Life-Cycle Wage Growth Across Countries*

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Abstract

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 use these data to 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 experience-wage profiles on average than those with less education; 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 over the life cycle and theories in which more severe search frictions in poor countries hamper worker reallocation and lower aggregate productivity.

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1 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 (Manuelli and Seshadri, 2014; Klenow and Rodriguez-Clare, 1997; Bils and Klenow, 2000; Caselli, 2005; Burdett, 1978; Jovanovic, 1984).

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 seventeen countries with individual-level data on educational attainment, labor earnings and the number of hours worked. This allows us to construct similar 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 where experience is measured as years of potential experience, i.e. years elapsed since finishing school. To do this, we compute mean wages for each five-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 they increase by only around fifty 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.[1] 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.

There are two important caveats for the interpretation of our main result that experience-wage profiles are steeper in rich countries. The first is that age and education, and thus experience (which is the difference between these two variables) may be measured with more error in poor countries. We address this concern in two ways. First, we show that our results are similar when using an alternative measure of experience based on age-and-education-specific employment rates. Second, we show that 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. The second caveat is that our main results restrict the sample to full-time, male wage workers in the private sector. With the possible exception of the restriction to private-sector workers, these restrictions are standard in the literature. However, since we make comparisons across countries, a natural concern is that our results are caused by differential selection into our sample across countries. We use panel data 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 have negligible effects on the estimated relationship between experience and wages in the United States and Mexico, which suggests that selection is unlikely to play an important role for our main results. Moreover, we provide evidence that the inclusion of females, part-time or public-sector workers and self-employed are unlikely to alter our main finding.

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 U.S. 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 seventeen countries, more educated workers have steeper experience-wage profiles on average

[1] 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" (p.4).

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 broader implications of our findings. As we noted above, there are two main theories of life-cycle earnings patterns in the literature, human capital accumulation, and search and matching frictions. Both theories suggest that our findings may help explain cross-country income differences. Through the lens of human 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 lifecycle 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, non-representative 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 2 describes our household-survey data. Section 3 documents that simple cross-sectional experience-wage profiles are flatter in poorer countries. Section 4 measures experience-wage profiles using the Deaton-Hall and Heckman-Lochner-Taber methods. Section 5 investigates the robustness of our estimated experience-wage profiles. Section 6 considers interactions between schooling and experience, and the role of schooling in accounting for aggregate experience profiles. Section 7 discusses broader implications and interpretations of our findings. Section 8 concludes.

2 Data

Our analysis uses large-sample household survey data from seventeen 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 (i) is important for estimates which 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 fifteen or more years. This additional restriction is necessary for our method to disentangle experience, time, and cohort effects in Section 4.[2]

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 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. By "rich countries" we mean those with greater than $20,000 per capita income in 2011 at PPP (from the World Bank's World Development Indicators), and by "poor countries" we mean those with per capita income below this threshold.

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 zero to forty years of experience who have positive labor income and non-missing age and schooling information. In all surveys, we impute the years of schooling using educational attainment data. For all countries, we 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

[2]An earlier version of our paper (Lagakos et al., 2012) used data from thirty-five countries. For fifteen of these countries, the data did not satisfy all of the criteria (i) to (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 upon 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.

literature on returns to education and experience (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 Deaton, 1997; Hurst et al., 2014; Gollin, 2002, for example). 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 non-wage 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 *experience = age – schooling – 6* for individuals with twelve or more years of schooling and as *experience = age – 18* for individuals with fewer than twelve years of schooling. This definition implies that individuals begin to work at age eighteen or after they finish school, whichever comes later. The cutoff at age eighteen is motivated by the fact that few individuals have positive wage income before the age of eighteen in the data. Although each of these sample restrictions and the definition of potential experience are fairly standard in the literature, we re-consider each of them in Section 5.

3 Life-cycle Wage Growth Across Countries: 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.

3.1 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. This is because 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 6.1 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 five-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.[3] For expositional purposes we plot the profiles for rich countries on the left-hand panel and for poor countries on the right-hand panel. In all countries, profiles are increasing until at least twenty years of potential experience, and then flatten or decline afterwards. Among the rich countries, Germany has the steepest profile, at above 100 percent higher wages by twenty 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 seventy-five percent higher wages by twenty years of experience. Among the poor countries, Brazil is the steepest, reaching a height of just above seventy percent, followed by Chile, Mexico and then Jamaica.

To summarize these findings and more formally compare experience-wage profiles across countries, we compute four summary statistics for each country. The first is the height of the profile at 20-24 years of experience, or twenty years more experience than the least experienced bin. The second is the height of the profile at 35-39 years of experience, which is the highest experience bin. The third is the average height of the profile, computed as the average across all experience bins other than the lowest. The fourth is the average height when discounting each year at four percent per year, which is meant to be a simple measure of the discounted value of lifetime income gains.[4]

Panel A of Table 2 reports the summary statistics for each country. The reported heights are relative to the least experienced group, which comprises of workers with zero to 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 (ninety percent), the United Kingdom (85 percent) and Canada (eighty percent).[5] Brazil's profile is the steepest amongst poor countries, at approximately seventy 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.

[3] See Appendix Figure A.1 for the same figure with the 95% confidence intervals.

[4] A convenient property of the discounted average height is that it appropriately trades off wage gains that occur early versus late in life, and it therefore can, for example, be used 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, Section 8.2 and references cited there).

[5] Our estimated experience-wages profiles for the rich countries are largely in line with previous estimates in the literature. In the United States, for example, Lemieux (2006) uses CPS data to estimate an increase in wages of 0.7 log points, or roughly one hundred percent, between zero and twenty years of experience. Our estimates of other measures of life-cycle income growth, for example age-earnings profiles, also line up well with previous estimates in the literature. Guvenen et al. (2014b) 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.

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 mean 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 five 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 five 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 twenty years of experience.

The profiles are also roughly twice as steep in rich countries according to the other summary statistics. 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 is below five 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.

3.2 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 non-core countries cover fewer individuals and years than the core countries.

Figure 2 presents experience-wage profiles for all seventeen 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 to the those of the four rich core countries (Figure 1). The top right panel includes the second richest group of countries: France, South Korea, Uruguay and Chile; the bottom left panels include 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, 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 twenty 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. Taking an average across all rich countries (in the core and full sample), 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 one-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 the sample of core countries.

4 Life-cycle Wage Growth: Controlling for Education, Time, and Cohort Effects

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 starting 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

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

w_{ict} is the wage of individual i, who is a member of birth cohort c and observed at time t. s_{ict} and x_{ict} are her years of schooling and experience. γ_t is a vector of time-period dummy variables, ψ_c is a vector of cohort dummy variables and ε_{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 6.1, 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.

4.1 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, due to collinearity. In this section, we consider the effects of cohort and time controls following the approach proposed by Hall (1968) and Deaton (1997) for estimating returns to experience using repeated cross sections. 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 only be identified with additional assumptions, which, as is well-known in the literature, are identical for both types of data.[6]

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

$$\log w_{ict} = \alpha + \theta s_{ict} + \sum_{x \in X} \phi_x D^x_{ict} + \gamma_t + \chi_c + \varepsilon_{ict}, \tag{2}$$

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

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

[6] See for example Heckman and Robb (1985, p.140) who note that "it is by now well known (Cagan, 1965) 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."

to a time trend. See 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 3a plots the estimates from the first version, in which all income growth is attributed to cohort effects.[7] The left-hand panel shows that Germany and the United Kingdom have the steepest profiles, with more than 100 percent growth by twenty years of experience, while the United States and Canada have around sixty percent growth by twenty 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 like Brazil and Jamaica that have experienced high rates of aggregate growth over this period, the size of the effects attributed to experience is large.[8]

Figure 3b 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 ninety percent growth. The right-hand panel shows that the poor countries have flatter profiles than the rich countries, with Brazil still highest at around seventy percent growth, followed by Chile at 65 percent growth and Mexico and Jamaica at just under fifty percent growth. These profiles are very similar to the cross-sectional profiles in Section 3 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 four summary statistics when all growth is explained by cohort effects. By 20-24 years of experience, profiles are on average 10.8 percentage points higher in the rich countries, though the difference is statistically insignificant. By 35-39 years of experience, profiles are on average higher in the poor countries by 38.7 percentage points, though again the difference is statistically insignificant. The average and discounted heights are slightly higher in the rich countries, but the magnitudes are small and statistically insignificant.

[7] The confidence intervals tend to be narrow for most countries, so we omit them for brevity.

[8] Brazil and Jamaica had wage growth of 3.5 percent per year and 2.1 percent per year on average, with 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.

Panel B of Table 3 shows the intermediate case when growth is explained equally by cohort and time effects. 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 ten 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 among the rich, with the latter being statistically significant at the ten percent level.

Panel C of Table 3 reports the results when all growth is explained by time effects. The mean for rich countries is 44.4 percentage points higher by 20-24 years of experience and 31.1 percentage points higher by 35-39 years of experience. 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 five 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.

4.2 Heckman-Lochner-Taber Approach: No Growth at End of 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.[9] 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 et al. (2011), Bowlus and Robinson (2012) and Schulhofer-Wohl (2013).[10]

[9]See for example the review by Rubinstein and Weiss (2006).

[10]Heckman, Lochner and Taber (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

A simple example helps motivate how this method identifies the effect of wages due to experience (or age) rather than time or cohort. Imagine 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 five percent between 2000 and 2005, while the old cohort has growth of only one percent over the same period. Under the assumption that the old cohort has no wage growth coming through experience, the difference in the time effects between 2000 and 2005 must be one percent. Thus, we infer that the young cohort had wage increases of four percent (five minus one) 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 five or ten years with no experience effects. We consider two alternative depreciation rates of either zero or one 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 on average declined 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.[11]

Figure 4 plots the experience-wage profiles estimated using the HLT method under the assumption that

using economic theory. Similarly, Schulhofer-Wohl (2013) argues that one should use the curvature of wage profiles to identify parameters of structural models.

[11] The most widely applied alternative theoretical restriction, proposed by Deaton (1997), restricts time effects to sum to zero, as in Figure 3a 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" (p.126). This restriction is less relevant for our analysis given that our sample includes many fast-growing countries.

there are no experience effects in the last ten years of the life cycle and no depreciation. In the rich countries, the experience-wage profiles are concave and grow by seventy to one hundred percent by twenty years of experience. Profiles for the poor countries are also concave, but are flatter, and wage growth ranges between forty and sixty percent.[12]

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 ten years and zero depreciation (as in Figure 4), panel (b) summarizes the case with no experience effects over the last five years and zero depreciation, panel (c) summarizes the case with no experience effects over the last ten years and one percent depreciation, and panel (d) summarizes the case with no experience effects in the last five years and one percent depreciation.[13]

In all four panels the rich-poor country differences in heights at 20-24 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 five years and no depreciation (Panel b), while the differences are smallest when depreciation is one percent and there are no experience effects in the last ten 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.

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.

5 Robustness and Additional Results

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 Heckman-Lochner-Taber (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

[12] Appendix Figure A.2 presents the same profiles with their 95% confidence intervals.

[13] Note that assuming a depreciation rate of 1% is rather extreme as it causes poor countries to experience almost no growth over the life cycle. This is because 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.

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 3 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 seventeen countries.

5.1 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 upwards.

5.1.1 Alternative Measure of Experience

One potential concern with our main measure of experience is that we may mis-date the start of work, either because we mis-date 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."[14] 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.[15] We then normalize this employment rate by dividing it by the employment rate of an arbitrary group, which we choose to be forty-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 forty-, eighteen- and nineteen-year olds, then we infer that

[14]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 six (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 U.S.).

[15]We use the three groups to be consistent with the exercises later in Section 6.1. The robustness results presented here are similar when we use more disaggregated groups (e.g., each year of education). These are available upon request.

the average high school graduate who is 20 years old has $35/70 + 50/70 = 1.21$ of constructed experience.[16]

We calculate constructed experience for each country. This allows us to test whether our results are sensitive, for example, to differences in post-graduation employment patterns between poor and rich countries. Row (3) of Table 5 shows that the results using constructed experience are, if anything, slightly larger than our baseline results.

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 years of experience at age eighteen 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.

5.1.2 Measurement Error in Age

Since the main explanatory variable, experience, is constructed using reported age and estimated years of schooling, mismeasurement of age in poor countries could cause the experience-wage profiles of poor countries to attenuate more than that of rich countries. This concern is motivated by the observation that survey respondents in poor countries sometimes round their ages. Appendix Figure A.3 plots the histograms of ages for each country. We only observe age heaping in Mexico and Chile, where there are small spikes in population frequency at every ten years of age (i.e., round number ages). Specifically, the spike in population equals approximately 3.3% of the Chilean sample and 5% of the Mexican sample.

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 and re-estimate the experience-wage profiles. To be conservative, we take 10% of the population in each of the rich countries and randomly round their ages to the nearest round number. The actual and distorted age distributions for each rich country are presented in Appendix Figures A.3a-A.3d. We re-construct potential experience using the distorted age data in each country. We then re-estimate the experience-wage profiles using our HLT approach. The left panel in Figure 5 plots the profiles using both the real data (solid lines) and distorted data (dashed lines) for the four rich countries. The profiles show that the distortion causes the profiles to be only slightly flatter. The right panel presents the profiles using the real data of the poor countries (these are the same as in Figure 4). A comparison of the two panels shows clearly that age heaping cannot drive the differences between rich and poor countries.

Row (4) in Table 5 presents the mean of the height of the profiles for rich and poor countries, and the mean difference. It is very similar to the baseline result in the first row.

[16] The results are very similar when we use other age groups as the reference group for the normalization. They are available upon request.

5.1.3 Measurement Error in Schooling

Another concern is that the years of educational attainment are more mismeasured in poor countries. Specifically, the main measure of potential experience uses years of schooling that are estimated based on the variable for the level of highest educational attainment. Thus, the concern is that the relationship between the level of educational attainment and the age at graduation is weaker in poor countries. For example, it could be the case that the attainment "high school degree" implies graduation at age 18 for most people in the United States, but a wide range of ages in poor countries. Since we construct experience using age at graduation, this discrepancy between rich and poor countries would cause more measurement error in experience for poor countries.

To address this, we investigate the distribution of the years of schooling for each reported educational attainment. We are able to do this for Chile (2000, 2003, 2006, 2009) because the surveys for the specified years ask respondents to both report the number of years they attended school and the highest level of attainment.[17] The data show that there is indeed variation in the number of years of actual schooling for a given level of attainment. The dispersion for Chile is nearly identical across survey years. Thus, we focus on one year, 2009, for brevity. Appendix Table A.1 panel A presents the distribution of the number of years for each level of attainment for Chile in 2009. Panel B shows that there is more dispersion (in terms of percentage differences from the years of imputed education) at lower levels of schooling. For example, in Chile, the years of schooling for someone who completed "some primary" ranges from three to eight years. For those who complete "college", the number of years only vary between sixteen to eighteen years. Thus, those who report having "some primary" range between 33% fewer and 100% more than the imputed number of years of schooling. And those who complete college range between 0% less and 12.5% more than the imputed number of years of schooling (see Panel B).

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 (see Appendix Table A.1 panel B). 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. The distribution of the years of schooling data before and after the distortion are shown in Appendix Figure A.4.

We then re-estimate the experience-wage profiles with the distorted data. Figure 6 presents the experience-

[17] The 1991 and 2001 waves of the Jamaican survey 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 range from zero to fifteen years). Thus, we do not use these data from Jamaica.

wage profiles estimated with the HLT specification. The panel of rich countries on the left shows that the profiles with the distorted data (dashed lines) are similar to those using the actual data (solid lines). A comparison of the left panel and the right panel shows that the profiles of rich countries would be steeper than poor countries even if rich countries had the same dispersion as poor countries.

Table 5 row (5) shows the means for rich and poor countries and the differences in the means when we use the distorted data for rich countries. The estimates are similar to the baseline.

5.1.4 Measurement Error in Age and Education

Finally, we allow for measurement error in both the age and education variables of rich countries to investigate whether this causes their profiles to look like the profiles of poor countries. We distort the age variable as in Section 5.1.2 and the years of education variable as in Section 5.1.3. The estimated profiles are shown in Figure 7. As before, the left panel shows the profiles using the actual data (solid line) and distorted data (dashed line) of the rich countries, and the right panel shows the profiles using the actual data of the poor countries. We see that the profiles of rich countries with the added noise to both education and age are still higher than that of the poor countries. This can also be seen in the rich and poor country means and the differences in means in row (6) of Table 5. We conclude that even if rich country data were initially perfectly measured and poor country data noisily measured, this noise is unlikely to explain a substantial fraction of the difference in experience profiles between rich and poor countries.

5.2 Sample Selection

Our baseline analysis focused on a sample that is designed to maximize comparability between countries and minimize measurement concerns: 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.[18] 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 to include women, part-time workers, public sector workers and self-employed workers.

[18] Note that for the eight core countries, the size of our sample as a percentage of total male workers is 63% (USA), 66% (U.K.), 65% (Mexico), 45% (Jamaica), 67% (Germany), 70% (Chile), 67% (Canada) and 61% (Brazil).

5.2.1 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 the 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 1975-1997, bi-annually 1999-2013), and one poor country, Mexico *(Mexican Family Life Survey*, FLS, 2002, 2005 and 2009). In the main analysis, U.S. workers have very steep profiles, 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 address the concern of selection by following the same individuals in the panel and showing that the experience-wage profiles estimated with panel data are similar to the baseline cross-sectional estimates that use 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 only available for the years 2002, 2005 and 2009, we use waves of the PSID from a comparable time period, 2003-2013. 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 five 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 8a shows that the U.S. profile is higher than the Mexican profile. Each line segment in figure is the normalized wage of a cohort over time. Figure 8b shows the analogous profiles from the repeated cross-sectional data (these are identical to those in Figure 1). A comparison of the two figures show that the panel and repeated cross-sectional data are broadly similar.

Selection into and out of wage employment Next, we use the panel data to explicitly estimate the wages of workers who switch from wage employment to self employment. For selection into self-employment to cause experience-wage profiles to be steeper in rich countries, it must be the case that workers who exit wage work for self-employment in rich countries are less productive than workers who make the same switch in poor countries.

To address the difficulty that self-employed workers are more likely to mismeasure their wages, we use wage data for workers *before* they move into self-employment. Each wave of the FLS and PSID observes occupation and wages. Thus, we can examine the difference in wages in year $t-1$ between workers with experience level x who stay in wage employment in year t and those with the same level of experience who move into self-employment in year t. Specifically, we estimate the relative wage for each experience bin by regressing wages earned in the previous year on dummy variables for the experience bins and the interactions of each experience-bin dummy variable with a dummy variable for whether the worker is self-employed during the current year, controlling for the years of educational attainment and year fixed effects. The reference group is the 0-4 years of experience bin for workers who remain in wage work. From this regression, we can predict the relative wage residuals for each experience bin for workers who remain in wage employment and workers who exit.

In other words, this regression recovers the wage difference between two workers on the same point in the life cycle: one who remains in wage employment and one who moves into self-employment. We would be concerned if Mexican workers who move into self-employment earn higher wages than workers who stay in wage-employment, while this is not (or less) true in the United States. Alternatively, we would be concerned if U.S. workers who move into self-employment have lower wages than workers who remain in wage-employment and that the difference is larger in magnitude later in the life cycle, and this was not (or less) true in Mexico.

For this exercise, we use all of the available waves of the Mexican FLS and the U.S. PSID. Because we control for time effects in this estimate, it is less important that we truncate the U.S. sample to be comparable to the Mexican data in terms of the time period. Because we need to observe past wages, this estimate uses a sample of individuals who appear in at least two consecutive survey waves. Note that our estimates control for time effects and we do not implement the HLT method because the panel data (particularly for Mexico) have smaller sample sizes such that there are very few workers with high levels of experience.

Figures 9a and 9b plot differences in residualized wages between the two types of workers at each point of the life cycle (i.e., the wage residuals of workers who remain in wage employment minus those of workers who move to self employment) and their 95% confidence intervals.[19] They show that U.S. and Mexican workers who remain in wage employment earn similar wages except during 15-20 years of experience in the United States, and 25-30 and 35-40 years of experience in Mexico.[20] Since the wage gap is small or not significantly different from zero throughout the lifecycle, the exit of workers to self-employment is unlikely to significantly affect our estimated wage profiles. Moreover, such moves are relatively infrequent; only 3% of workers in the United States and 5-11% in Mexico exit in a given year (see the thin dashed line in Figures 9a and 9b). What matters for our profiles is the product of these two variables: the frequency of exiting multiplied by the selectivity of those who exit, measured as their wage gap. We plot this product as well as the solid line in Figures 9a and 9b. The line is positive but small in both countries at approximately 1-2%. This indicates that in a typical year, the exit of low-wage workers to self-employment pushes wages up by 1-2% as compared to keeping a constant sample in both countries. This small and balanced effect has little scope to affect our cross-country patterns.

We can also address the concern that workers select from self-employment into wage employment. An example of how this can cause steeper profiles for richer countries is if workers who enter wage work from self-employment in rich countries are more productive than workers who make the same switch in poor countries. To investigate this, we conduct an exercise very similar to before and compare wages in year t of workers who were self-employed in year $t + 1$ to wages of workers who worked for wages in year $t{+}1$.

Figures 9c and 9d plot the difference in wage residuals between workers who are in wage employment in both years and workers who moved from self-employment into wage employment and their 95% confidence intervals. They show that workers who are in wage employment earn higher wages in the United States throughout the life cycle. In Mexico, such workers earn less when they have 25-30 years of experience. As in the earlier results, moves are uncommon; roughly 3% per year in the United States and 10% in Mexico. The net effect of entry is given by the product of the two and is shown with the solid line in Figures 9c and 9d. These effects are small and positive, meaning that workers who switch into wage employment earn less and drag down wage profiles by roughly 1-2% per year in both the United States and Mexico.

Note that we ignore attrition from panels when we estimate these profiles. In Appendix Section A.4, we show that our estimates are very similar using bounded samples where we add those who exit the panel into the sample.

The examination of workers who move into and out of self-employment in the United States and Mexico

[19] The estimates are more precise for the United States because the PSID has a much larger sample size than the FLS.
[20] During these points of the life cycle, workers who remain in wage employment earn approximately 30% more.

shows that such selection is very unlikely to cause the estimated experience-wage profiles of rich countries to be steeper. Since these results are specific to workers who move between wage- and self-employment, it is natural to wonder whether we will find steeper profiles in richer countries if we include workers who remain in self-employment for their entire life cycle (and had accurate wage data for these workers). Note that for their inclusion to drive our results, self-employed workers will need to have relatively steeper profiles than wage workers in poor countries.[21] However, this goes against the conventional wisdom that self-employment in poor countries is largely disguised unemployment.[22] If self-employed workers in rich countries are more likely to include successful entrepreneurs while self-employed workers in poor countries are more likely to disguise unemployment, then our exclusion of self-employed workers will, if anything, cause us to understate the difference in the steepness of profiles between rich and poor countries.

5.2.2 Private-Sector Workers

The restriction to private-sector workers has a similar motivation and similar limitations to the restriction to self-employed workers. There is a general concern that public-sector wages are less likely to reflect a worker's compensation per hour worked than private-sector wages (e.g., because there are more non-wage payments such as pensions, housing, etc.). However, we may be concerned that workers select into and/or out of public-sector employment in a way that causes the profiles in rich countries to be steep and those in poor countries to be flat.

Row (8) of Table 5 shows that our results are very similar if we include public-sector employees. However, as with self-employed workers, this result is subject to the concern that public-sector workers may not be paid their actual hourly compensation.

To address this concern, we conduct a similar exercise with the U.S. PSID and Mexican FLS and use information on wages earned in the private sector for workers who switch in and out of the public sector. As in the previous exercise, we first investigate whether workers who exit private-sector employment in the U.S. and Mexico differ in a way that can cause the U.S. profile to be substantially steeper than the Mexican profile.

We plot the difference in wage residuals for workers who remain in the private sector and for workers who move to the public sector at the same points in the life cycle.[23] As with selection into and out of self-employment, there is no obvious pattern over the life cycle and the flow of workers from one sector to

[21] Alternatively, self-employed workers can have steeper profiles in both rich and poor countries, but the difference between is larger in magnitude in poor countries.

[22] For survey evidence, see Lerner and Schoar (2010) and Poschke (2013). Also see recent studies by Schoar (2010), which documents that operations run by self-employed individuals have very different growth dynamics from conventional entrepreneurs, and La Porta and Shleifer (2008), which divide subsistence and transformational entrepreneurship. Similarly, the notion that much self-employment in developing countries is disguised unemployment is supported by evidence that self-employment and small-scale entrepreneurship increases during economic downturns (Adhvaryu et al., 2014; Gunther and Launov, 2012; Paulson and Townsend, 2005).

[23] These are presented and discussed in Appendix A.3.

the other is very low such that selection into and out of the private sector can only have negligible effects on our estimates.

The results show that selection into and out of public employment does not drive our main estimates. As with the examination of self-employed workers, the robustness exercise focuses on workers who move between the private and public sectors. Thus, one naturally wonders whether we would still find steeper profiles in rich countries if we included those who work in the public sector for their entire life cycle (and had accurate wage data). To see that their inclusion is unlikely to make a significant difference, note that very few workers are employed in the public sector – on average, 8% in the rich countries in our sample, and 3% in the poor countries in our sample.

5.2.3 Female Workers

The main analysis also excludes female workers. Unlike self-employed or public-sector workers, we are not concerned that the wages of female workers do not reflect their compensation per hour worked. Instead, the concern is that potential experience has a different mapping to the actual experience of female workers relative to male workers because the former may temporarily exit the labor force for reasons such as childbirth. 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).

To address the concern that potential experience is a poor measure for female workers, we calculate the constructed experience for women using a method similar to section 5.1.1. Row (10) presents the rich and poor country means and the mean differences when we estimate the experience-profiles for male and female (full-time, private-sector) workers with constructed experience, which is calculated separately for male and female workers. Note that this allows employment rates to vary between men and women within each country, as well as across countries. The results are very similar to the estimate using reported potential experience and our baseline in row (1).

5.2.4 Part-time Workers

Finally, we investigate the importance of the exclusion of part-time workers (those who work less than thirty hours a week). As with women, this exclusion is made because the mapping between potential experience and actual experience may differ between part-time and full-time workers. This problem cannot be easily resolved by using constructed experience because that method requires the assumption that workers are part-time or full-time for their entire life cyle. Instead, we argue that the inclusion of part-time workers is unlikely to alter our main findings because only 11% of male workers in rich countries and 4% in poor countries work part-time.

With the caveats stated above, Table 5 rows (11) and (12) show that the HLT estimates change little when we include workers who work at least twenty hours a week and 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.

As with wage- and private-sector employment, one can ask whether selection of workers from full- to part-time (or vice versa) differ between rich and poor countries in such a way that can cause the profiles to be steeper in richer countries. Thus, we conduct analogous exercises to the previous sections.[24] We find no evidence to support this concern. See Appendix Section A.3 for a detailed discussion.

In summary, we find that life-cycle wage profiles are consistently steeper in rich than in poor countries. Our results are not sensitive to the sample selection criteria we impose or how we measure potential experience.

6 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.

6.1 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 non-separable 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), Kambourov and Manovskii (2009) or Guvenen (2007). Thus, we first check whether these patterns also exist in our data. Figure 10 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. For each country, we keep only education groups for which there are at least ten 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.

[24] Note that since we are less concerned that reported wages for part-time workers mismeasure hourly labor payments, we could also use wages earned in the current year (instead of wages earned the year prior to moving or out of part-time employment) for these regressions. The results are nearly identical and are available upon request.

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.[25] 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.

Figure 11 plots experience-wage profiles separately for our three education groups. 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.[26] Amongst poor countries, the differential returns to experience for different education groups are particularly pronounced in Mexico and Brazil. This finding is not obvious *a priori*. In the next section, we explore its implications in more detail.

6.2 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 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 where 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.[27] If all of the cross-country differences in experience-wage profiles were due to

[25] This is the reason that Mincer (1974) controls for experience instead of age in the wage regression.

[26] Recall that we defined *experience* = *age*–18 for individuals with fewer than twelve years of schooling. In the event that individuals start accumulating experience before the age of 18, part of the difference between the "less than high school" and "high school" groups may be due to a similar mechanical effect as discussed above. Experience-wage profiles by education level with alternative experience definitions are available upon request.

[27] We also conduct a similar exercise for age-wage profiles, and find modestly higher explanatory power of education composition. Though, given the mechanical composition effect for age profiles discussed in the preceding subsection, we view this

differences in educational attainment, then this counterfactual would eliminate all such differences.

Figure 12 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%", 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%". For exposition we also added lines at 25% and 50%. We find that most of our countries lie between the zero- and the fifty-percent lines. For example, for Chile, Mexico and Jamaica, differences in the distribution of educational attainment account for around thirty to forty 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 the United States to begin with, which means that the gap is small in the first place.

Overall, we find that for countries with substantially different experience-wage profiles from the United States, differences in the composition of educational attainment account for twenty-five to forty percent of the difference in experience-wage profiles with the United States. We view this finding as progress towards understanding the underlying cause for cross-country differences in life-cycle wage growth. However, with the exception of a few countries, composition effects do not account for the entire difference. 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.[28]

7 Implications of Slow Life-cycle Wage Growth

In this section we discuss the broader implications of lower life-cycle income growth in poor countries through the lens of the two main theories of life-cycle earnings patterns: human capital accumulation, and search and matching. Each literature has proposed multiple mechanisms that could explain why life-cycle wage growth varies across countries. Our data speak to how these processes differ systematically between poor and rich countries and offer the potential to discipline quantitative exercises along these lines. The common implication of these mechanisms is that low life-cycle wage growth implies low growth of labor productivity over the life-cycle. In the aggregate, this implies that our findings can contribute to understanding cross-

exercise as less informative and therefore did not include it in the paper. They are available upon request.

[28]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, etc.). For example, a key difference between rich and poor countries is that poor countries tend to have a much larger share of workers that 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, undated). We therefore conducted an analogous exercise to the one discussed in the text, except that we estimate profiles separately for agriculture and non-agriculture 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 upon request.

country income differences.

7.1 Human Capital

A first candidate explanation for our finding is that workers accumulate less human capital over the life cycle in poor countries. Low human capital accumulation can be an endogenous choice of the workers or an exogenous feature of the environment. Manuelli and Seshadri (2014) propose a theory of the first type where low TFP 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. They explicitly propose this theory to help explain cross-country income differences; our paper provides direct support for their work.

Alternatively, extractive institutions in poor countries may discourage workers from investing in human capital, since their returns can be arbitrarily expropriated (Bhattacharya et al., 2013). This logic is consistent with recent evidence that higher taxation of labor income in Europe can explain a substantial fraction of European-U.S. differences in wage inequality and life-cycle wage growth (Guvenen et al., 2014a).

Alternatively, workers in poor countries may accumulate less human capital due to the characteristics of the work done, the technology used, or the way workers interact in poor countries. 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.[29]

As we noted in the introduction, an older literature found no relationship between returns to experience and GDP per capita Psacharopoulos (1994); Bils and Klenow (2000). Based on these results, much of the development literature concluded that human capital from experience is unlikely to account for much of cross-country income differences (Klenow and Rodriguez-Clare, 1997; Bils and Klenow, 2000; Caselli, 2005; Hsieh and Klenow, 2010). Recent work by Manuelli and Seshadri (2014) suggests that it might be time to reconsider this conclusion. Our new evidence offers support for this idea.

7.2 Search and Matching Frictions

Another candidate explanation for slow life-cycle income growth in poor countries are 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); Bagger et al. (2014) emphasize search as a model 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 forego some of the

[29]Recent work by Seshadri and Roys (2012) and Stokey (2014) go a step further and link human capital accumulation to the life cycle of firms. In this case, our facts may also have implications for theories of why the life cycle of firms looks different in rich and poor countries (Hsieh and Klenow, 2014).

potential increase in labor productivity over the life cycle.[30] Although these ideas have been applied to studying labor productivity over the business cycle or across developed countries, the large cross-country differences in life-cycle wage profiles suggests a new avenue for exploration (Lise and Robin, 2013; Postel-Vinay and Turon, 2014). Alternatively, long-lasting frictions may prevent workers from sorting to the jobs that are most suitable to their heterogeneous skills and tastes. Again, the implication would be that workers forego labor productivity increases as they age (Hsieh et al., 2013).

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 (Restuccia et al., 2008; Caselli, 2005; Gollin et al., 2014). Viewed through the lens of a search and matching model, our findings suggest that it may be time to incorporate analogous frictions to job shopping 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."

8 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 one hundred 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 fifty percent larger than 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. Flatter life-cycle profiles in poor countries may reflect less human capital accumulation in poor countries or more severe search frictions that result in a less fluid labor market and workers climbing the job ladder more slowly. Since human capital accumulation and labor market fluidity likely determine a country's standard of living, our findings may help explain cross-country income differences.

The results of this paper suggest several interesting avenues for future research. First, the life-cycle wage profiles documented in this paper can be used to empirically discipline the theories discussed in Section 7. Second, it is important to understand the determinants of different life-cycle wage profiles between rich and poor countries. In ongoing work, Lagakos et al. (2014) document that among new U.S. immigrants, returns to experience accumulated in their home countries are higher for immigrants from rich countries than

[30] Burdett (1978, p.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."

immigrants from poor countries. 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. Similarly, future research should also assess the importance of search and matching frictions in accounting for flat life-cycle wage profiles in poor countries. A natural first step is to examine whether labor markets are indeed less fluid in poor countries, for example whether workers change jobs less frequently. A recent study by Seok and You (2015) finds some evidence consistent with this.

References

Adhvaryu, Achyuta, Namrata Kala, and Anant Nyshadham, "Booms, Busts, and Household Enterprise: Evidence from Coffee Farmers in Tanzania," 2014. University of Michigan Working Paper.

Aguiar, Mark and Erik Hurst, "Deconstructing Life Cycle Expenditure," *Journal of Political Economy*, 2013, *121* (3), 437–492.

Bagger, Jesper, Francois Fontaine, Fabien Postel-Vinay, and Jean-Marc Robin, "Tenure, Experience, Human Capital, and Wages: A Tractable Equilibrium Search Model of Wage Dynamics," *American Economic Review*, June 2014, *104* (6), 1551–96.

Bhattacharya, Dhritman, Nezih Guner, and Gustavo Ventura, "Distortions, Endogenous Managerial Skills and Productivity Differences," *Review of Economic Dynamics*, January 2013, *16* (1), 11–25.

Bils, Mark and Peter J. Klenow, "Does Schooling Cause Growth?," *American Economic Review*, December 2000, *90* (5), 1160–83.

Bowlus, Audra J. and Chris Robinson, "Human Capital Prices, Productivity, and Growth," *American Economic Review*, 2012, *102* (7), 3483–3515.

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

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

Cagan, Phillip, "Measuring Quality Changes and the Purchasing Power of Money: an Exploratory Study of Automobiles," *The National Banking Review: a Journal of Policy and Practice*, 1965.

Carroll, Christopher D. and Lawrence H. Summers, "Consumption Growth Parallels Income Growth: Some New Evidence," in B. Douglas Bernheim and John B. Shaven, eds., *National Saving and Economic Performance*, Chicago: University of Chicago Press, 1991, pp. 305–43.

Caselli, Francesco, "Accounting for Cross-Country Income Differences," in P. Aghion and S. Durlauf., eds., *Handbook of Economic Growth*, 679-741, Elsevier, 2005.

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

Duflo, Esther, "Schooling and Labor Market Consequences of School Construction in Indonesia: Evidence from an Unusual Policy Experiment," *American Economic Review*, 2001, *91* (4), 795–813.

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

_ **, David Lagakos, and Michael E. Waugh**, "The Agricultural Productivity Gap," *Quarterly Journal of Economics*, 2014, *129* (2), 939–993.

Gould, William and Finis Welch, "Imputing Labor Market Experience," 1976. mimeograph, Rand Corporation.

Gunther, Isabel and Andrey Launov, "Informal employment in developing countries: Opportunity or last resort?," *Journal of Development Economics*, 2012, *97* (1), 88 – 98.

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

_ **, Burhanettin Kuruscu, and Serdar Ozkan**, "Taxation of Human Capital and Wage Inequality: A Cross-Country Analysis," *Review of Economic Studies*, 2014, *81* (2), 818–850.

— , **Fatih Karahan, Serdar Ozkan, and Jae Song**, "What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Risk?," 2014. mimeo, Federal Reserve Bank of Minneapolis.

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

Hanoch, Giora, "An Economic Analysis of Earnings and Schooling," *Journal of Human Resources*, 1967, *2* (3), 310–329.

Heckman, James and Richard Robb, "Using Longitudinal Data to Estimate Age, Period and Cohort Effects in Earnings Equations," in William M. Mason and Stephen E. Fienberg, eds., *Cohort Analysis in Social Research*, Springer New York, 1985, pp. 137–150.

— , **Lance Lochner, and Christopher Taber**, "Explaining Rising Wage Inequality: Explanations With A Dynamic General Equilibrium Model of Labor Earnings With Heterogeneous Agents," *Review of Economic Dynamics*, January 1998, *1* (1), 1–58.

Herrendorf, Berthold and Todd Schoellman, "Why is Measured Productivity so Low in Agriculture?," *Review of Economic Dynamics*, undated.

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

— **and** — , "The Life Cycle of Plants in India and Mexico," *Quarterly Journal of Economics*, 2014, *129* (3), 1035–1084.

— , **Erik Hurst, Charles I. Jones, and Peter J. Klenow**, "The Allocation of Talent and U.S. Economic Growth," NBER Working Papers 18693 January 2013.

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

Hurst, Erik, Geng Li, and Ben Pugsley, "Are Household Surveys Like Tax Forms: Evidence from Income Underreporting of the Self Employed," *Review of Economics and Statistics*, 2014, *96* (1), 19–33.

Jovanovic, Boyan, "Matching, Turnover, and Unemployment," *Journal of Political Economy*, 1984, *92* (1), 972–990.

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

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

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

La Porta, Rafael and Andrei Shleifer, "The Unofficial Economy and Economic Development," *Brookings Papers on Economic Activity*, 2008, *39* (2 (Fall)), 275–363.

Lagakos, David, Benjamin Moll, Tommaso Porzio, Nancy Qian, and Todd Schoellman, "Experience Matters: Human Capital and Development Accounting," NBER Working Papers 18602 December 2012.

— , — , — , — , **and** — , "Lifecycle Human Capital Accumulation Across Countries: Lessons From U.S. Immigrants," 2014. Working Paper, University of California.

Lehmann, Erich Leo and Joseph P. Romano, *Testing Statistical Hypotheses* Springer Texts in Statistics, New York, NY: Springer Science+Business Media, 2005.

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

Lerner, Josh and Antoinette Schoar, *International Differences in Entrepreneurship*, National Bureau of Economic Research, 2010.

Lise, Jeremy and Jean-Marc Robin, "The macro-dynamics of sorting between workers and firms," IFS Working Papers W13/22, Institute for Fiscal Studies August 2013.

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

_ **and Benjamin Moll**, "Knowledge Growth and the Allocation of Time," *Journal of Political Economy*, 2014, *122* (1), 1 – 51.

Manuelli, Rodolfo E. and Ananth Seshadri, "Human Capital and the Wealth of Nations," *American Economic Review*, 2014, *104* (9), 2736–62.

McKenzie, David J, "Disentangling age, cohort and time effects in the additive model*," *Oxford Bulletin of Economics and Statistics*, 2006, *68* (4), 473–495.

Mincer, Jacob A., *Schooling, Experience, and Earnings*, National Bureau of Economic Research, 1974.

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

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

Paulson, Anna and Robert Townsend, "Financial Constraints and Entrepreneurship: Evidence from the Thai Financial Crisis," *Economic Perspectives*, 2005, *29*, pp. 34–48.

Perla, Jesse and Christopher Tonetti, "Equilibrium Imitation and Growth," *Journal of Political Economy*, 2014, *122* (1), 52 – 76.

Poschke, Markus, "Entrepreneurs out of necessity: a snapshot," *Applied Economics Letters*, 2013, *20* (7), 658–663.

Postel-Vinay, Fabien and Hélène Turon, "The Impact of Firing Restrictions on Labour Market Equilibrium in the Presence of On-the-job Search," *Economic Journal*, 2014, *124* (575), 31–61.

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

Restuccia, Diego, Dennis Tao Yang, and Xiaodong Zhu, "Agriculture and Aggregate Productivity: A Quantitative Cross-Country Analysis," *Journal of Monetary Economics*, 2008, *55*, 234–250.

Rubinstein, Yona and Yoram Weiss, "Post Schooling Wage Growth: Investment, Search and Learning," in Erik Hanushek and F. Welch, eds., *Erik Hanushek and F. Welch, eds.*, Vol. 1 of *Handbook of the Economics of Education*, Elsevier, 2006, chapter 1, pp. 1–67.

Schoar, Antoinette, "The Divide between Subsistence and Transformational Entrepreneurship," in "Innovation Policy and the Economy," Vol. 10, National Bureau of Economic Research, 2010, pp. 57–81.

Schulhofer-Wohl, Sam, "The Age-Time-Cohort Problem and the Identification of Structural Parameters in Life-Cycle Models," 2013. mimeo, Federal Reserve Bank of Minneapolis.

Seok, Byoung Hoon and Hye Mi You, "Why Do Returns to Experience Differ across Countries?," Work in Progress, Ohio State University 2015.

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

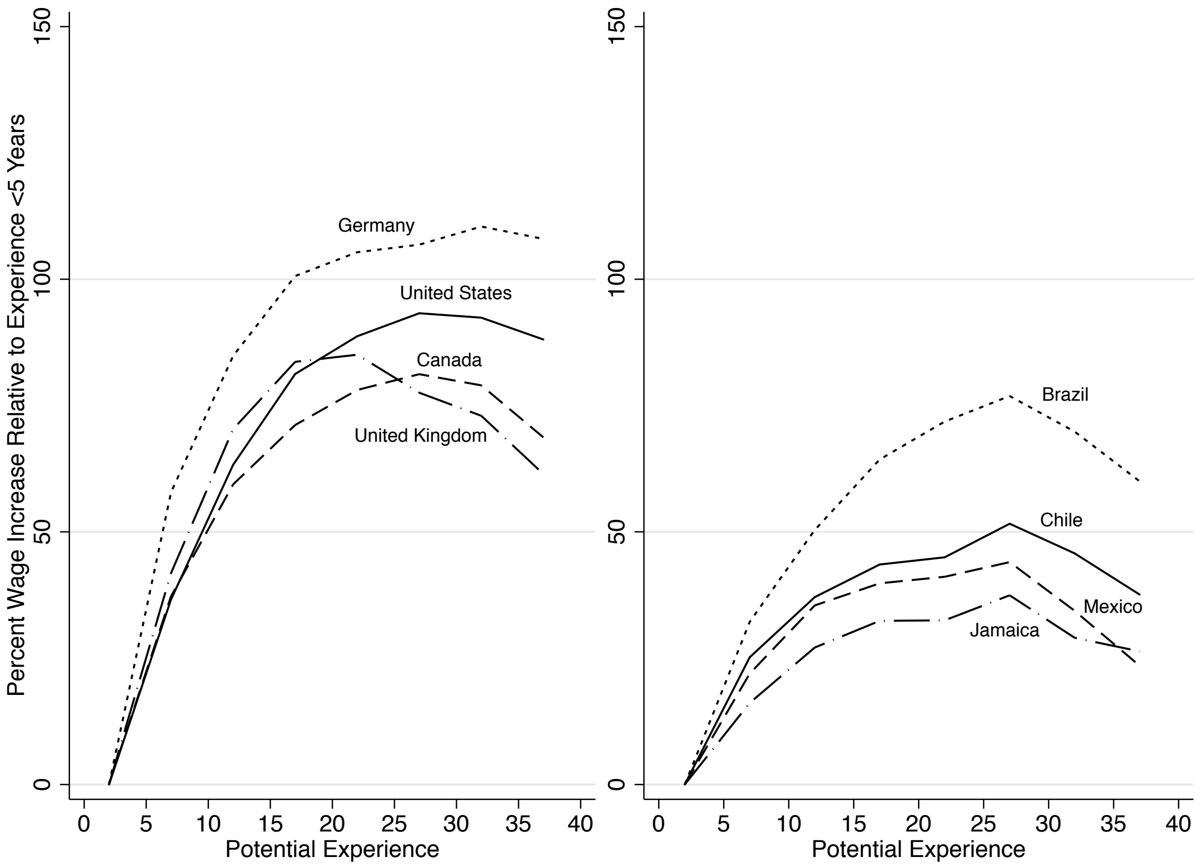
Smith, James P. and Finis Welch, "Race Differences in Earnings: A Survey and New Evidence," Technical Report R-2295-NSF, Rand Corporation 1978.

Stokey, Nancy L, "The Race Between Technology and Human Capital," 2014.

Todaro, Michael P. and Stephen C. Smith, *Economic Development*, 11th edition ed., Addison Wesley, 2012.

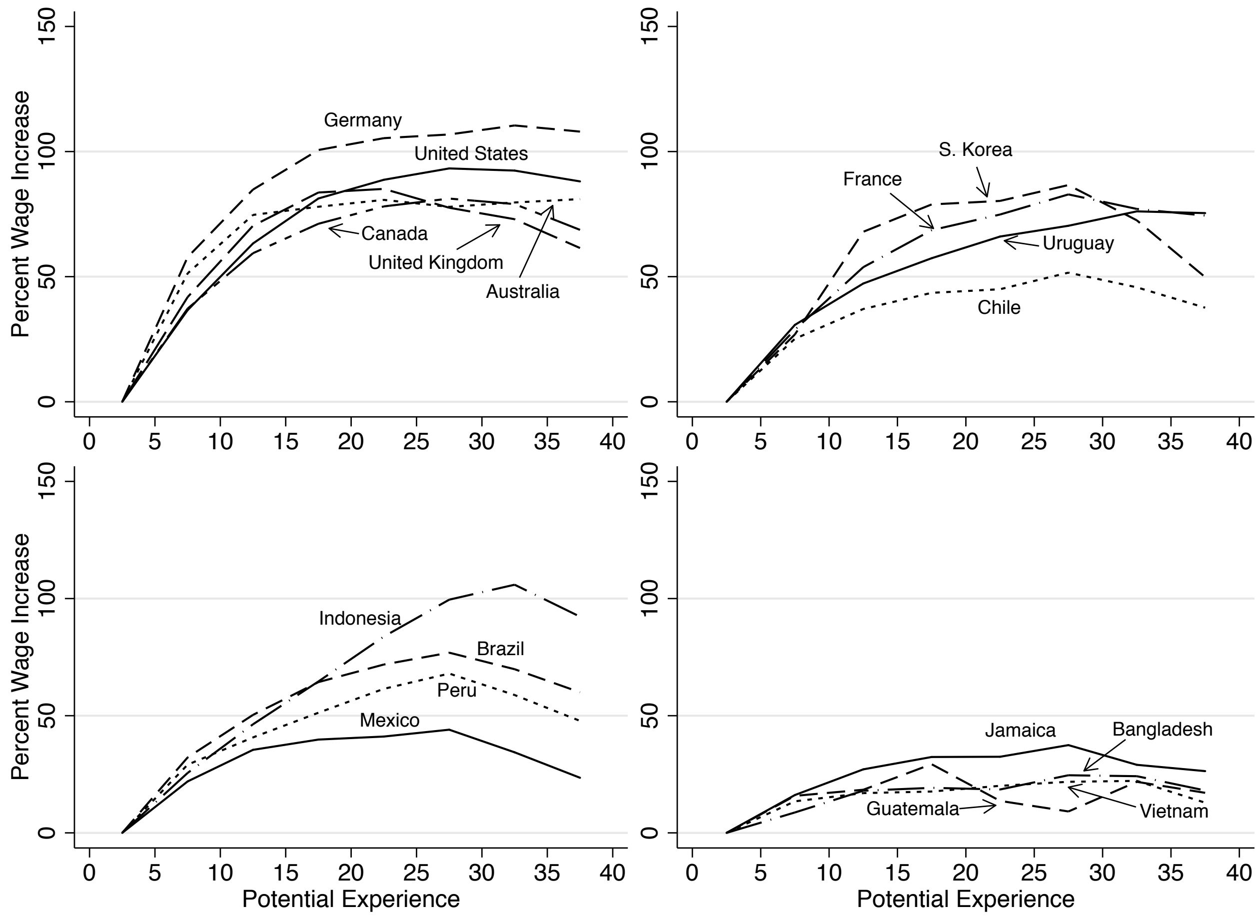
Welch, Finis, "Effects of Cohort Size on Earnings: The Baby Boom Babies' Financial Bust," *Journal of Political Economy*, 1979, *87* (5), S65–S97.

Figure 1: Cross-Sectional Experience-Wage Profiles, Core Countries



Note: 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 five 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 are the rich countries, defined as those with greater than twenty thousand dollars GDP per capita in 2011 at PPP, and the right-hand panel are the poor countries, defined as those with less than twenty thousand dollars GDP per capita in 2011 at PPP.

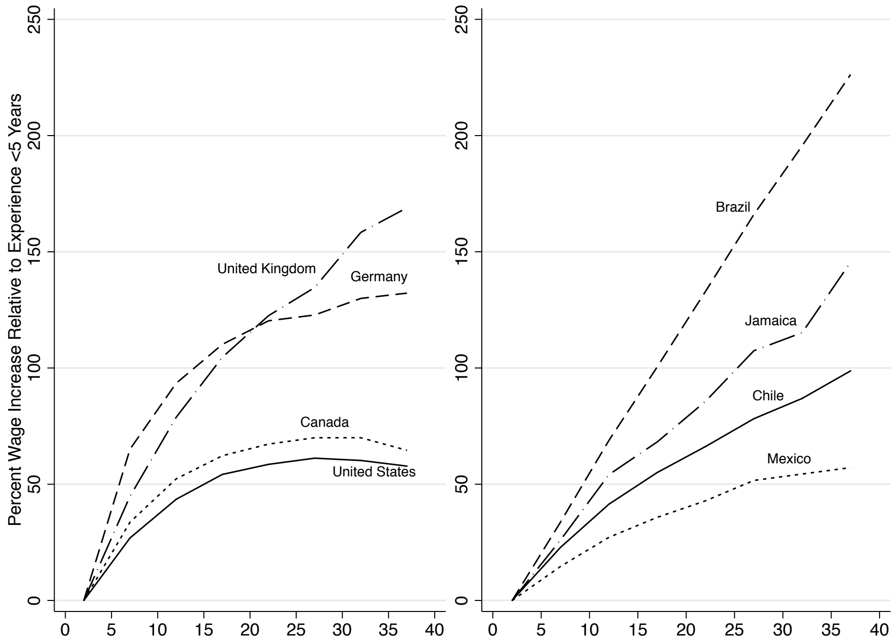
Figure 2: Cross-Sectional Experience-Wage Profiles, All Countries



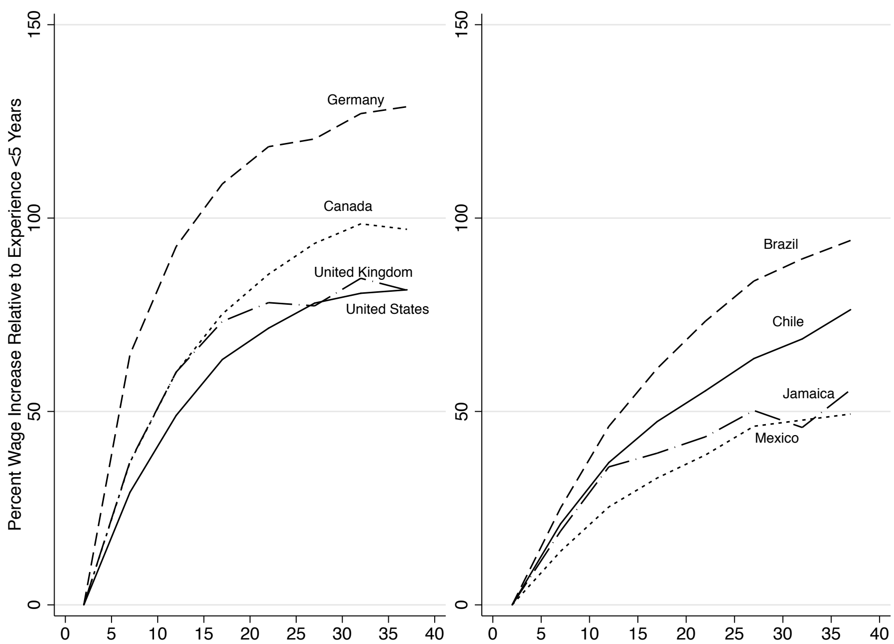
Note: Experience-wage profiles are for full-time males working in the private sector, and are calculated using all available years of data for each country. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is 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 five 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

Figure 3: Deaton-Hall Experience-Wage Profiles

(a) All Growth Driven by Cohort Effects

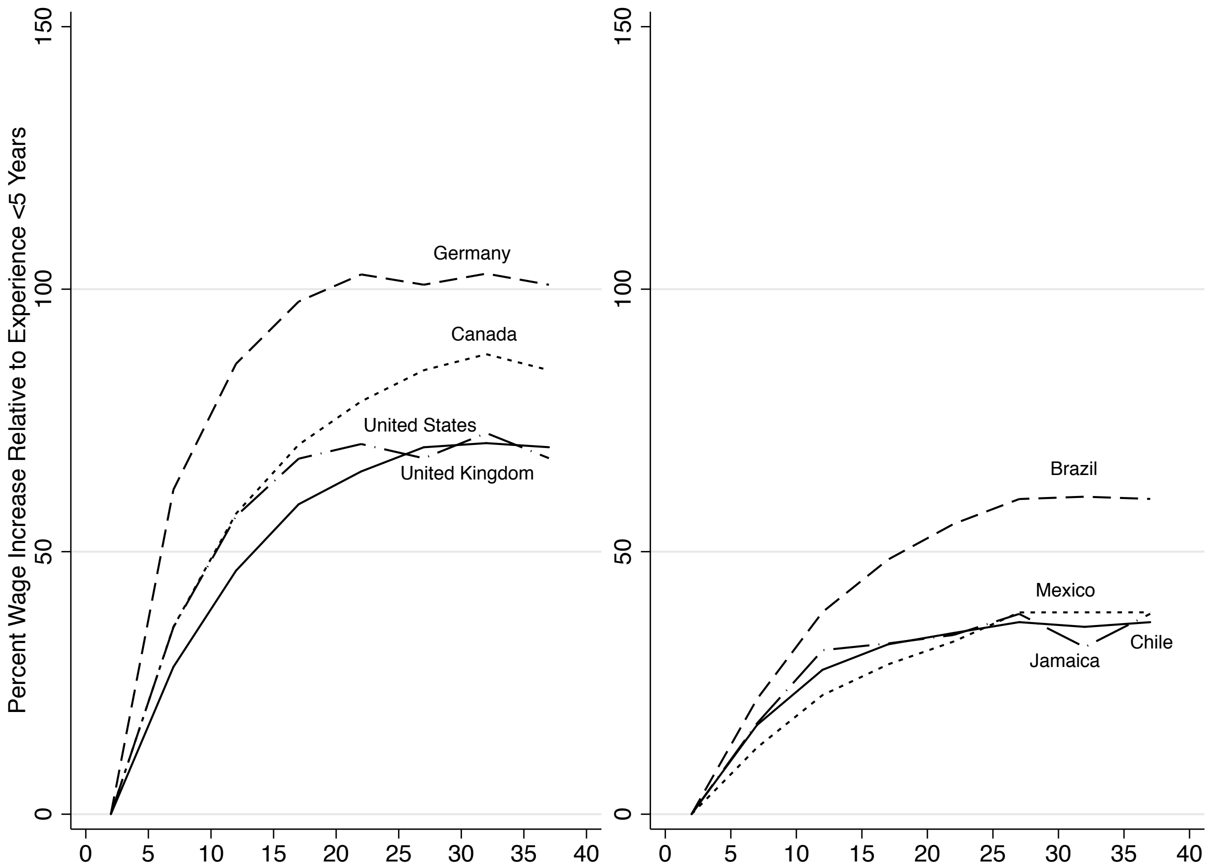


(b) All Growth Driven by Time Effects



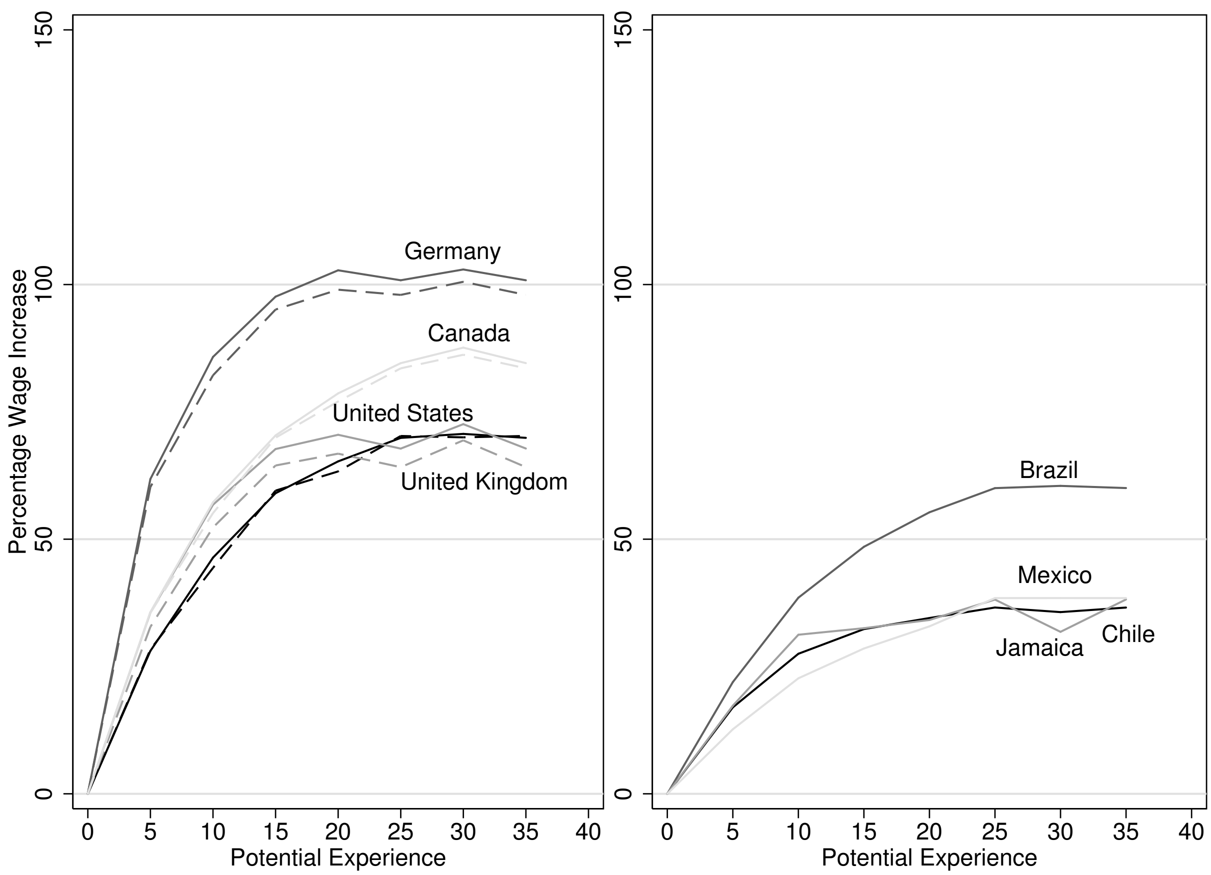
Note: Experience-wage profiles are for full-time males working in the private sector. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. The top panel shows the experience-wage profiles estimated using equation (2), with time controls as well as cohort controls, assuming that all growth is driven by cohort effects. The bottom panel 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 4.2 and Appendix A.3 for a detailed description of our methodology.

Figure 4: Heckman-Lochner-Taber (HLT) Experience-Wage Profiles



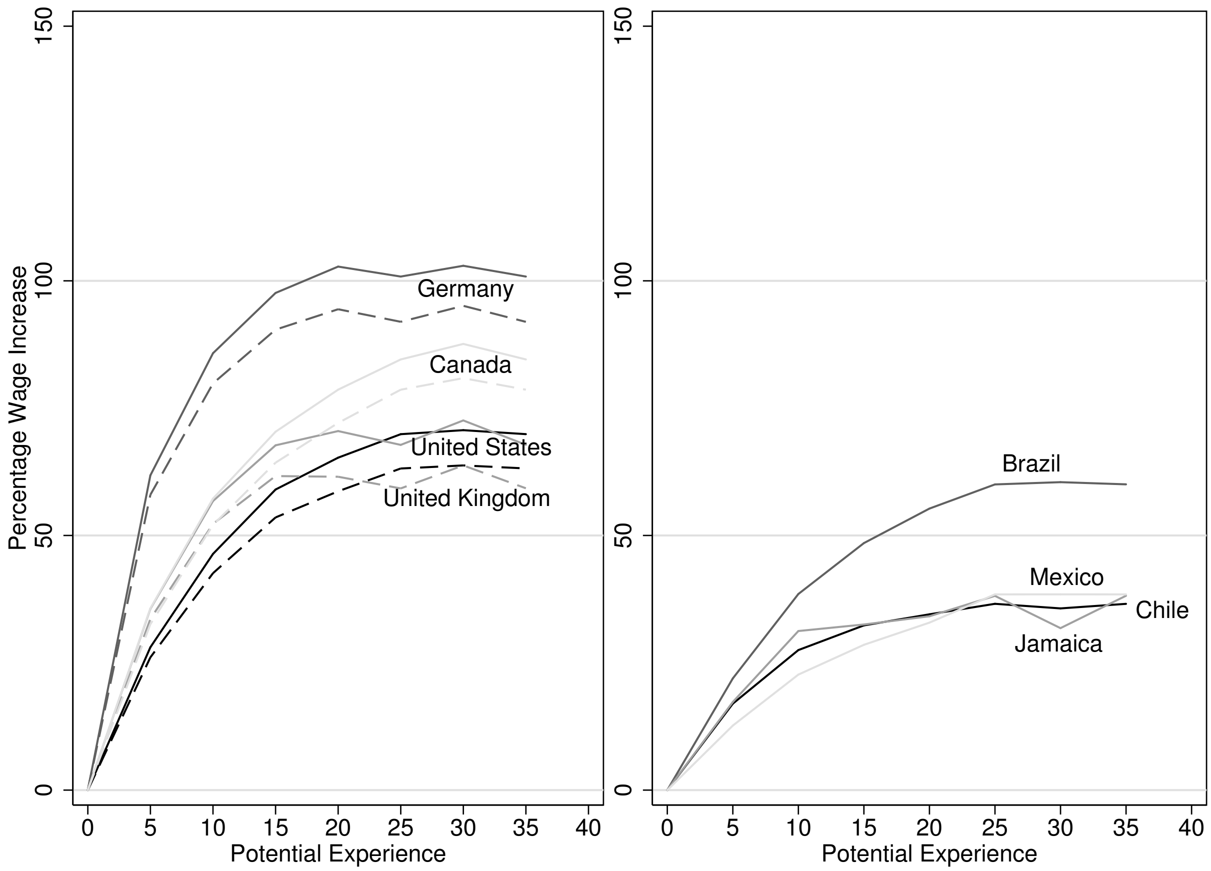
Note: Experience-wage profiles are for full-time males working in the private sector. Potential experience is defined as the number of years elapsed since a worker finished schooling or turned 18, whichever is smaller. The wage is defined to be earnings divided by hours worked. The experience-wage profiles are estimated using equation (2) with time controls as well as cohort controls, assuming that the last ten years of potential experience have zero percent growth. See Section 4.3 for a detailed description of our methodology.

Figure 5: HLT Experience-Wage Profiles – Robustness to Age Heaping



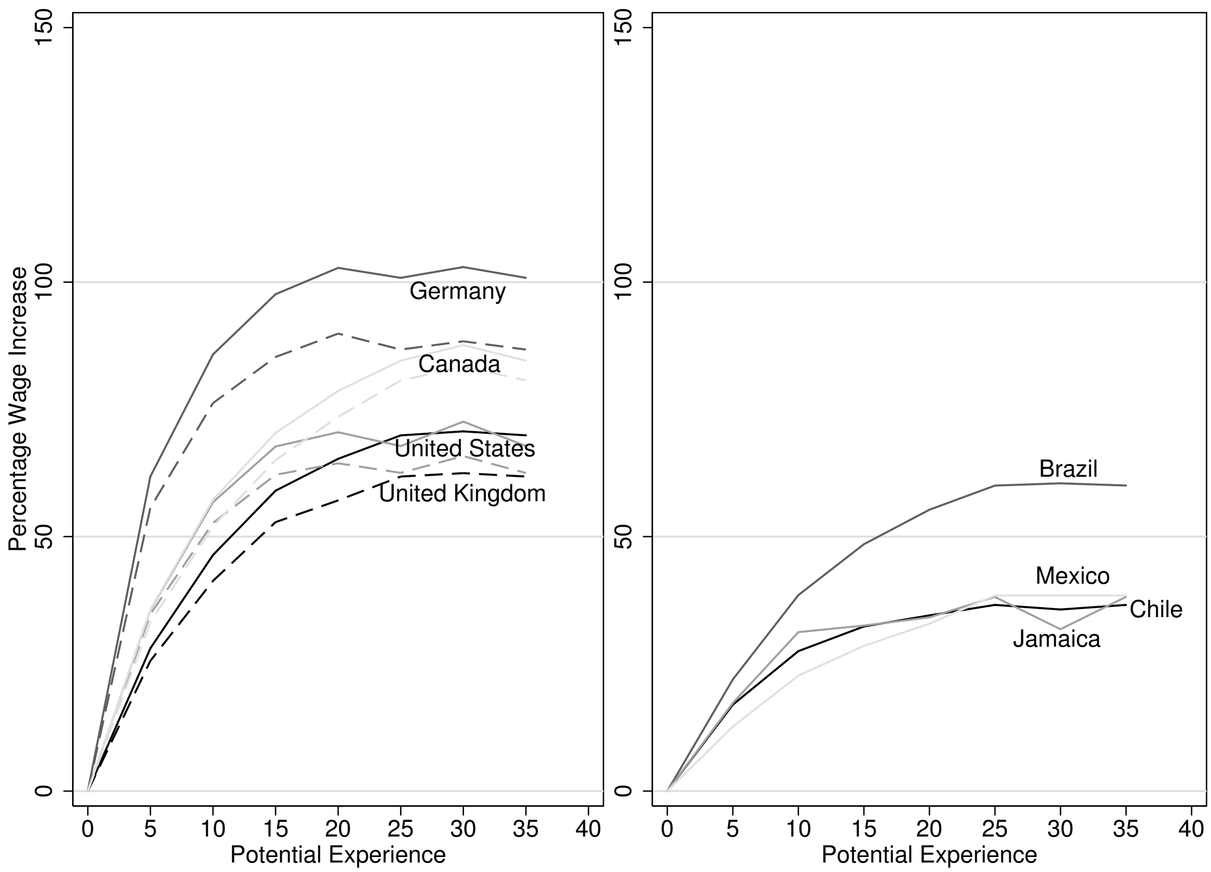
Notes: These figures plot the experience-wage profiles estimated using the HLT method as in Figure 4. In both panels, the solid lines are estimated using actual data. In the left panel, the dashed line is estimated using data where the ages of 10% of randomly selected workers from each country are artificially rounded up or down to the nearest round number.

Figure 6: HLT Experience-Wage Profiles – Robustness to Dispersion in the Years of Education



Notes: These figures plot the experience-wage profiles estimated using the HLT method as in Figure 4. In both panels, the solid lines are estimated using actual data. In the left panel, the dashed line is estimated using data where the years of education for workers are forced to have the same distribution for each reported level of educational attainment as in Chile (shown in Appendix Tables A.1).

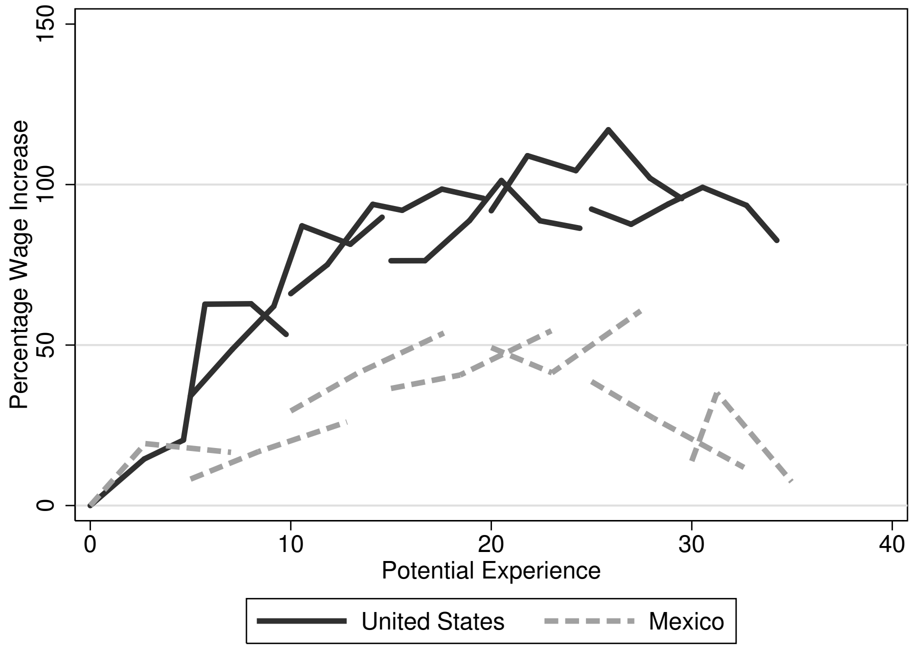
Figure 7: HLT Experience-Wage Profiles – Robustness to Age Heaping and Dispersion in the Years of Education



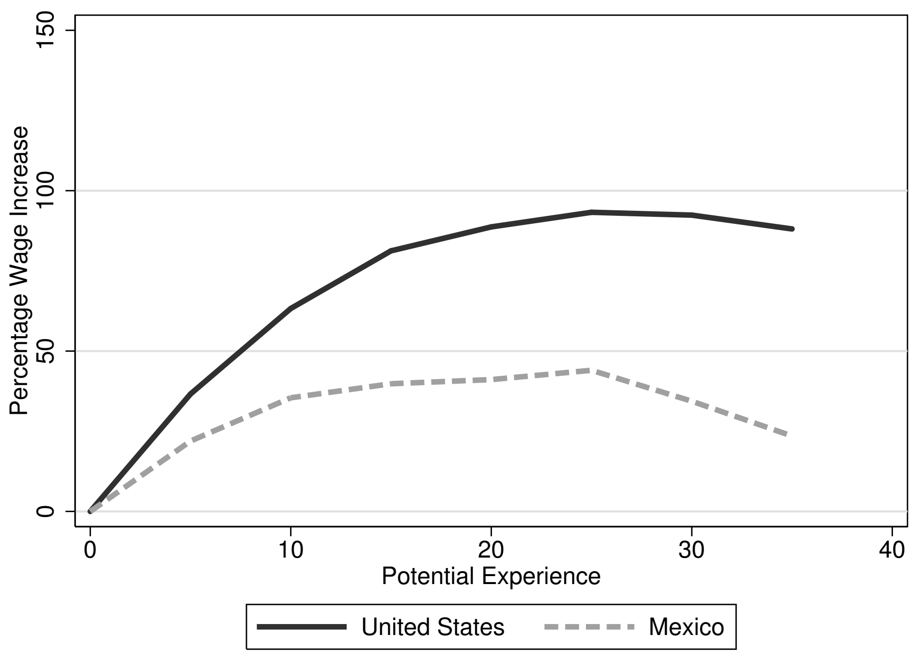
Notes: These figures plot the experience-wage profiles estimated using the HLT method as in Figure 4. In both panels, the solid lines are estimated using actual data. In the left panel, the dashed line is estimated using data where the age for 10% of workers in each country is rounded to the nearest round number and the years of education for workers are forced to have the same distribution for each reported level of educational attainment as in Chile (shown in Appendix Tables A.1).

Figure 8: Experience-Wage Profiles using Panel Data

(a) Panel (U.S. PSID and Mexico FLS)



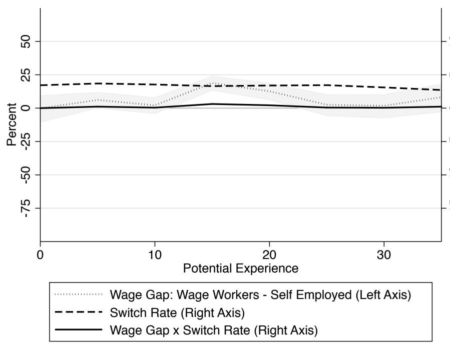
(b) Repeated Cross-Sections for Comparison (reproduced from Figure 1)



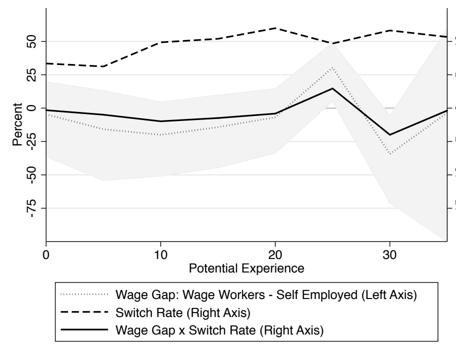
Notes: In Figure 8a, a cohort group comprises fives years of experience levels (e.g., the youngest cohort in Mexico had 0-4 years of experience in 2002). Each line segment in the figure is the normalized mean wage of a cohort over time. Figure 8b shows the analogous profiles from the repeated cross-sectional data (these are identical to those in Figure 1). The data are from the U.S. PSID (bi-annually, 2003 – 2013) and the Mexican FLS (2002, 2005 and 2009).

Figure 9: Selection into and out of Self-Employment – Panel Data Estimates

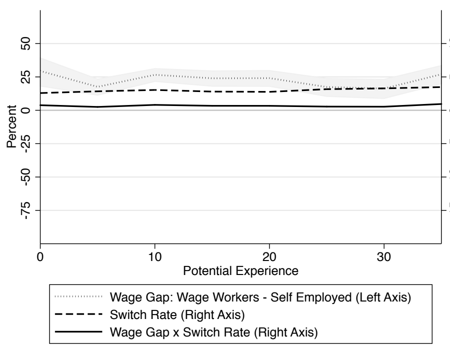
(a) Selection *into* self-employment – U.S.



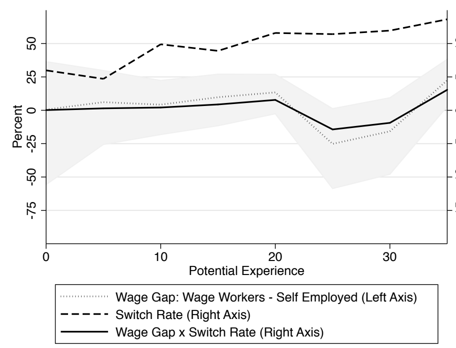
(b) Selection *into* self-employment – Mexico



(c) Selection *out of* self-employment –U.S.

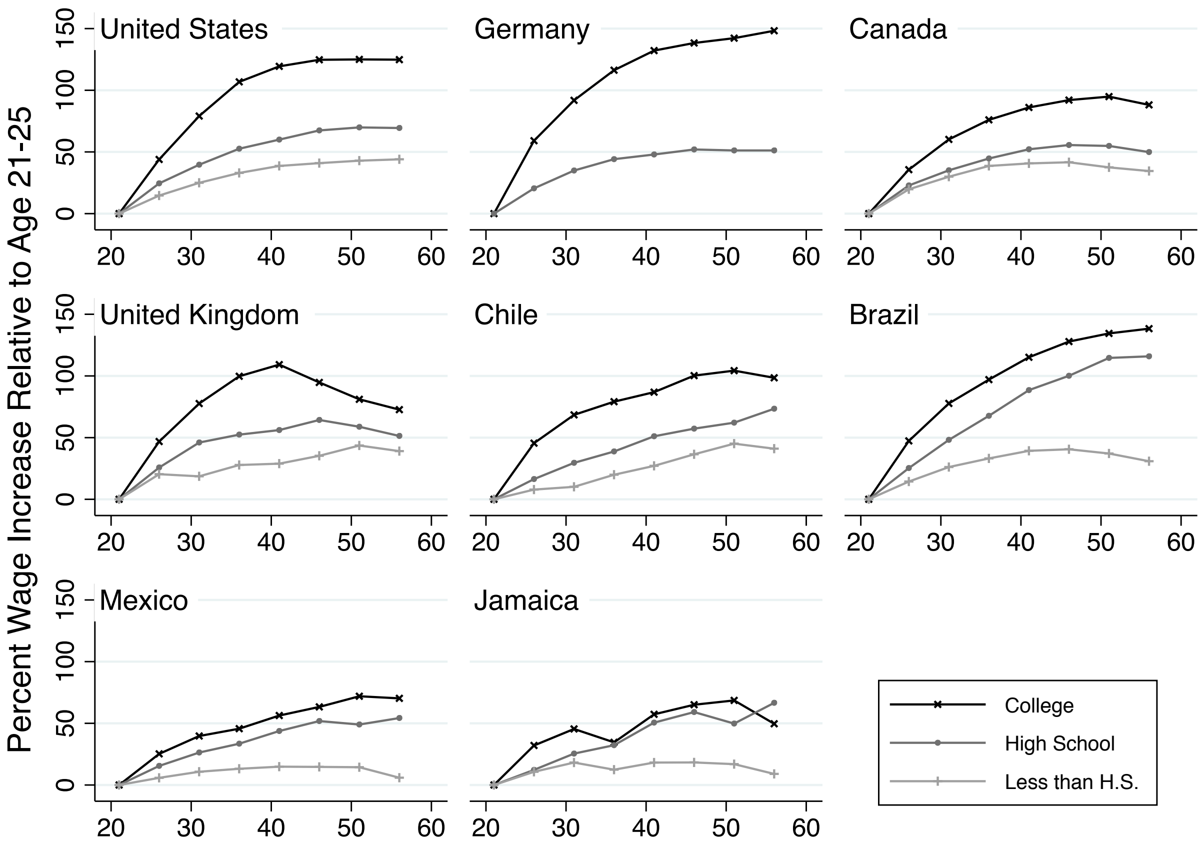


(d) Selection *out of* self-employment – Mexico



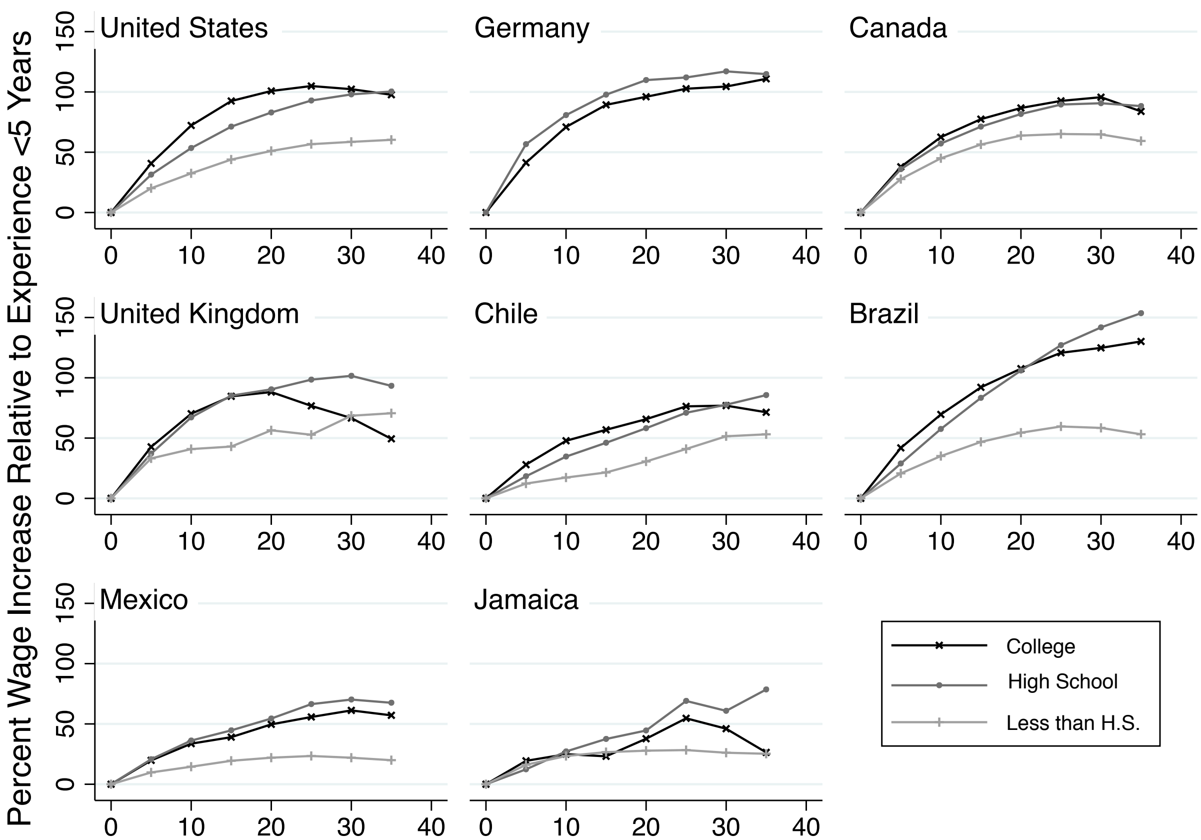
Notes: Figures 9a and 9b plot the estimated differences in wage residuals and their 95% confidence intervals for those who move from wage employment in year $t-1$ to self-employment in year t and those who are in wage employment in both years. Wages are predicted from regressing log wages$_{t-1}$ on dummy variables of five-year experience bins, the interactions of each experience-bin dummy variable with a dummy variable for whether the worker is self-employed$_t$, controlling for the years of educational attainment and year fixed effects. The reference group is the 0-4 years of experience bin for workers who remain in wage work. t refers to the year of the survey. We transform the coefficients from logs to levels so that the y-axis reflects the level of percentage increase relative to the reference group. The figures also present the rate at which workers move from wage- to self-employment at each point on the life cycle and the product of this rate and the wage-gap. An analogous regression predicts the wages of those who move from self employment in year $t-1$ to wage employment in year t and those who are in wage employment in both years shown in Figures 9c and 9d. The figures also present the rate at which workers move from self- to wage-employment at each point in the life cycle and the product of this rate and the wage-gap. The data are from the U.S. PSID (1975-1997 annually, 1999-2013 bi-annually) and the Mexican FLS (2002, 2005 and 2009).

Figure 10: Age-Wage Profiles by Education Group



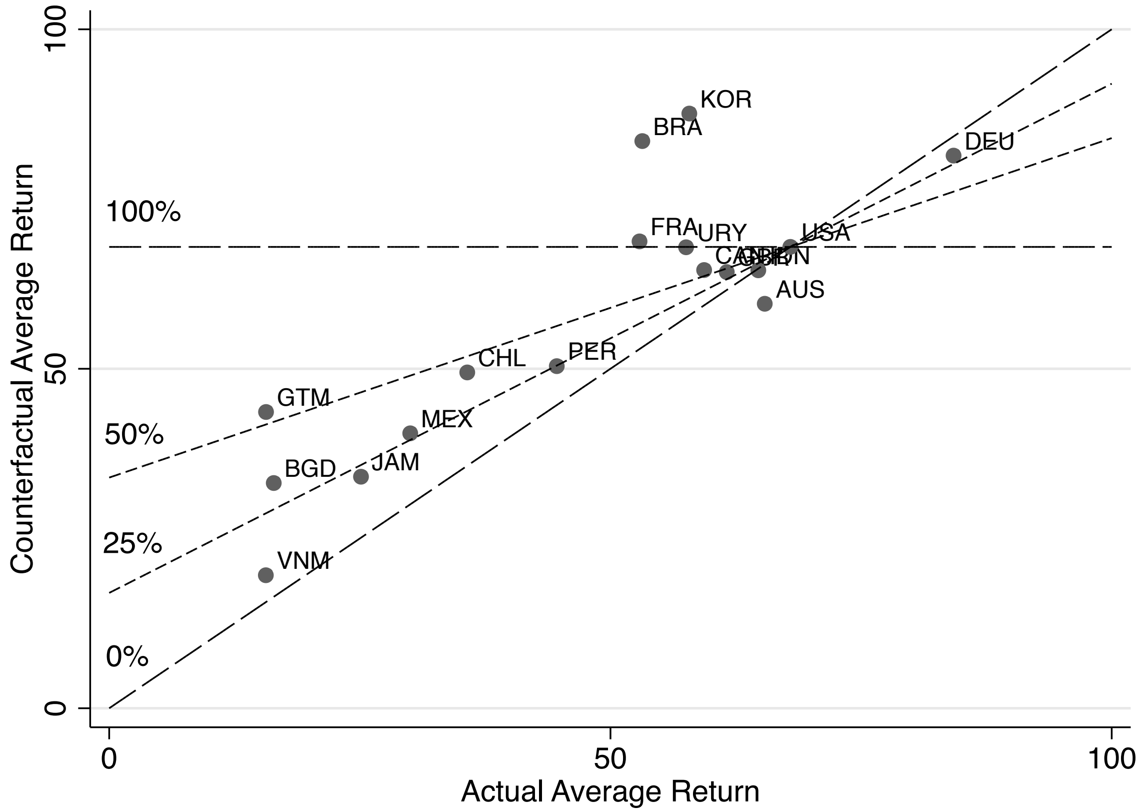
Note: Age-wage profiles are for full-time males working in the private sector, and are calculated for each educational attainment group. The wage is defined to be earnings divided by hours worked. College, High School and Less than H.S. mean that the individual (i) attended some college or graduated from college, (ii) attended some high school or graduated high school, and (ii) 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 11: Experience-Wage Profiles by Education Group



Note: 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 high school, and (ii) 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 five 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.

Figure 12: Contribution of Education to Cross-Country Differences in Experience-Wage Profiles



Note: 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 6 for a more detailed description of our methodology.

Table 1: Summary of Data

	(1) GDPpc (2011)	(2) Data Source	(3) Years Covered
United States*	49,803	Census of Population, American Community Survey	1960-2013
Germany*	42,080	German Socioeconomic Panel (SOEP)	1991-2009
Australia	41,706	Household Income & Labour Dynamics	2001-2009
Canada*	41,333	Census of Canada	1971-2001
France	37,325	Survey of Employment	1993-2001
United Kingdom*	36,549	British Household Panel Survey (BHPS)	1994-2008
South Korea	31,327	Korea Labor and Income Panel Study	1999-2008
Chile*	18,118	National Socioeconomic Survey (CASEN)	1990-2011
Uruguay	17,645	Extended National Survey of Households	2006
Mexico*	15,887	General Population and Housing Census	1990-2010
Brazil*	14,301	General Census of Brazil	1991-2010
Peru	10,429	National Household Survey	2004, 2010
Jamaica*	8,485	Population Census	1982-2001
Indonesia	8,438	National Labor Force Survey	2001-2010
Guatemala	6,957	National Living Standards Survey	2000, 2006
Vietnam	4,717	Living Standards Survey	1998, 2002
Bangladesh	2,589	Household Income and Expenditure Survey	2005, 2010

Note: * indicates core countries. GDP data are from the World Bank's World Development Indicators (2014), and the measure used is 2011 GDP per capita (PPP) in constant 2011 international dollars. For exact years of each survey, see Appendix A.1.

Table 2: Experience-Wage Profiles

Panel A: Summary Statistics by Country

	(1) Height at Experience 20-24	(2) Height at Experience 35-39	(3) Average Height	(4) Discounted Avg Height
United States	88.7	88.1	67.9	30.5
Germany	105.3	108.0	84.2	38.8
Canada	78.1	68.7	59.3	27.3
United Kingdom	85.1	61.5	61.6	29.3
Chile	45.0	37.6	35.7	16.7
Brazil	71.8	60.0	53.2	24.3
Mexico	41.1	23.5	30.0	14.5
Jamaica	32.5	26.4	25.1	11.8

Panel B: Test of Differences in Means, Rich and Poor Groups

	(1) Height at Experience 20-24	(2) Height at Experience 35-39	(3) Average Height	(4) Discounted Avg Height
Rich Mean	89.3	81.6	68.3	31.5
Poor Mean	47.6	36.9	36.0	16.8
Rich - Poor	41.7**	44.7**	32.3**	14.7**
	(.012)	(.014)	(.014)	(.015)

Note: The first column of Panel A is the average height of the experience-wage profile at potential experience of 20-24 years, defined as the ratio of average wages for workers with 20-24 years of potential experience to average wages for workers with 0-4 years of potential experience. The second column is the average height of the experience-wage profile at experience 35-39 years, defined as the ratio of average wages for workers with 35-39 years of potential experience to average wages for workers with 0-4 years of potential experience. The third column is the average height of the profile relative to workers with 0-4 years of potential experience. The fourth column 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 four 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. *** denotes p-value less than 0.01; ** denotes p-value less than 0.05; * denotes p-value less than 0.10.

Table 3: Deaton-Hall Experience-Wage Profiles

Panel A: All Growth Explained by Cohort Effects

	(1) Height at Experience 20-24	(2) Height at Experience 35-39	(3) Average Height	(4) Discounted Avg Height
Rich Mean	90.9	94.1	70.9	32.0
Poor Mean	80.1	132.7	70.5	28.9
Rich - Poor	10.8	−38.7	0.4	3.1
	(.352)	(.839)	(.489)	(.365)

Panel B: Growth Explained Equally by Cohort and Time Effects

	(1) Height at Experience 20-24	(2) Height at Experience 35-39	(3) Average Height	(4) Discounted Avg Height
Rich Mean	93.2	96.7	72.7	32.7
Poor Mean	65.8	99.5	56.6	23.7
Rich - Poor	27.4*	−2.8	16.1	9.0*
	(.082)	(.562)	(.106)	(.089)

Panel C: All Growth Explained by Time Effects

	(1) Height at Experience 20-24	(2) Height at Experience 35-39	(3) Average Height	(4) Discounted Avg Height
Rich Mean	95.8	101.1	75.0	33.6
Poor Mean	51.4	69.9	43.4	18.6
Rich - Poor	44.4**	31.1	31.6**	15.0**
	(.029)	(.117)	(.042)	(.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 that 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. *** denotes p-value less than 0.01; ** denotes p-value less than 0.05; * denotes p-value less than 0.10. The first column is the average height of the experience-wage profile at potential experience of 20-24 years, defined as the ratio of average wages for workers with 20-24 years of potential experience to average wages for workers with 0-4 years of potential experience. The second column is the average height of the experience-wage profile at experience 35-39 years, defined as the ratio of average wages for workers with 35-39 years of potential experience to average wages for workers with 0-4 years of potential experience. The third column is the average height of the profile relative to workers with 0-4 years of potential experience. The fourth column 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 four percent per year.

Table 4: Heckman-Lochner-Taber (HLT) Experience-Wage Profiles

Panel A: No Experience Effects in last 10 Years, 0% Depreciation

	Height at Experience 20-24	Height at Experience 35-39	Average Height	Discounted Avg Height
Rich Mean	79.3	80.8	62.5	28.5
Poor Mean	39.2	43.3	31.3	14.0
Rich - Poor	40.1**	37.5**	31.2**	14.5**
	(.013)	(.013)	(.013)	(.013)

Panel B: No Experience Effects in last 5 Years, 0% Depreciation

	Height at Experience 20-24	Height at Experience 35-39	Average Height	Discounted Avg Height
Rich Mean	90.3	100.7	72.1	32.3
Poor Mean	33.2	33.1	26.2	12.0
Rich - Poor	57.0**	67.6**	45.9**	20.3**
	(.013)	(.013)	(.016)	(.015)

Panel C: No Experience Effects in last 10 Years, 1% Depreciation

	Height at Experience 20-24	Height at Experience 35-39	Average Height	Discounted Avg Height
Rich Mean	47.1	27.5	35.2	17.7
Poor Mean	14.3	1.3	10.0	5.6
Rich - Poor	32.7**	26.2**	25.3**	12.2**
	(.015)	(.017)	(.015)	(.014)

Panel D: No Experience Effects in last 5 Years, 1% Depreciation

	Height at Experience 20-24	Height at Experience 35-39	Average Height	Discounted Avg Height
Rich Mean	59.4	58.7	46.2	20.9
Poor Mean	29.1	25.2	22.3	10.5
Rich - Poor	30.2**	33.5**	23.9 **	10.5**
	(.014)	(.014)	(.014)	(.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 ten years of potential experience and no depreciation (Panel A), no experience effects in the last five years and no depreciation (Panel B), no experience effects in the ten years and one percent depreciation (Panel C), and no experience effects in the last five years and one percent depreciation (Panel D). The rows present the average of the rich countries, the average of the poor countries and the difference between the rich and poor mean, plus the results of permutation tests of the null hypothesis that the experience-wage profiles for rich and poor are the same. *** denotes p-value less than 0.01; ** denotes p-value less than 0.05; * denotes p-value less than 0.10. The first column is the average height of the experience-wage profile at potential experience of 20-24 years, defined as the ratio of average wages for workers with 20-24 years of potential experience to average wages for workers with 0-4 years of potential experience. The second column is the average height of the experience-wage profile at experience 35-39 years, defined as the ratio of average wages for workers with 35-39 years of potential experience to average wages for workers with 0-4 years of potential experience. The third column is the average height of the profile relative to workers with 0-4 years of potential experience. The fourth column 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 four percent per year.

Table 5: Robustness

Height at 20-24 Years Experience, HLT Profiles

		Rich	Poor	Rich - Poor
(1)	Baseline	79.3	39.2	40.1**
(2)	Experience at 16	82.1	45.8	36.2**
(3)	Constructed experience	90	43.5	46.6**
(4)	Measurement error: age	76.5	39.2	37.3**
(5)	Measurement error: education	71.7	39.2	32.5**
(6)	Measurement error: age and education	71.2	39.2	32.0**
(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**
(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, incl. Part-Time	100	42	58.0**

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 Section 5.1.1). Row (4) adds noise to the age variable in rich countries by assuming that 10% of workers in each rich country rounds his age (see Section 5.1.2). 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 Section 5.1.3). 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 use measures of constructed experience, where it is 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 use constructed experience, where it is constructed separately for full-time and part-time workers. *** denotes p-value less than 0.01; ** denotes p-value less than 0.05; * denotes p-value less than 0.10.

A Appendix – For Online Publication

A.1 Data Sources

The surveys we employ in our analysis are listed below for each country. All surveys are nationally representative unless noted. We attempted to obtain data for every country in the world with a population greater than one million people. We obtained a number of surveys through the Integrated Public Use Microdata Series (IPUMS) (Minnesota Population Center, 2011; King et al., 2010), which can be found here: www.ipums.org. The remaining surveys were made available to us by the statistical agencies of the countries in question or other sources, as listed below.

- Australia: *Household Income and Labour Dynamics in Australia,* yearly from 2001 to 2009, from the Australian Department of Families, Housing, Community Services and Indigenous Affairs, available from the Cornell Department of Policy Analysis and Management.
- Bangladesh: *Household Income and Expenditure Survey,* 2005 and 2010, from the Bangladesh Bureau of Statistics, available from the FAO RIGA database.
- Brazil: *Recenseamento Geral do Brasil, Censo Demográfico,* 1991 (5.8% sample), and 2000 (6% sample), 2010 (5% sample) from the Instituto Brasileiro de Geografia e Estatística (IBGE), available from IPUMS.
- Canada: *Census of Canada,* 1971 (1% Sample), 1981 (2% Sample), 1991 (3% Sample) and 2001 (2.7% Sample), available from IPUMS.
- Chile: *National Socioeconomic Characterization Survey (CASEN),* 1990, 1992, 1994, 1996, 1998, 2000, 2003, 2006 and 2009, 2011 from the Chilean Ministry of Planning and Cooperation.
- France: *Enquete Emploi*, yearly from 1993 to 2001, from the Ministre de l'Économie de l'Industrie et de l'Emploi.
- Germany: *German Socioeconomic Panel (SOEP),* yearly from 1991 to 2009, from the German Institute for Economic Research (DIW Berlin).
- Guatemala: *Encuesta Nacional de Condiciones de Vida,* 2000 and 2006, from the Instituto Nacional de Estadistica.
- Indonesia: *National Labour Force Survey* (SAKERNAS), 2001 to 2010 from the Indonesia Badan Pusat Statistik.
- Jamaica: *Population Census*, 1982, 1991 and 2001, (10% samples) from the Statistical Institute of Jamaica, available from IPUMS.
- Mexico: *XI General Population and Housing Census*, 1990 (10% sample); *Population and Dwelling Count*, 1995 (0.4% of sample); *XII General Population and Housing Census*, 2000 (10.6% of sample); *Population and Housing Census*, 2010 (10% of sample) available from IPUMS.
- Peru: *Encuesta Nacional de Hogares,* 2004 and 2010, from the from the Instituto Nacional de Estadística y Informática.
- South Korea: *Korea Labor and Income Panel Study,* yearly from 1999 to 2008, from the Korea Labor Institute, available from the Cornell Department of Policy Analysis and Management.
- United Kingdom: *British Household Panel Survey,* yearly from 1994 to 2008, from the Institute for Social & Economic Research at the University of Essex.

- United States: *Census of Population and Housing,* 1960 (1% Sample), 1970 (1% Sample), 1980 (5% Sample), 1990 (5% Sample) , 2000 (5% Sample); *American Community Survey*, yearly from 2005 to 2013 (1% Sample); all available from IPUMS.

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

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

For larger surveys, we conduct our analysis on a random subsample of ten million individuals (per country-year). All calculations in our analysis are weighted using the applicable sample weights for each survey. We express all earnings and wage data in local currency units of the most recent year in the data using the consumer price index of the country in question, taken from the IMF's International Financial Statistics database. In each survey, we drop the top and bottom one percent of earners to remove potential outliers, and to minimize the impact of potential cross-country differences in top-coding procedures.

For most countries, we measure hours as the actual hours worked in the past week (or in some recent reference week.) For the United States and Brazil, we measure hours as the *usual* weekly hours worked (which is what is available). We define an individual to be a full-time worker if she works more than 30 hours per week.

For most countries, labor earnings and hours worked are for both primary and secondary jobs. In Chile, France, South Korea and Uruguay, labor earnings and hours worked are for just the primary job. In Australia, Canada, Germany, Jamaica, South Korea, and the United States, earnings are measured at the annual frequency. In the remaining countries, earnings are measured at the monthhly frequency. In all surveys, earnings are before taxes. The numbers for per capita GDP at PPP that we use are taken from the World Bank's World Development Indicators (WDI) for 2011.

A.2 Details on Deaton-Hall Approach

As stated in the main text, we use an approach suggested by Deaton (1997) and Hall (1968) and impose one additional linear restriction to estimate (1) (or in practice (2)). We report results for three different versions of this approach. The purpose of this Appendix is to explain in detail the three different linear restrictions we impose and how we implement these in practice. To derive restrictions on these, consider total wages in year t

$$W_t = \sum_{c \in C_t} \sum_{i=1}^{N_{ct}} w_{ict}$$

where C_t is the set of cohorts working at time t and N_{ct} is the number of members of cohort c working at time t. Assuming that wages satisfy the Mincerian equation (1), it is not hard to show that total wages can be written as

$$W_t = \Gamma_t \bar{X}_t \bar{F}_t \tag{3}$$

$$\Gamma_t = \exp(\gamma_t) \tag{4}$$

$$\bar{X}_t = \sum_{c \in C_t} \exp(\chi_c) \frac{F_{ct}}{\bar{F}_t} \tag{5}$$

$$\bar{F}_t = \sum_{c \in C_t} F_{ct}, \quad F_{ct} = \sum_{i=1}^{N_{ct}} \exp(\theta s_{ict} + f(x_{ict}) + \varepsilon_{ict}) \tag{6}$$

Now consider the growth of total wages from one year to the next. Equation (3) says that there are three sources to total wage growth: growth due to time effects Γ_t, growth due to cohort effects $\bar{X}_t$, and growth due to changes in the composition of schooling and experience as captured by $\bar{F}_t$. We will impose restrictions on the term

$$\Omega_t = \Gamma_t \bar{X}_t, \tag{7}$$

which can be thought of as a year-specific aggregate labor productivity term. This term can improve over time for two reasons: (i) directly, due to increases in cohort-neutral changes captured by Γ_t; and (ii) indirectly, due to changes in the composition of cohorts active in the labor market captured by $\bar{X}_t$. For example, suppose that young cohorts are more productive than old ones (i.e. they have higher χ_c). Then aggregate productivity will improve over time as old cohorts exit the labor force and young cohorts enter.

Equation (7) is the key equation we use to derive meaningful restrictions on cohort and time effects. The basic idea is to decompose the time series for Ω_t into a trend component and a cyclical component and to make assumptions on whether the trend component ("productivity growth") is attributed to time or to cohort effects.

In practice, this is implemented as follows. First, it is convenient to work in logs: $\omega_t = \log \Omega_t$, $\bar{\chi}_t = \log \bar{X}_t$. Second, define time periods in deviations from the sample mean, i.e. such that $\frac{1}{T}\sum_{t=0}^{T} t = 0$, and similarly renormalize γ_t and $\bar{\chi}_t$ such that $\frac{1}{T}\sum_{t=0}^{T}\gamma_t = \frac{1}{T}\sum_{t=0}^{T}\bar{\chi}_t = 0$. This can be achieved by writing $\omega_t = \log \Omega_t$ as

$$\omega_t = \bar{\omega} + \gamma_t + \bar{\chi}_t, \tag{8}$$

where $\bar{\omega}$ is an appropriately chosen constant. Second, the series for γ_t and $\bar{\chi}_t$ can be decomposed into a trend component and a cyclical component

$$\gamma_t = g_\gamma t + u_{\gamma,t}, \quad \bar{\chi}_t = g_\chi t + u_{\chi,t}, \tag{9}$$

where

$$g_\gamma = \frac{\sum_{t=0}^{T}\gamma_t t}{\sum_{t=0}^{T} t^2}, \quad g_\chi = \frac{\sum_{t=0}^{T}\bar{\chi}_t t}{\sum_{t=0}^{T} t^2}. \tag{10}$$

Intuitively, one simply runs a regression of γ_t and χ_t on time, thereby decomposing each time series into a trend component and a component that is orthogonal to the time trend. Finally, from (8) and (9), the logarithm of aggregate productivity $\omega_t = \log \Omega_t$ is

$$\omega_t = \bar{\omega} + g_M t + u_{M,t},$$

where $g_M = g_\gamma + g_\chi$ and $u_{M,t} = u_{\gamma,t} + u_{\chi,t}$. The different restrictions we use are then simply different ways of splitting g_M between g_γ and g_χ. The three restrictions for which we present results in the main text (see in particular Figure 3 and Table 3) are as follows.

Restriction 1 (All Growth Explained by Cohort Effects): the time trend in productivity growth is entirely due to cohort effects:

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

From (10) this implies the linear restriction $\sum_{t=0}^{T}\gamma_t t = 0$, i.e. that time effects are orthogonal to a time trend and capture only cyclical variation. This is the same restriction as equation (2.94) in Deaton (1997).

Restriction 2 (All Growth Explained by Time Effects): the time trend in productivity growth is entirely due to year effects:

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

From (10) this implies the linear restriction $\sum_{t=0}^{T}\bar{\chi}_t t = 0$ or

$$\sum_{t=0}^{T} \log\left(\sum_{c\in C_t} \exp(\chi_c)\frac{F_{ct}}{\bar{F}_t}\right) t = 0. \tag{11}$$

Note that the variable F_{ct} enters this restriction. Since this requires estimating equation (1), it is necessary to use an iterative procedure.

Restriction 3 (Growth Explained Equally by Cohort and Time Effects): a share β of the time trend in productivity growth is due to year effects:

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

From (10), this implies the linear restriction

$$\beta \sum_{t=0}^{T} \bar{\chi}_t t = (1-\beta) \sum_{t=0}^{T} \gamma_t t. \tag{12}$$

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

A.3 Selection into or out of the Public Sector and Part-Time Employment

This Appendix presents the empirical results examining the importance of selection into or out of the public sector as well as part-time employment discussed in sections 5.2.2 and 5.2.4. Figures A.5a and A.5b show that U.S. workers who remain in the private sector earn higher wages than those who move from the private to the public sector. In Mexico, such workers earn slightly lower wages when they have 25-30 years of experience. Similarly, Figures A.5c and A.5d show that workers who are in the private sector for two periods in a row always earn higher wages than workers who move in from the public sector in the United States, and slightly lower wages for workers who have 15 to 20 years of experience in Mexico.[31] The product of the wage gap between those who switch in and out of public-sector employment and the rate of moving across sectors is very small, which implies that selection into our out of public-sector employment is unlikely to drive our findings that experience-wage profiles are steeper in rich countries.

Figures A.6a – A.6d present analogous results for selection into and out of part-time employment, and show that U.S. workers who move into or out of part-time employment across survey waves earn lower wages, while wages for the different types of workers are similar in Mexico. The product of the wage gap between those who switch in and out of full-time employment and the rate of moving is very small, which implies that selection into our out of full-time employment is unlikely to drive our findings that experience-wage profiles are steeper in rich countries.

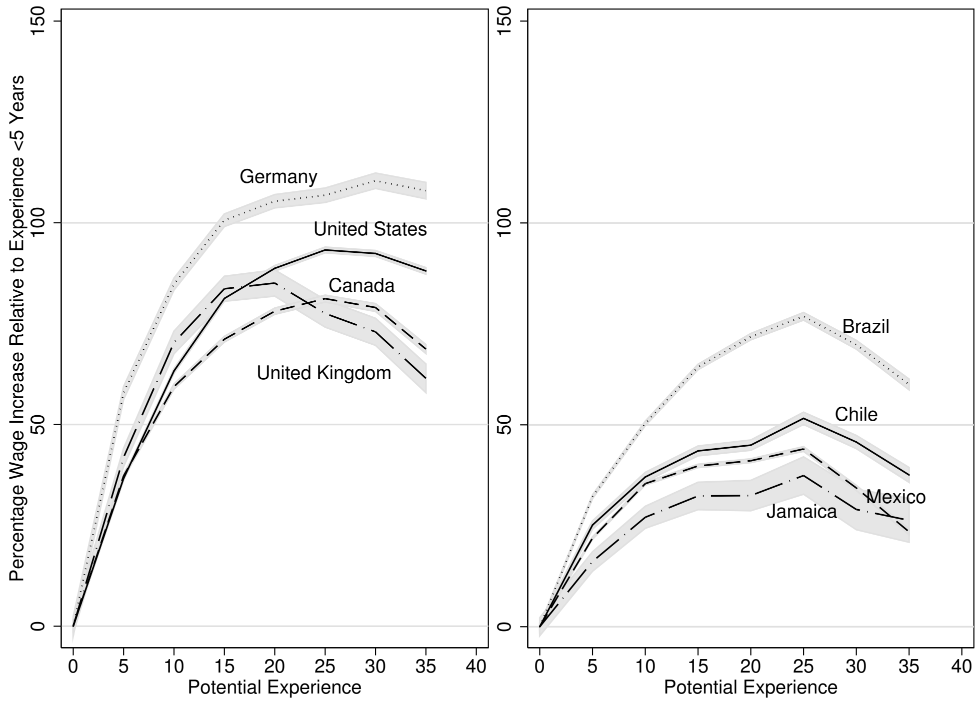
A.4 Attrition in Panel Data

In the main paper, we ignore attrition from the panels when we estimate the wage residuals for workers who remain in wage employment and those who move into self-employment, which is on average 23% and 9.3% across survey waves of the Mexican FLS and U.S. PSID. This can bias the estimates if attrition is correlated to wages and the propensity to move into self-employment. Since this propensity is unobservable, we address this concern by adding in all of the individuals that earned wages in year $t-1$, but who exited the panel in year t and estimate two bounds for the wages gaps. The first assumes that all those who drop out of the panel would have moved to self-employment. The second assumes that they all move into wage employment. The estimated wage gaps using these samples are shown in Appendix Figures A.7a - A.7d. They are very similar to the main results in the text because, on average, those who exit the sample earn slightly lower wages than those who remain in wage-employment and slightly higher wages than those who move to self-employment.[32]

[31] Note that in Figure A.5d for Mexico, there are two few workers with 0 to 5 years of experience who move into the private sector for us to estimate the differential wages for this bin.

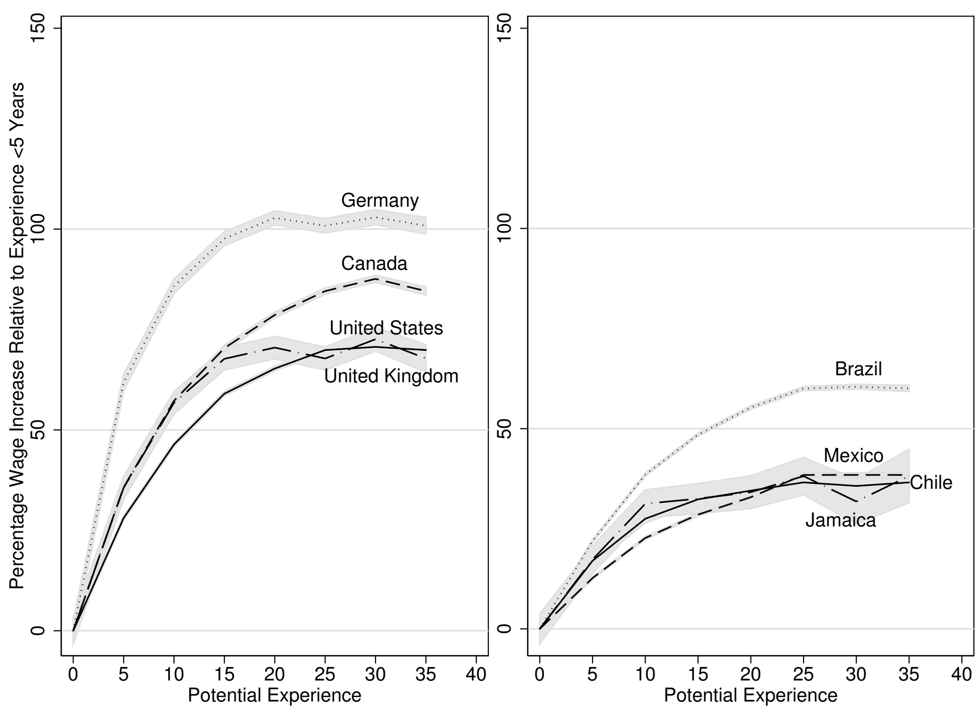
[32] A similar exercise addresses how attrition can affect our examination of selection out of self-employment, the main exercise ignores entrants into the panel data – i.e., it excludes workers in year t who were not also in the panel in year $t-1$, which is, on average, 24% and 8.5% across survey waves for the FLS and PSID. Thus, as before we can add these individuals into the sample and alternatively assume that all new entrants worked in wage or self-employment in year $t-1$. The results are similar. We conduct similar exercises to investigate whether attrition from the panel can affect our examination of selection into and out of the private sector and full-time employment. In all cases, we find that including those who exit the panel does little to change the main results. These results are available upon request.

Figure A.1: Experience-Wage Profiles (Cross-Sectional Estimates) with 95% Confidence Intervals



Note: These profiles are the same as Figure 1, except that they also plot the 95% confidence intervals.

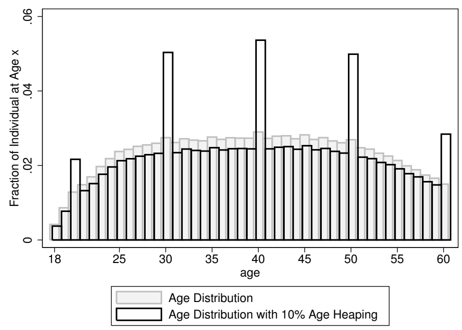
Figure A.2: Experience-Wage Profiles (HLT) with 95% Confidence Intervals



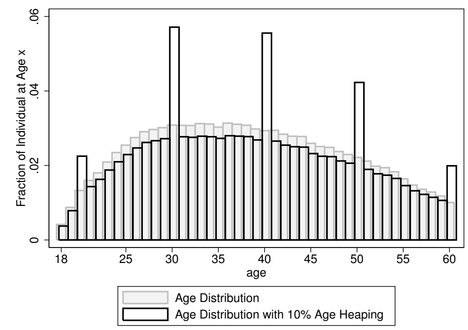
Note: These profiles are the same as Figure 4, except that they also plot the 95% confidence intervals.

Figure A.3: Actual and Distorted Age Distributions of Core Countries

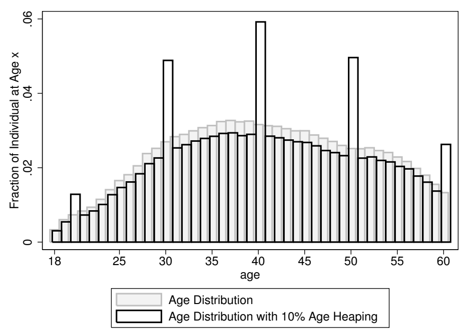
(a) United States



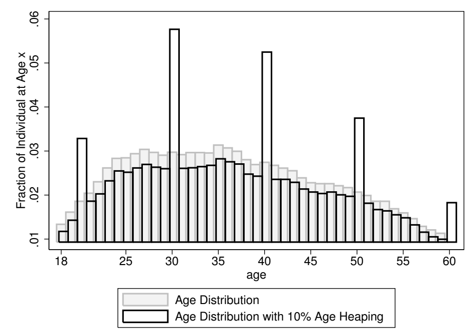
(b) Canada



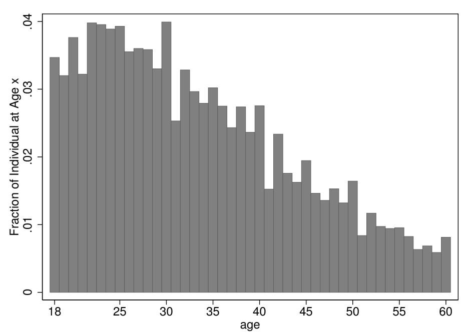
(c) Germany



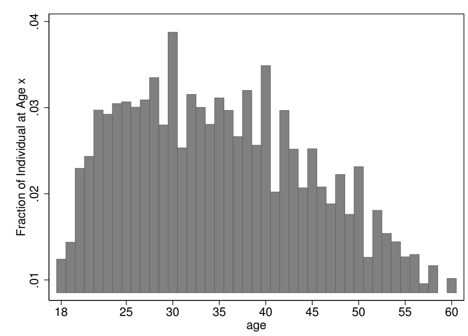
(d) United Kingdom



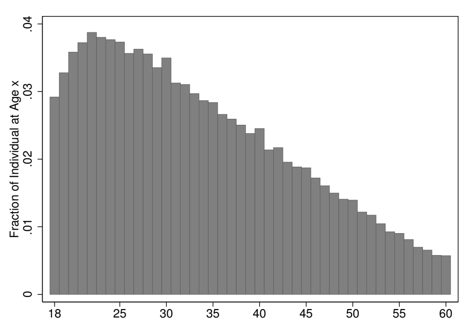
(e) Mexico



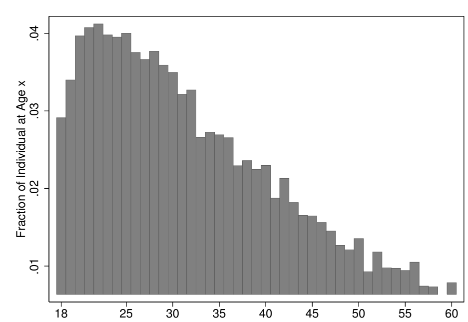
(f) Chile



(g) Brazil



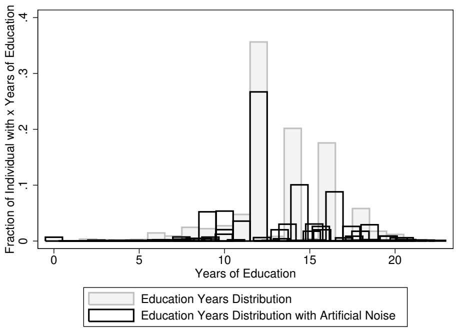
(h) Jamaica



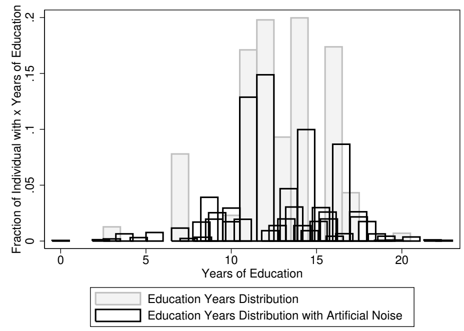
Notes: These figures are histograms of worker ages for each of the eight countries in the core sample. In Figures A.3a–A.3d, the light gray bars are the actual data while the white bars with black outlines are the artificially distorted data. Figures A.3e–A.3h only plot actual data. These data are used to estimate the profiles shown in Figure 5.

Figure A.4: Years of Educational Attainment Distribution of Core Countries

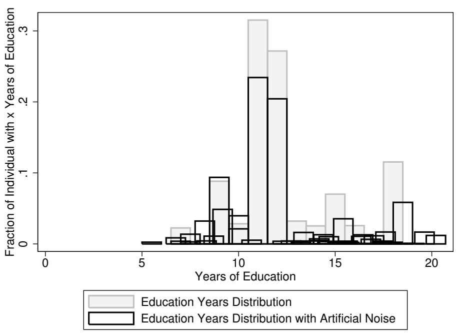
(a) United States



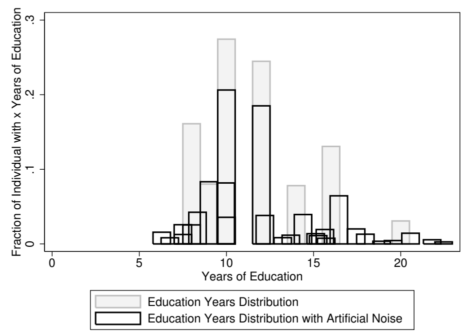
(b) Canada



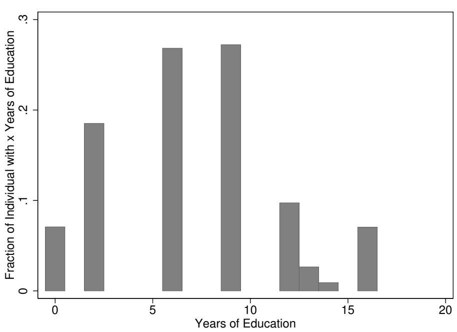
(c) Germany



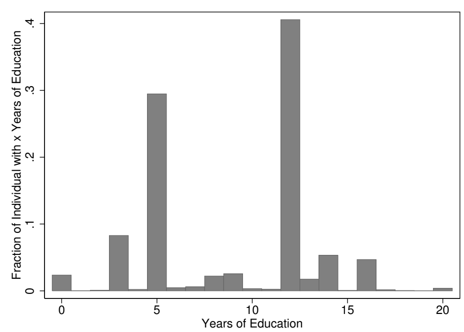
(d) United Kingdom



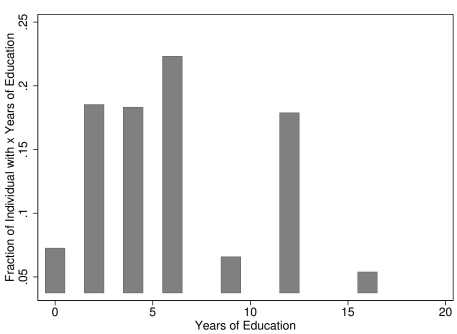
(e) Mexico



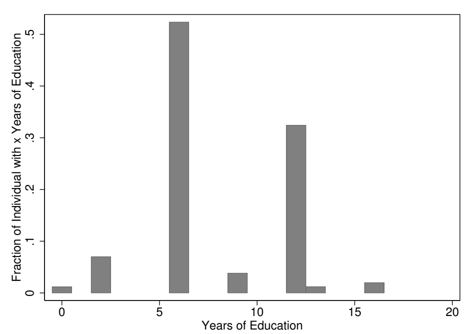
(f) Chile



(g) Brazil



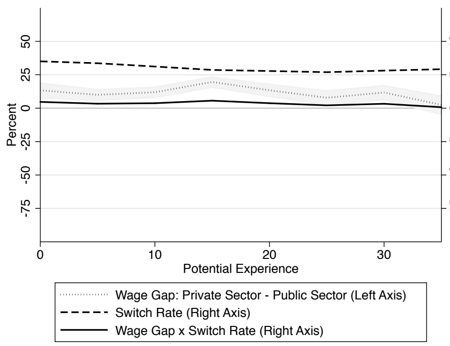
(h) Jamaica



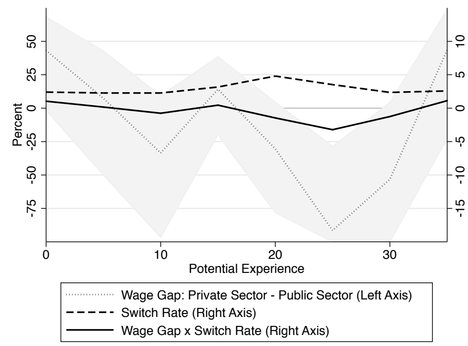
Notes: These figures are histograms of workers' years of educational attainment for each of the eight countries in the core sample. In Figures A.4a–A.4d, the light gray bars are interpolated years of education based on the reported highest level of educational attainament while the white bars with black outlines are the artificially distorted data. Figures A.4e–A.4h only plot actual data. These data are used to estimate the profiles shown in Figure 6.

Figure A.5: Selection into and out of Public Sector Employment – Panel Data Estimates

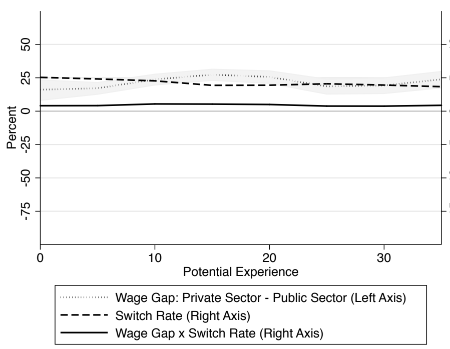
(a) Selection *into* the Public Sector – U.S.



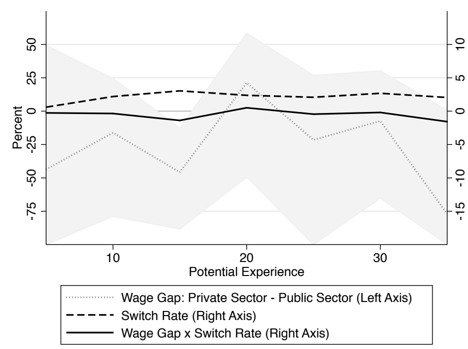
(b) Selection *into* the Public Sector – Mexico



(c) Selection *out of* the Public Sector – U.S.



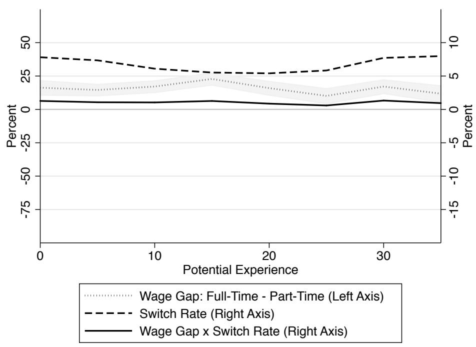
(d) Selection *out of* the Public Sector – Mexico



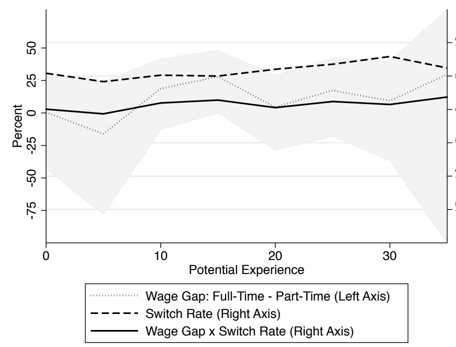
Notes: Figures A.5a and A.5b plot the estimated differences in wage residuals and their 95% confidence intervals for those who move from private-sector employment in year $t-1$ to public-sector employment in year t and those who are in private-sector employment in both years. Wages are predicted from regressing log wages$_{t-1}$ on dummy variables of five-year experience bins, the interactions of each experience-bin dummy variable with a dummy variable for whether the worker is in the public sector$_t$, controlling for the years of educational attainment and year fixed effects. The reference group is the 0-4 years of experience bin for workers who remain in wage work. t refers to the year of the survey. We transform the coefficients from logs to levels so that the y-axis reflects the level of percentage increase relative to the reference group. The figures also present the rate at which workers move from private-sector to public-sector employment at each point on the life cycle and the product of this rate and the wage-gap. An analogous regression predicts the wages of those who move from public-sector employment in year $t-1$ to private-sector employment in year t and those who are in private-sector employment in both years shown in Figures A.5d and A.5c. The figures also present the rate at which workers move from public-sector to private-sector employment at each point on the life cycle and the product of this rate and the wage-gap. The data are from the U.S. PSID (1975-1997 annually, 1999-2013 bi-annually) and the Mexican FLS (2002, 2005 and 2009).

Figure A.6: Selection into and out of Part-Time Employment – Panel Data Estimates

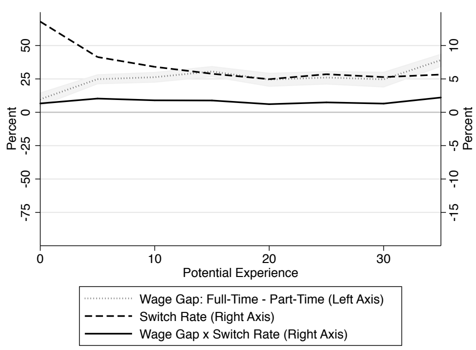
(a) Selection *into* Part-time Employment – U.S.



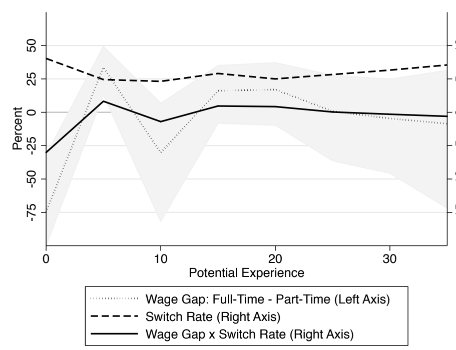
(b) Selection *into* Part-time Employment – Mexico



(c) Selection *out of* Part-time Employment – U.S.



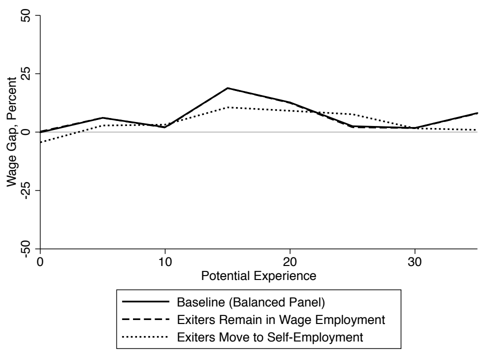
(d) Selection *out of* Part-time Employment – Mexico



Notes: Figures A.6b and A.6a plot the estimated differences in wage residuals and their 95% confidence intervals for those who move from full-time employment in year $t-1$ to part-time employment in year t and those who are in full-time employment in both years. Wages are predicted from regressing log wages$_{t-1}$ on dummy variables of five-year experience bins, the interactions of each experience-bin dummy variable with a dummy variable for whether the worker is part-time$_t$, controlling for the years of educational attainment and year fixed effects. The reference group is the 0-4 years of experience bin for workers who remain in full-time employment. t refers to the year of the survey. We transform the coefficients from logs to levels so that the y-axis reflects the level of percentage increase relative to the reference group. The figures also present the rate at which workers move from full-time to part-time employment at each point on the life cycle and the product of this rate and the wage-gap. An analogous regression predicts the wages of those who move from part-time employment in year $t-1$ to full-time employment in year t and those who are in full-time employment in both years shown in Figures A.6d and A.6c. The figures also present the rate at which workers move from part-time to full-time employment at each point on the life cycle and the product of this rate and the wage-gap. The data are from the U.S. PSID (1975-1997 annually, 1999-2013 bi-annually) and the Mexican FLS (2002, 2005 and 2009).

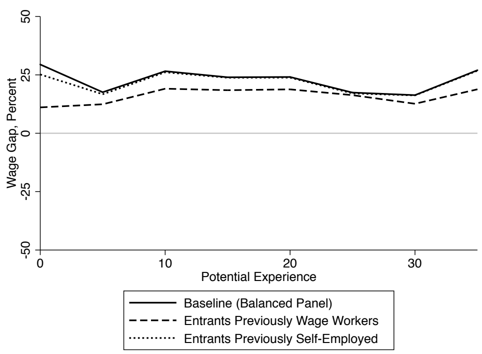
Figure A.7: Selection into and out of Self-Employment – Adding in individuals who exit the panel

(a) Selection *into* Self Emp./Attrition – U.S.



(b) Selection *out of* Self Emp./Attrition – Mexico

(c) Selection *into* Self Emp./Attrition – U.S.



(d) Selection *out of* Self Emp./Attrition – Mexico

Note: These figures are similar to those in Figure 9a to 9d of the paper. The solid lines plot the estimated wage gap between workers who remain in wage employment and those who move into/out of self-employment using the reported data. The thick dashed lines are the estimated wage gaps when individuals who exit the panel are added back as those who remain in wage employment. The thin dashed lines are the estimated wage gaps when individuals who exit the pannel are added back as those who switch into or out of self-employment.

Table A.1: Distribution of the Years of Education by Level of Highest Attainment in Chile

Panel A: Chile 2009

Highest Level of Education	Imputed Years of Schooling	Directly Reported Schooling Years, Percentiles of Distribution 10th	25th	50th	75th	90th
None	0	0	0	0	0	0
Preparatory	3	2	3	5	6	6
Primary School	5	3	5	7	8	8
Secondary, Humanities/Special	8	8	8	10	12	12
Secondary, Scientific/Commercial/Industrial	12	10	11	12	12	12
Some Tertiary Education	13	13	13	14	15	16
Two-year Tertiary Education	14	14	14	15	16	16
Four-year College Education	16	16	17	17	17	18
Post-graduate Studies	20	17	17	19	20	20

Panel B: Chile 2009 in Percents

Highest Level of Education	Imputed Years of Schooling	Percentage Deviation from the Imputed Years of Schooling 10th	25th	50th	75th	90th
None	0	0	0	0	0	0
Preparatory	3	-33	0	67	100	100
Primary School	5	-40	0	40	60	60
Secondary, Humanities/Special	8	0	0	25	50	50
Secondary, Scientific/Commercial/Industrial	12	-17	-8	0	0	0
Some Tertiary Education	13	0	0	8	15	23
Two-year Tertiary Education	14	0	0	7	14	14
Four-year College Education	16	0	6	6	6	13
Post-graduate Studies	20	-15	-15	-5	0	0

Note: Panel A presents the distribution of reported years of schooling for each reported educational attainment level in 2009 in Chile, as well as our imputed number of schooling years for each educational attainment level. Panel B presents the differences from our imputed years of schooling in percent. The sample is full-time males in the private sector.

Table A.2: Robustness of Cross-Sectional Estimates

Height at 20-24 Years Experience

Panel A: Cross-Section, Core Countries

		Rich	Poor	Rich - Poor
(1)	Baseline	89.3	47.6	41.7**
(2)	Experience at 16	91.5	47.6	43.9**
(3)	Constructed experience	112.4	48.2	64.2**
(4)	Measurement error: age	85.9	47.6	38.3**
(5)	Measurement error: education	76.7	47.6	29.1**
(6)	Measurement error: age and education	74.7	47.6	27.1**
(7)	Include Self-Employed	90.6	47.5	43.1**
(8)	Include Public-Sector Employees	89	51.9	37.1**
(9)	Include women	78.2	37.8	40.4**
(10)	Constructed experience, men and women	102.9	41.6	61.3**
(11)	Include Part-Time (20+ hours)	91.9	47.7	44.5**
(12)	Include Part-Time (> 0 hours)	89.3	44.5	44.8**
(13)	Constructed experience, incl. Part-Time	105.2	45.7	59.5**

Panel B: Cross-Section, All Countries

		Rich	Poor	Rich - Poor
(14)	Baseline	83.5	45.9	37.5***
(15)	Experience at 16	85.4	48.9	36.5***
(16)	Constructed experience	104.9	54.4	50.5***
(17)	Measurement error: age	79.7	45.9	33.8***
(18)	Measurement error: education	71.4	45.9	25.5**
(19)	Measurement error: age and education	70.5	45.9	24.6**
(20)	Include Self-Employed	84.2	43.4	40.8***
(21)	Include Public-Sector Employees	83.3	53	30.3***
(22)	Include women	69.3	40.5	28.8***
(23)	Constructed experience, men and women	87	50.5	36.5**
(24)	Include Part-Time (20+ hours)	82	47.8	34.3***
(25)	Include Part-Time (> 0 hours)	80.4	45.5	34.9***
(26)	Constructed experience, incl. Part-Time	98	56.2	41.8***

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 Section 5.1.1). Row (4) adds noise to the age variable in rich countries by assuming that 10% of workers in each rich country rounds his age (see Section 5.1.2). 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 Section 5.1.3). 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 use measures of constructed experience, where it is 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 use constructed experience, where it is constructed separately for full-time and part-time workers. *** denotes p-value less than 0.01; ** denotes p-value less than 0.05; * denotes p-value less than 0.10.