobs that are most suitable to their heterogeneous skills and tastes (Hsieh et al. 2013). Again, the implication would be that workers forgo labor productivity increases as they age.

### 3. Long-Term Contracts

Finally, if workers and firms form long-term contracts (e.g., Lazear 1979), wages may not equal workers' marginal product of labor, and this may lead to cross-country differences in returns to experience.

One version of these theories features back-loaded contracts, where workers get less than their marginal products when young and more when they are older. This is the typical prediction of theories with moral hazard or limited commitment on the part of workers. These theories have the potential to explain our finding that experience-wage profiles are steeper in rich countries if long-term contracts are more prevalent in rich countries or they are equally prevalent but more back-loaded. A second version of these theories features front-loaded contracts, where workers get paid more than their marginal product when young and less later in the life cycle. Front-loading could arise, for example, because firms implicitly lend to financially constrained workers (Azariadis 1988; Bernhardt and Timmis 1990). To explain our findings, one would need a theory with more front-loading in poor countries. In summary, long-term contracts have the potential to explain flatter experience-wage profiles in poor countries if wages are either more front-loaded in poor countries or more back-loaded in rich countries or both.

#### *B. Distinguishing between Mechanisms: Additional Moments*

We now examine some additional moments in our data to attempt to distinguish between potential mechanisms. We find several pieces of evidence that are consistent with human capital and search frictions contributing to our main findings and no obvious evidence that long-term contracts play an important role. Distinguishing between human capital

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employee data from Germany to compare wage dynamics in West Germany with those in the considerably poorer East. They find that, when moving job to job, workers in the East experience smaller wage gains than those in the richer West; i.e., they face a flatter job ladder.

and search is, in turn, more difficult for three reasons. First, our cross-sectional data do not allow us to construct moments typically thought to be informative about these two classes of theories, for example, wage changes with job-to-job transitions. Second, search and human capital accumulation are difficult to tell apart even with high-quality panel data or matched employer-employee data. One can think of workers in search models accumulating “search capital” while employed that is destroyed upon job loss (Manning 2000), and at an abstract level, certain search theories may be observationally equivalent to theories of human capital accumulation. A number of existing studies assess the relative contribution of human capital and job search in the United States and other high-income countries (see, e.g., Topel and Ward 1992; Rubinstein and Weiss 2006; Altonji, Smith, and Vidangos 2013; Bowlus and Liu 2013; Bagger et al. 2014). While these studies generally agree that both human capital and search are important determinants of life cycle wage growth, there is considerable debate about the precise quantitative importance of the two mechanisms, consistent with the idea that the two are hard to tell apart. Third, another difficulty is that there are likely nontrivial interactions between search and human capital (Bowlus and Liu 2013). With this in mind, we now present four pieces of evidence that make some progress in distinguishing between potential explanations for cross-country differences in life cycle wage growth.

### 1. Experience-Wage Profiles by Occupation

We first explore differences in wage profiles by occupations. Most of our samples report data on occupation. Although the occupational coding schemes vary by country, we are able to translate occupational codes into the International Labour Office’s International Standard Classification of Occupations (ISCO) at the one-digit level. We then aggregate the ISCO one-digit occupational categories further to two broad categories: manual and cognitive. The reason we choose this split is that manual occupations are relatively intensive in physical tasks, rather than mental ones, and may therefore have less scope for learning. If so, this may help explain our overall findings, since manual occupations are more common in poor countries.

In the data, we define manual occupations as elementary occupations, agricultural workers, and plant/machine operators and assemblers (ISCO codes 6, 8, and 9). Cognitive occupations include legislators and managers, professionals, technicians, clerks, service and sales, and craftsmen (ISCO codes 1–5 and 7). We exclude from this analysis workers with missing occupations or those in the armed forces.

For each country, we compute the life cycle wage profile of workers in manual and cognitive occupations following our cross-sectional method

of Section III.<sup>30</sup> In figure 10, we plot the resulting profiles by occupation for our core countries. Two facts stand out. First, for all of our core countries, the profiles are flatter for manual occupations than for cognitive occupations. Second, the difference is often substantial. For the average country in our sample the return to 20–24 years of experience is 23 percentage points higher for workers in cognitive than in manual occupations.

These differences potentially matter because of the sizable differences in employment composition by country (plotted in app. fig. A.13). Rich countries have considerably more workers in cognitive occupations, at roughly 80 percent, while in poor countries the labor force is fairly evenly split. For most countries, the employment composition across occupations changes little in magnitude over the life cycle, consistent with the idea that most workers will not systematically move from manual to cognitive work over the life cycle. The differences in life cycle wage growth across occupations we find are particularly remarkable given our crude classification of workers into manual and cognitive occupations and given the likely possibility that a given manual occupation may vary in its manual and cognitive intensity between rich and poor countries. We conjecture that more fine-grained data that allow for a less noisy proxy for occupations with different learning opportunities would likely result in even larger differences in employment shares between rich and poor countries.

As with education, we use a simple accounting exercise to quantify the importance of occupation for aggregate life cycle wage profile differences across countries. As a reminder, the accounting exercise holds fixed each country's experience profiles by occupation and asks how much steeper the country's experience profile would be if it instead had the US employment shares in cognitive and manual occupations. According to this accounting exercise, for most countries, the distribution of employment across occupations accounts for between 0 and 25 percent of the difference of each country's profile relative to the United States. Given the striking differences in experience-wage profiles across occupations in figure 10, it is surprising that this counterfactual does not have larger predictive power. Mechanically, this is true because with our crude occupational classification, even in our poorest countries, the employment share in manual occupations is only around 50 percent.

<sup>30</sup> The reason for presenting the cross-sectional estimates rather than our HLT estimates is that the accounting exercise below requires estimates by occupation groups for all our countries and not just our core countries. Moreover, the HLT methodology requires the assumption that there are no occupation transitions in the last 5 or 10 years of the life cycle, which could be more controversial than the analogous assumption about wage growth in our baseline HLT exercise. In any case, for our core countries, we have also computed profiles by occupation using our HLT methodology. These are similar to the cross-sectional estimates and are available on request.

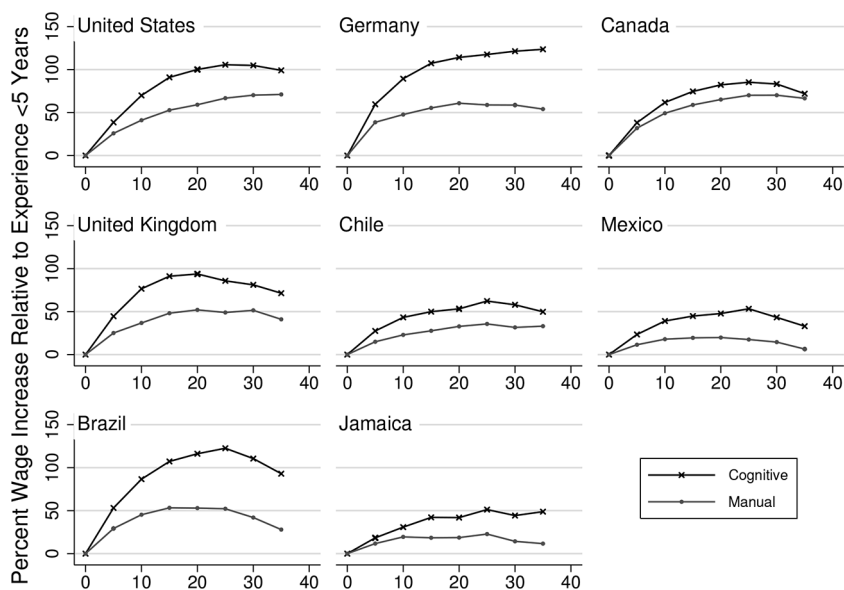


FIG. 10.—Experience-wage profiles by occupation group. Experience-wage profiles are for full-time males working in the private sector and are calculated separately for each occupation group. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. Cognitive occupations comprise categories 1–5 and 7 of the ISCO-08 (International Standard Classification of Occupations). They are (1) managers, (2) professionals, (3) technicians and associate professionals, (4) clerical support workers, (5) service and sales workers, and (7) craft and related trades worker. Manual occupations comprise categories 6, 8, and 9 of the ISCO-08. They are (6) skilled agricultural, forestry, and fishery workers, (8) plant and machine operators and assemblers, and (9) elementary occupations. For each country, year, and occupation group, we compute the ratio of average wages for workers in each 5-year experience bin relative to the average wages of workers in the same education group with less than 5 years of experience. The experience-wage profiles in the figure are the unweighted average wage ratios by experience, for each occupation group, across all years. Countries are sorted in order of 2011 PPP GDP per capita from the top-left to the bottom-right panel.

Our findings are consistent with a simple human capital interpretation, namely, that there are simply fewer learning opportunities in poor countries over the life cycle. They also parallel our previous results that more educated workers have steeper experience-wage profiles in all countries. In that case, the simple human capital interpretation is that education helps one learn how to acquire human capital later in life.<sup>31</sup>

<sup>31</sup> One possible concern is that we may be replicating the results from the education section to the extent that less educated workers are employed in manual occupations. We explore this idea by estimating separately life cycle wage profiles by education and occupation. Appendix fig. A.14 plots the profiles by occupation conditional on workers having a high school education (i.e., we drop workers in the “less than high school” and “college” categories). We find that each dimension matters, and the accounting results are similar.

## 2. Experience-Wage Profiles of Day Laborers

We next explore the importance of labor market contracts for our patterns. We note first that theories of long-term contracting all refer to the returns to tenure (experience at a specific firm) rather than the return to lifetime potential experience. Thus, long-term contracts are unlikely to have large quantitative effects on experience-wage profiles unless average worker tenure is reasonably long. The limited data on worker tenure do not support this: for example, in the United States, the median tenure is 4.6 years (Bureau of Labor Statistics 2012), and for Brazil, Chile, Guatemala, Jamaica, Peru, and Uruguay, it ranges between 1.5 and 5.5 years (Interamerican Development Bank 2016).<sup>32</sup>

To provide additional evidence on this point, we study the life cycle wage profiles of workers employed without long-term contracts. The rationale is that these profiles speak directly to the question of whether our patterns are likely to be explained by contractual arrangements between workers and firms that introduce a wedge between life cycle wage and life cycle productivity profiles. We provide such evidence for three countries for which we can identify workers who are unlikely to be on long-term contracts. For India and Mexico, we can identify a subset of workers who are daily workers: those whose employer varies on a day-to-day basis. Clearly, these workers' profiles are not driven by employer-specific contracting. For the United States, we draw on the Current Population Survey (King et al. 2010), where we can identify workers who work part-time and are not interested in working full-time even if it were available. These workers report other commitments (home, family, and so on) that make full-time work undesirable. Since these workers apparently value the flexibility and lack of commitment that come with short-term work arrangements, our interpretation is that they are also unlikely to be taking part in long-term contracts.

Appendix figure A.15 presents the experience-wage profiles for workers on short-term contracts and the rest of the workforce in these three countries. Recall from above that long-term contracts can explain flatter experience-wage profiles in poor countries in two scenarios. The first scenario is that wages are more front-loaded in poor countries. In this case we would expect day laborers in poor countries to have steeper profiles than the rest of the workforce. The second scenario is that wages are more back-loaded in rich countries. In this case, we would expect day laborers in rich countries to have flatter profiles. We find no evidence of either of these scenarios. In India and the United States the two sets

<sup>32</sup> The Interamerican Development Bank (2016) provides estimates only for Central and South American countries, and we are not aware of corresponding data for other countries in our sample. The numbers for Brazil, Chile, Guatemala, Jamaica, Peru, and Uruguay are median tenure for the most recent year in which these data are available.

of profiles are quite similar, and in Mexico the day laborers have flatter profiles than other workers. An obvious caveat to this exercise is that day laborers are likely a selected group of workers who differ from the rest of the workforce in a number of other characteristics, for example, their skills. Nevertheless, the comparison of day laborers to other workers together with the relatively short job tenure of the typical worker in both rich and poor countries suggests that long-term contracts are unlikely to explain our cross-country patterns.

### 3. Variance Profiles

Thus far, we have focused on mean wages by experience. Now we turn our attention to the variance of wages by experience to see if they can provide any additional information. Both human capital and search models make a wide variety of predictions for how the variance of wages might evolve over the life cycle. Hence, these predictions are useful for discriminating among specific human capital theories or among search theories, but not between the two.

For human capital models, the key determinant of the shape of variance profiles is the correlation between learning ability and initial human capital (Huggett et al. 2011). Intuitively, individuals with higher learning ability endogenously choose to invest more at the beginning of the life cycle. These choices lead them to have steeper wage profiles than individuals with low learning ability. The level of initial human capital mostly affects the intercept of the profile. Hence, if the two are weakly correlated, the model predicts that high-learning ability individuals have lower levels but steeper slopes of wages than their low-learning ability counterparts. Therefore, profiles cross at some point, implying a U-shaped pattern for the variance of wages over the life cycle (Mincer 1974; Rubinstein and Weiss 2006). On the other hand, if the two are sufficiently strongly positively correlated, then high-learning ability individuals will have higher levels and steeper slopes of wages, implying that the variance of wages rises continuously over the life cycle.

Among search theories, we focus on theories of on-the-job search because these have implications for life cycle wage profiles. Hornstein, Krusell, and Violante (2011) show that some recent theories of on-the-job search have the potential to generate realistic levels of wage dispersion. The implications for the shape of variance profiles over the life cycle are less clear. Among existing theories, the study by Bagger et al. (2014) stands out for making quantitative predictions about the life cycle profile of wage dispersion, finding that it rises at a decreasing rate.<sup>33</sup> The key

<sup>33</sup> Burdett, Carrillo-Tudela, and Coles (2011) also formulate a model with life cycle patterns of dispersion, but they do not calibrate or estimate the model to provide a full description of what the profile might look like.

mechanism is a rise in the heterogeneity of firms that workers are matched with over the life cycle. In contrast, Manning (2000) presents a simple model of on-the-job search that generates a U-shaped life cycle variance profile.

To compute variances over the life cycle, we take the variance of log wages in each experience bin, by the three education groups discussed above. We then take the weighted average log wage variance across experience bins, where each education group is weighted by its share among all workers. Figure 11 plots profiles for the variance of the logarithm of wages across countries. The empirical results generally follow one of two patterns. In four of the five richest countries (top-left quadrant) as well as in South Korea and Jamaica, variance profiles follow a U shape: declining at the beginning of the life cycle and then rising toward the end. In the remaining countries (the United States and most poorer countries), the profiles are generally rising throughout the life cycle.<sup>34</sup> In summary, the evidence on variance profiles is mixed and appears consistent with different versions of both human capital and search theories. For both classes of theories, our empirical results imply restrictions on the range of plausible parameterizations that will be consistent with the data in different countries. This is an interesting avenue for future research.<sup>35</sup>

#### 4. Evidence from Immigrants to the United States

In a companion paper (Lagakos et al. 2016), we study how wages in the United States vary for immigrant workers of different experience levels. We document that, for immigrants from rich countries, more experienced immigrants tend to earn substantially more than less experienced immigrants. In contrast, for immigrants from poor countries, more experienced immigrants tend to earn only somewhat more than the less experienced. We show that this is true for new immigrants, who earned all their experience abroad, as well as for all immigrants when we control for the amount of US work experience.

<sup>34</sup> In some countries, the variance profiles are mildly declining at the end of the life cycle, a pattern that could be interpreted as an inverse U shape.

<sup>35</sup> In Ben-Porath-type models, one form of investment in human capital accumulation may be reflected in part-time work and low hours worked more broadly. To investigate this possibility, in online app. A.7 we relax the restriction to only full-time workers that we have made so far and examine hours and earnings profiles over the life cycle in this larger sample. We find that in rich countries, hours rise steeply early on in the life cycle, largely reflecting movements from part-time into full-time work. These cross-country patterns are consistent with theories of human capital accumulation, in particular, the prediction that workers in rich countries initially invest a lot of time in human capital accumulation, and therefore work little, but then increase their time working over their life cycle. The fact that poor countries generally do not see such hours increases is consistent with the prediction of less investment early in the life cycle. We also examine variance profiles in the larger sample including both part-time and full-time workers and find stronger evidence of a U shape (perhaps unsurprisingly given the evidence on hours profiles).

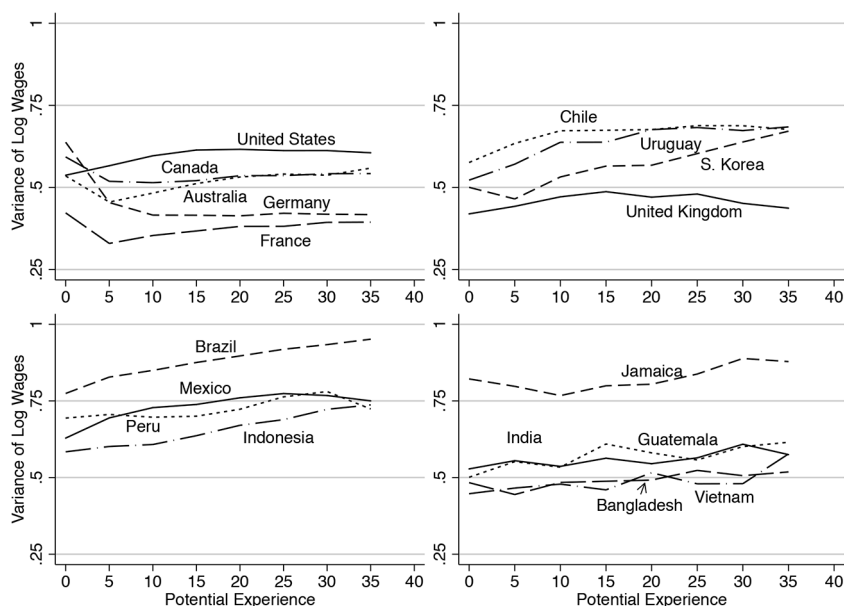


FIG. 11.—Wage-variance profiles, all countries. The wage-variance profiles are for males working in the private sector and are calculated using all available years of data for each country. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. For each country, year, and education group, we compute the variance of log wages. The wage-variance profiles in the figure are the weighted averages of the log wage variances across years and education groups, weighted by the shares of workers in each education group. Countries are sorted in order of 2011 PPP GDP per capita from the top-left to the bottom-right panel.

Since all individuals are observed in the same labor market, this finding is consistent with the hypothesis that immigrants from poor countries accumulate less life cycle human capital than immigrants from rich countries before coming to the United States. It is also consistent with the theories based on differential selection and skill loss, though our companion paper provides evidence against these theories. Perhaps the most powerful piece of evidence supporting the human capital interpretation of these findings is that the returns to experience we estimate from nonmigrants (e.g., the estimates in the current paper) line up closely with the returns we estimate using US immigrants. In figure 3 we showed that regressing the height of the profile at 20–24 years of potential experience on log GDP per capita yields a coefficient of 26.2. When looking at US immigrants, the same regression yields a coefficient of 20.0, or 29.6 when restricting attention to the 16 (of 18) countries for which we have data on both immigrants and nonmigrants.



## 5. Summary of Evidence

In summary, the four pieces of evidence we presented in this section suggest that long-term contracts are unlikely to be an important driver of cross-country differences in life cycle wage growth. In contrast, both human capital and search appear consistent with the moments we have presented here. A particularly simple explanation for slow life cycle wage growth in poor countries is that workers in poor countries may simply have fewer opportunities for learning because of the nature of the occupations or tasks they perform, consistent with the evidence on experience-wage profiles across occupations we presented above. At the same time and as noted in the beginning of this section, it is generally hard to tell apart human capital and search as drivers of life cycle wage growth, and as such, more severe labor market frictions are an equally promising candidate explanation for flat experience-wage profiles in poor countries.

## VIII. Conclusion

This paper documents that experience-wage profiles are steeper in rich countries than in poor countries. In the rich countries, the wages of the most experienced workers are, on average, almost 100 percent larger than the wages of the least experienced workers. In contrast, in the poor countries, the wages of the most experienced workers are only around 50 percent larger than the wages of the least experienced workers. We find that some, but not all, of this pattern is accounted for by differences in education levels across countries, with more educated workers having steeper profiles.

While it is difficult to provide a definitive explanation of our findings, several additional moments of our data support human capital or search frictions as promising explanations. Providing a more definitive explanation for cross-country differences in life cycle wage growth is an important task for future research. In particular, doing so could help account for cross-country income differences. Earlier studies in this literature found no relationship between returns to experience and GDP per capita (Psacharopoulos 1994; Bils and Klenow 2000) and concluded that it was safe to ignore any cross-country human capital differences arising through experience rather than schooling. Recent work by Manuelli and Seshadri (2014) predicts that workers in rich countries accumulate more human capital over the life cycle as well, and our evidence offers support for this idea. If true, the importance of human capital in accounting for income differences is substantially higher than previously concluded.<sup>36</sup>

<sup>36</sup> Any development accounting exercise along these lines would need to be careful to distinguish between two different forms of human capital accumulation with potentially different quantitative implications: on-the-job training as in Ben-Porath (1967) and learn-

Turning to the implications of a search-based explanation of flat experience profiles in poor countries, the macro-development literature generally assumes competitive labor markets. The main exceptions are papers that focus on distortions to the allocation across sectors or locations, which generate misallocations of labor (Caselli 2005; Restuccia, Yang, and Zhu 2008; Gollin, Lagakos, and Waugh 2014). Viewed through the lens of a search and matching model, our findings suggest that it may be time to incorporate analogous frictions to on-the-job search or job choice that generate misallocation of labor over the life cycle. Explorations along these lines would be particularly interesting given that low labor market turnover in poor countries could have implications for a number of important issues besides aggregate productivity. For example, low turnover could hamper mobility if poor workers escaping poverty involves an element of “job shopping.”

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ing by doing. Through the lens of models of on-the-job training, the steep wage growth in early years of the life cycle in rich countries may partly reflect a declining time investment in human capital accumulation, so that the underlying human capital profile is flatter than the observed wage profile. Therefore, cross-country differences in life cycle human capital would be smaller than those implied by simple learning-by-doing models in which a worker's wage is proportional to her human capital.

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