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Human Capital Accumulation at Work

Estimates for the World and Implications for Development

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Abstract

In this paper, the authors: (i) study wage-experience profiles and obtain measures of returns to potential work experience using data from about 24 million individuals in 1,084 household surveys and census samples across 145 countries; (ii) show that returns to work experience are strongly correlated with economic development—workers in developed countries appear to accumulate twice more human capital at work than workers in developing countries; (iii) use a simple accounting framework to find that the contribution of work experience to human capital accumulation and economic development might be as important as the contribution of education itself; and (iv) employ panel regressions to investigate how changes in the returns over time correlate with several factors such as economic recessions, transitions, and human capital stocks.

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1. Introduction

Human capital - regarded as the "stock of skills and productive knowledge embodied in people" (Rosen, 2008) - is the main determinant of modern economic development (Lucas, 1988; Romer, 1990; Jones and Romer, 2010; Jones, 2019). Work is a form of school - it teaches new skills, updates old ones, and gives purpose. However, its contribution to human capital is underappreciated. Since human capital accumulation has a long-lasting impact, a pertinent query is whether returns to work could serve as a measure of current and/or future economic development, especially given that it does not require tracking quantities and prices as GDP per capita does. Returns to work may focus on aspects of welfare improvements that may capture whether an economy is "truly" developing instead of, for example, seeing its GDP increase as a result of natural resource exploitation. We explore this by first measuring the returns to potential work experience and then by investigating how they behave across several dimensions. These include the level of development, economic transitions, and recessions.

Since the seminal works of Schultz (1961), Becker (1964, 1975) and Mincer (1974), there is a broad consensus that human capital is obtained during childhood, at school, *and* at work (World Bank, 2018b). Heckman (2019) hypothesizes that the returns to early childhood investments are likely higher than the returns to education, which are in turn possibly higher than the returns to work experience. Subsequently, the literature has focused on estimating the *returns to education* or the *returns to early childhood investments*. While a substantial literature exists on the *returns to experience*, the contributions of experience to human capital and economic development have attracted comparatively less attention (for exceptions, see Lagakos et al. (2018b,a)).[1]

However, the respective contributions of ECIs, education and experience to the total stock of human capital, and thus economic development, are a function of both their respective returns *and* the period over which these returns are accumulated. Indeed, most children in the world do not attend primary school before age 6, and the average person in the world accumulates schooling for 10 years *but* works up to 50 years. In addition, schools and firms may "teach" different skills (e.g., more theoretical skills vs. more applied skills), and the skills learned at work may be more directly relevant

[1] Banerjee and Duflo (2005) survey the literature on the returns to human capital but do not mention experience. Likewise, excellent surveys provided by Caselli (2005), Flabbi and Gatti (2018) and Rossi (2020) focus on education.

to the operations of firms. Therefore, it could be that work experience contributes significantly to human capital in a way that deserves more attention.

Few studies have consistently estimated returns to experience and explored how they vary across a sample of developing and developed countries (Lagakos et al., 2018b,a). Even less is known about the patterns of returns to experience for a global sample, and how they are affected by policy. Human capital accumulation at work could have important implications for long-run growth and the divergence in income between rich and poor countries. Since output per worker is the main contributor of output per capita, if workers see their earnings increase due to higher returns to experience in their economy, then tracking the evolution of these returns over time could provide valuable information regarding the ability of developing economies to eventually catch up to the income level of developed economies. In this paper, we provide additional evidence that work experience is a key factor of economic development.

First, we study wage-experience profiles, and obtain returns using data from 1,084 household surveys and census samples across 145 countries (1990-2016). We find average population-weighted returns to experience of 2% for the world as a whole. Returns to education are 4 times higher, at 8%. However, returns to education do not vary much across income levels, whereas returns to experience are strongly correlated with economic development. We find returns of 1.7% for developing economies and 3.2% for developed economies, which suggests that workers in developed economies accumulate almost twice as much human capital at work than workers in developing economies. In our preferred specifications, returns are then higher in middle-income countries than in low-income countries, but only significantly so for a few specifications. Significantly higher returns to experience in all specifications are only observed when an economy achieves high-income status. These patterns could support our conjecture that the evolution of a country's returns to experience could proxy for this country's ability to "catch up" with the most developed economies.

Second, we explore how returns to experience vary across several economic and policy-relevant dimensions. Exploiting the fact that we are able to estimate returns to experience for more than 100 countries and multiple years of data during the period 1990-2016, we employ panel regressions to investigate how changes in the returns to experience over time correlate with several important time-varying factors. We find that returns are lower for individuals that experienced a recession in the initial years of their career, showing how recessions can have permanent effects via experience losses. We find that economies that transitioned out of communism suffer the obsolescence of past experience, also exhibiting lower returns to experience going forward for many years. We also find that returns to experience are not correlated with initial stocks of experience nor education. This suggests that experience may not suffer from decreasing aggregate returns, and that experience may not be easily substituted by more education.

Third, our accounting framework shows that the contribution of experience to economic development might be as important as the contribution of education. Indeed, education and experience both account for about one third of the income gap between developing and developed economies. Likewise, the long run impact is similar whether developing countries attain the same distribution of education as developed economies *or* achieve the returns to experience of developed economies. However, raising returns to experience has a *faster* impact. This is notable as significant reform to the schooling system is likely costly and slow. On the other hand, if reforms that improve the returns to experience are institutional, implementation costs may be lower.

Our study makes several contributions to the literature. We build on a relatively sparse literature on the relationship between experience and economic development (Manuelli and Seshadri, 2014; Lagakos et al., 2018b,a; Dauth et al., 2019; Islam et al., 2019; Deming, 2021).[2] We first produce global estimates of the returns and confirm the results of Lagakos et al. (2018b) who study how wages vary with experience for 125 samples in 18 countries, however for a much larger sample of 1,084 samples in 145 countries.[3] Our sample includes 38 high, 81 middle and 26 low income countries, which allows us to examine whether the returns vary non-linearly with economic development. Second, we account for several empirical challenges in estimating the returns. We use two methods inspired by Heckman and Robb (1985) to attempt to reduce the experience-time-cohort problem when estimating returns to experience.[4] Our large data sets allow us to include decadal cohort fixed effects or country-specific

[2] See Rubinstein and Weiss (2006), Rosen (2008) and Polachek (2008) for surveys of the literature.

[3] Lagakos et al. (2018b) use for robustness checks an expanded set of 263 samples in 35 countries. In a related paper, Islam et al. (2019) use the same 1,084 samples as in the present study to investigate within-country gaps in the returns to experience between sectors and locations.

[4] Due to collinearity, experience, time and cohort effects cannot be simultaneously estimated. If year fixed effects are added, the estimated experienced effects may then also capture cohort effects.

period dummies based on important historical events that affected individuals during their lifetime. Third, we highlight various stylized facts regarding the determinants of the returns to experience. Fourth, we study the implications of these returns for aggregate income. We build on Lagakos et al. (2018a) that uses returns to experience accumulated in an immigrant's birth country before migrating to the U.S., by relying on estimates of the returns directly estimated in each country. More generally, similar to Lagakos et al. (2018b,a), we attempt to provide a clearer picture of the contribution of experience to human capital and economic development, and its determinants.

Our study is part of a long literature that has explored the determinants of human capital accumulation, whether at the individual or country level. A few studies have provided a variety of global estimates of the returns to education from 1950 onwards (Psacharopoulos, 1994; Psacharopoulos and Patrinos, 2004; Banerjee and Duflo, 2005; Caselli et al., 2016b; Psacharopoulos and Patrinos, 2018a). These earlier studies *compiled* estimates from different studies that use different methodologies given that the explosion and harmonization of micro-data sets is a relatively new phenomenon. We expand on these studies by directly *estimating* returns using a consistent methodology and for the recent period. We also carefully address specific econometric challenges related to the measurement of these returns.[5]

A sizeable literature has then used cross-country regressions (Romer, 1989; Mankiw et al., 1992; Hanushek and Kimko, 2000; Hanushek and Woessmann, 2012) or development/growth accounting analyses (Klenow and Rodriguez-Clare, 1997; Hall and Jones, 1999; Bils and Klenow, 2000; Caselli, 2005; Hanushek and Woessmann, 2012; Schoellman, 2012; Caselli and Ciccone, 2013, 2019; Jones, 2014, 2019; Manuelli and Seshadri, 2014; Hanushek et al., 2017; Hendricks and Schoellman, 2018) to quantify the contributions of human capital to economic development. We add to these studies by showing, with our consistently estimated global returns, that experience might directly explain as much as a third of cross-country differences, which is about as much as

[5]Banerjee and Duflo (2005) argue that the conclusions of the works of Psacharopoulos and co-authors might depend on the "quality" of the estimated returns considered. When excluding low-quality observations (see their Table 2), their cross-sectional regressions suggest that returns to education are lower in countries with a higher mean number of years of education as well as in richer countries. Using our consistently estimated returns and *panel* analyses, we find that returns might possibly be lower in countries with more education. However, poorer and richer countries do not appear to have significantly different returns to education. We then explore the same relationships for the returns to experience.

schooling. Interestingly, one quarter of the impact of schooling on income is because schooling indirectly raises returns to experience.

One important caveat of this study is that we do not uncover the exact mechanisms by which experience is associated with higher earnings. We assume that the measured differences in returns to human capital reflect differences in human capital accumulated in different countries, as in Lagakos et al. (2018b). An alternative perspective is that agents with the same amount of human capital are rewarded differently in different countries due to technological, institutional, organizational or other factors (Caselli and Ciccone, 2019). Labor market frictions in developing economies could for example prevent workers from moving up the ladder to better jobs that fit their skills profile, so that experience generates lower earnings (Lagakos et al., 2018b). As explained by Caselli and Ciccone (2019), one issue then is that we likely over-estimate the contribution of human capital to the variation in income across countries. Their reasoning should apply to both education and experience, and without further research we cannot assess how this issue differentially affects across income levels the respective contributions of education and experience to economic development.

Likewise, human capital could be accumulated at work *passively* or *actively*. We could first assume passive accumulation in the form of learning-by-doing. There is a long tradition in the growth literature where final output and productive resources are jointly produced.[6] By operating the production technology, agents learn more about it and improve their ability to operate it. Jovanovic and Nyarko (1996) provide a micro-foundation for this process by modeling the accumulation of experience as an agent gradually learning the value of a hidden parameter through Bayesian updating. An alternative would be to assume that human capital requires investment and that agents are only compensated for hours worked, as in Ben-Porath (1967) and Rosen (1972). We find this model to be natural for thinking about education, but less so about experience since formal (or informal) job training typically only takes a tiny share of the total number of hours worked in a year. Indeed, Rosen (2008) writes that “Only a small part of the overall concept is included in formal training programs, apprenticeships and the like. The greater part is associated with learning from experience.” Still, to the extent that some of the workers’ reported hours are spent in active training rather

[6]See for example the “learning by doing” models of Arrow (1962), Uzawa (1965) and Lucas (1988).

than in production, this leads to the underestimation of early-career wages, implying an overestimate of the returns to experience due to learning-by-doing only, particularly in developed economies where more time is spent in training. Given that we do not have information on how much time each worker in our data spends working or training, we cannot directly assess the contribution of each mechanism. However, indirect robustness checks based on cross-country data on the number of hours spent in formal or informal training suggest that our results are more consistent with learning-by-doing than the learning-versus-doing model of Ben-Porath (1967).

2. Data Used to Estimate the Returns

Sources. The data source for the analysis is the *International Income Distribution Database* (I2D2) of the World Bank. The database consists of a large number of individual-level surveys and census samples. The surveys include household surveys and labor force surveys. The data was initially compiled by the World Bank's *World Development Report* unit between 2005 and 2011. The original version was used by Montenegro and Hirn (2009) to study the labor market characteristics of developing countries for the 2009 *World Development Report* of the World Bank. The database has since been expanded and used by some of the members of the original *World Development Report* unit.[7] We use the expanded December 2017 vintage of the I2D2 database. Only select members of the research team or individuals in charge of harmonizing the data can access the database. However, a significant number of the surveys can be accessed online or after entering an agreement with the countries' respective statistical office. Finally, the surveys are nationally representative and large enough (i.e., typically have more than 10,000 observations) for our purpose.

Sample Size. The version of the I2D2 database that we use includes about 1,500 survey/census samples. However, wages are only reported for about two thirds of them. In addition, we restrict our analysis to workers aged between 18 and 67 with data on age and education as well as samples with at least 10 observations in each experience bin (see details below) to ensure results are not driven by small samples.

The baseline sample that we obtain includes 24,437,020 individuals from 1,073 surveys and 11 censuses in 145 countries from 1990-2016 (median number of samples

[7] The I2D2 database has been used to study labor markets or returns to education (Montenegro and Patrinos, 2014; de Hoyos et al., 2015; Gindling and Newhouse, 2014; Gindling et al., 2016).

per country = 6; mean = 7.5; min = 1; max = 44). We then include surveys from the 1990s to make sure we increase the number of countries in our sample. In particular, data is available for 176 survey/census samples in 63 countries in 1990-1999, 630 samples in 129 countries in 2000-2009 and 278 samples in 107 countries in 2010-2016. Note that several survey samples may be available for a same country-year.[8] Finally, the data is highly representative of the world economy. The 145 countries comprise about 95% of the world's population today. The data is representative for both developed countries (76% of their population) and developing countries (98%).

Main Variables. For the 24,437,020 individuals, we know their monthly wage, age, and number of years of education. For a substantial subsample, we know the hourly wage and the number of hours worked. Lastly, we know their employment status (e.g., self-employed or paid employee) their sector (ISIC-1: agriculture, industry, services), their occupation (ISCO-08: managers, professionals, technicians, clerks, crafts, sales, machinists, elementary occupations, skilled agriculture, other), and whether they work in the formal sector or live in urban areas. Finally, note that I2D2 mostly calculated the wage of self-employed individuals as the amount of salary taken from the business.

Data Limitations. While I2D2 is particularly useful in terms of external validity, the fact that all these surveys/censuses had to be harmonized implies that few variables are available (about 70). Also, the I2D2 team does not provide details on how the harmonized variables were created for each survey, and thus the level of consistency across surveys. However, given the wide use of the data across flagship World Bank reports, we feel compelled to trust that the I2D2 team did a good enough job that the results generated in our study do not capture statistical artefacts. Having said that, the only significant issue comes from the potential mismeasurement of wages. There could be issues with how self-employed individuals calculate and self-report the amount of salary taken from the business. As a result, we will examine the robustness of our results when excluding self-employed individuals. Next, 99% of these samples are surveys because censuses rarely include data on wages. In addition, we measure *potential* work experience as I2D2 does not include direct measures of work experience. Ability (e.g., test scores) is also not measured. Finally, the data are not panelized.

[8] Web Appx. Fig. A.1 shows the number of countries with available data for each year from 1990-2016. The Web Appendix is available on the website of Remi Jedwab: www.remijedwab.com.

Data Quality. In Web Appx. Section A.1,[9] we verify that the I2D2 database generates global patterns that are broadly consistent with patterns observed when using other global databases such as the *World Development Indicators* (WDI) database of the World Bank. More precisely, we find that our samples are globally representative in terms of per capita incomes, age structure, education, and self-employment.[10]

3. Methodology for the Estimated Returns

We calculate *potential work experience* – which we call "experience" in the rest of the analysis – as follows: (i) For individuals with at least 12 years of education, we assume children start school at age 6 and calculate experience as age - years of education - 6; (ii) For individuals with less than 12 years of education, we assume that experience before age 18 is inconsequential and calculate experience as age - 18. With these calculations, the mean (population-weighted) number of years of experience differs little between developing economies – 19 – and developed economies – 22. Indeed, while workers in developed economies study longer on average, they also tend to live longer.

Estimated Returns. For individual i and sample t, we use OLS to estimate the following model for *each* country one by one:

$$lnW_{it} = \sum_{e=1}^{7} \beta_e exp_{ite} + \gamma edu_{it} + \theta_t + \varepsilon_{it} \tag{1}$$

where the dependent variable is the log of monthly wages (lnW_{it}). Experience is categorized into seven bins (exp_{ite}). The bins are [5-9 years] (which we call 5), [10-14] (10), [15-19] (15), [20-24] (20), [25-29] (25), [30-34] (30), and [35+] (35). The omitted bin is [0-4] (0). We control for the number of years of education (edu_{it}). We include sample fixed effects (θ_t) to capture country-year-sample unobservables.[11]

Profiles. For illustration, we use the coefficients of the experience dummies to construct wage-experience profiles for the United States and Bangladesh (see Figure 1). In the U.S., a worker with 30 years of experience earns almost twice more than a worker with zero experience. The steepness in the profile is attributed to the first 25 years, particularly the first 15 or even 5. In Bangladesh, the profile is flatter. The same patterns

[9]The Web Appendix is available on the website of Remi Jedwab: www.remijedwab.com.

[10]For example, we find that log mean earnings in I2D2 are strongly correlated across country-years with log per capita GDP in WDI. We show that wage variance is in line with what is expected. Finally, we verify that the resulting Mincerian R-squared are not too different across various groups of countries.

[11]Most countries having several samples, we use individual weights divided by the size of the sample.

are observed if we widen the scope by replacing the United States with all developed countries and Bangladesh with all developing countries (developed countries are high-income countries in 2017 according to the World Bank classification). To obtain these profiles, we obtain the average wage differential for each country (1990-2016) and construct the mean wage differentials for each group of countries weighted by the population of each country in 2017. The "median" developed (developing) country is Belgium (Jordan).

Returns. Measures of the returns to experience should take the integral below the profiles.[12] For each bin (5, 10, etc.) one by one, we estimate an annualized return and then take the mean of the annualized returns across the seven bins to obtain the *mean annualized return* throughout the experience distribution. More precisely, for individuals belonging to bin e, we obtain the *bin-specific annualized return* as $((\beta_e + 1)^{(1/e)} - 1) * 100$, with β_e being the estimated coefficient for bin e in equation (1). For this subgroup of individuals in the society, it tells us by how many percentage points wages increased on average for each extra year of experience. We then take the average of these seven bin-specific annualized returns so that each bin is represented.[13]

We find average population-weighted returns of 2.0% for the world. In contrast, returns to education, measured by the coefficient of schooling, are 4 times higher, at 8.2%. Our specification has several advantages over the Mincerian specification that includes a quadratic function of experience: (i) With seven coefficients, it is more flexible and informative, especially given that 34 countries have non-monotonic wage-experience profiles; (ii) We construct returns that are independent of the distribution of experience in the country. Since we keep samples with at least 10 observations in each bin, and then give each bin the same weight, the constructed returns are less affected by the facts that developed countries and developing countries have more experienced workers and more inexperienced workers, respectively;[14] and (iii) We can construct measures using only specific parts of the experience distribution (e.g., 0-25 or 0-15),

[12] Lagakos et al. (2018b) calls this the "sum of heights".

[13] In our view, it is important to use information from the seven experience coefficients. However, we acknowledge that there is no right or wrong way to use this information to construct the returns.

[14] A related issue with the Mincerian specification is how to calculate returns from the coefficients of experience (β_1) and its square (β_2). It is common to calculate the returns as $\beta_1 + \beta_2 \times$ the median number of years of experience. However, this number varies across countries. This method then captures the *local* return at the median experience level, not for the full distribution of experience in the country.

which will prove important when dealing with changes in a country's economic system and selection effects in and out of the workforce or selection effects related to mortality.

4. Returns for Developed versus Developing Economies

4.1. Baseline Results

Figure 2 shows the strong positive relationship between returns to experience and log per capita GDP for the mean year in the data for each country (slope = 0.33***).[15] The main sample of Lagakos et al. (2018b) excludes countries from the former Soviet Union and Sub-Saharan Africa. Some ex-USSR countries (e.g., UZB for Uzbekistan) have relatively low returns and some African countries (e.g., UGA for Uganda) have relatively high returns for their income level.[16] Regarding the former, a change in the economic system made experience obsolete (details will be provided in Section 5.3.). Regarding the latter, high mortality may lead to a selection effect where late-age workers are more able in unobservable ways (Section 4.6.). As a result, the returns of poorer countries may be over-estimated, causing the returns gap between developed and developing countries to be under-estimated. However, a downward bias is less consequential than an upward bias for our analysis. Finally, we will examine in Section 4.6. below how results vary between low-, middle- and high-income countries.

For 145 countries c, we then regress the returns ($RetExp$) on a dummy equal to one if the country is classified as high-income by the World Bank (Dev):

$$Returns\,to\,Experience_c = \alpha + \beta\,Deveveloped\,Country\,Dummy_c + \epsilon \tag{2}$$

Row 1 of Col. (1) in Table 1 shows the baseline results. The first subcolumn shows the constant (α), i.e. the mean return for developing countries (*G*). The second subcolumn shows the coefficient (β) of the developed (high-income) country dummy, i.e. the difference between the mean returns of developed countries and developing countries. (*D-G*). Finally, the mean return for developed countries (*D*) is obtained by adding the constant and the coefficient of the developed country dummy and is shown in the third subcolumn. The mean returns for developing countries and developed countries are 1.7*** and 3.2***, respectively. The difference between the two is significant (1.5***).

[15] The GDP is in PPP terms and constant 2011 USD. For countries with multiple years of data, the mean year is the average sample year using as weights the number of observations in each sample.

[16] Web Appx. Fig. A.2 shows a world map of the returns. Web Appx. Table A.7 lists all the returns.

4.2. Robustness when Attempting to Control for Cohort Effects

Without retrospective data on individual employment, experience is necessarily estimated as age minus schooling. Time is then equal to age plus the year of birth. Thus, one cannot simultaneously include schooling, experience, age, time fixed effects and cohort fixed effects in the same estimation (Heckman and Robb, 1985, p.137), in our case equation (1). Therefore, we cannot include year of birth fixed effects and we also cannot distinguish the effects of experience and age. See Web Appx. Section A.2 for details on what is commonly called the experience-time-cohort problem.

HLT Approach. The “HLT” approach is coined by Lagakos et al. (2018b) to describe their main empirical strategy as it is inspired by Heckman, Lochner and Taber (1998). As described in Lagakos et al. (2018b), some theories of life cycle wage growth claim that there should be “no effect of experience on wages near the end of the life cycle”. One can then “follow a fixed cohort across multiple cross sections for the last years of their working life” and attribute any wage changes for them to time effects. Once time effects are recovered, “it is straightforward to estimate the experience and cohort effects of workers who are not near the end of the life cycle”. However, wage profiles could decrease at the end of the life cycle because of human capital depreciation. Thus, “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”. They consider 5 or 10 years and 0 or 1%. While this approach has clear merits, it posits that there are no experience effects near the end of the life cycle. Also, selective early retirement in developed countries and selective mortality in developing countries complicate the analysis, since estimated time effects near the end of the life cycle could capture unobservable compositional changes in the population of the older cohorts across years.

Our Approach. Heckman and Robb (1985, p.145) propose to include cohort effects consisting of “a sequence of adjacent years (e.g., Depression or 1950s youth, etc.)”. In Col. (2), we include decadal cohort fixed effects in the country-specific regressions estimating the returns, but only for 122 countries with at least two years of data. Since we focus on workers aged 18-67 in samples from 1990-2016, we study individuals born between 1923 and 1998. We thus include 8 cohort dummies (1920s, ..., 1990s). This approach is only valid if cross-sections are fewer than ten years apart. As explained in Web Appx. Section A.3, this issue only affects a few older individuals in the earliest surveys of 12 countries. Using returns based on the 0-25 bins, as we estimate later, also eliminates the issue. Finally, results hold if we exclude the 12 countries or exclude only the problematic surveys that number 12 in total and involve 7 countries.[17]

An alternative approach is to construct for each country periods based on important years, e.g. for the United States, 1923-1928, 1929-1932, 1933-1940, 1941-1944, 1945-1953, 1954-1961, 1962-1963, 1964-1967, 1968-1973, 1974-1979, 1980-1989, 1990-1993 and 1994-2000, due to important events in 1929 (Great Depression), 1933 (New Deal), 1941 (Pearl Harbor), 1945 (World War II ends), 1954 (ends of racial segregation in schools), 1962 (Cuban Missile Crisis), 1964 (Civil Rights Act), 1968 (Martin Luther King assassinated), 1974 (Watergate), 1980 (Reagan), 1990 (Gulf War starts, Cold War ends), 1994 (NAFTA), 2001 (9-11), and 2007 (Great Recession).[18] We identify important events using information from standard sources such as Wikipedia. For each country, we read the top of the Wikipedia webpage of the country (in English as well as in the main language of the country) as well as the "contemporary/modern period" and "colonial period" sections.[19] We cross-check this information using other sources, e.g. the BBC Profile of each country.[20] We then include in the regressions estimating the returns country-specific period dummies equal to one if the individual was aged between 18 and 67 during the period(s), for countries with at least two years of data. Doing so captures the fact that each person was affected by multiple events during her lifetime. For example, an American person born in 1931 was 18 in 1949 and 67 in 1998. For her, the 1945-1953, 1954-1961, ..., 1990-1993 and 1994-2000 period dummies are equal to one. Of course, blindly following Wikipedia-BBC may lead us to include events that might not be that "important" for workers. At the same time, it is better if we

[17]Web Appx. Section A.3 and Web Appx. Table A.8 show that effects do not vary much if we increase the number of years of data required for a country to be considered or use 20-year cohort fixed effects. The 5-year cohort fixed effects preserve the difference between developed and developing countries. However, returns are lower across all countries, since collinearity increases as one uses more refined cohort fixed effects.

[18]For Kenya: 1920 (Crown Colony), 1940 (Italian attack), 1944 (Kenyan African Union), 1947 (Kenyatta becomes KAU leader), 1952 (Mau Mau rebellion), 1956 (rebellion ends), 1960 (state of emergency ends), 1963 (Independence), 1969 (Mboya assassinated), 1978 (Kenyatta dies, rule of Moi), 1982 (one-party state), 1987 (opposition suppressed), 1992 (elections, conflict), 1996 (constitution amended), 2002 (Moi's reign ends), 2007 (electoral violence), 2010 (constitution, East African market), 2013 (terrorist attacks).

[19]See https://en.wikipedia.org/wiki/United_States for the United States. Accessed 03-15-2019.

[20]See https://www.bbc.com/news/world-us-canada-16761057 for the United States. Accessed 03-15-2019.

blindly follow their selection of important events rather than us cherry-picking the events ourselves. Selecting too many events by including events that might not appear so "important" should also lead to more conservative estimates because the included cohort fixed effects are then more refined, i.e. lump together fewer years than if we were not using these events. However, in the rest of the analysis, we will privilege the results with decadal cohort fixed effects.

Both approaches reduce returns for both developing countries and developed countries, to 0.8-1.1*** and 2.6-2.8*** respectively (N = 122; row 1). They accentuate the gap between developed and developing countries (to 1.7***-1.8***). However, while these two approaches help capture cohort effects, they do not fully solve the experience-time-cohort problem since there may still be yearly cohort effects.

Web Appx. Section A.3 and Web Appx. Table A.8 show results hold if: (i) periods are constructed based on ages 18-40 or 18-30, in case important events are more consequential in the first decades or years after high school; (ii) we add as a control the country's average per capita GDP growth rate for those years during which the individual was aged between 18 and 67, since the identified important years may not capture well uneventful periods of growth or recessions; (iii) add country-specific period dummies equal to one if the individual was aged between 0 and 17 during the period(s), and the individual's corresponding growth rate, in case important events are consequential during childhood; (iv) combine the decade fixed effects, events fixed effects and growth rate approaches; and (v) use Lagakos et al. (2018b)'s HLT approach. Like them, we consider four versions of the HLT approach, based on the last 5 or 10 years of experience and using a depreciation rate of human capital of 0 or 1% (see rows 12-15).

4.3. Other Main Results

Hourly Wages vs. Hours Worked. Results hold if we use returns based on hourly wages (row 2 of Table 1). Indeed, monthly wages can be decomposed into hourly wages and hours worked (N = 131; 105; 105). Hours worked slightly increases with development when ignoring cohort effects (Col. (1) in row 3). Yet, since this effect is very small, hourly wages, and thus hourly productivity, explains most of the returns based on earnings. However, using monthly wages allows us to use the full sample of 145 countries.

Selected Bins. Results hold if we use returns (N = 145; 122; 122): (i) Based on the 0-25 (row 4) or 0-15 bins (row 5), to minimize selection issues due to changes in economic systems and selective mortality or early retirement disproportionately affecting more experienced workers; (ii) Based on the 5-35 bins (row 6).[21]

Excluding Selected Types of Workers. Results hold for returns excluding female, part-time, self-employed and public sector workers, considering both monthly wages (row 7; N = 124; 101; 101) and hourly wages (row 8; N = 122; 98; 98).[22] Web Appx. Table A.14 (rows 2-5) shows results hold if we exclude each group of workers at a time. Excluding female workers slightly raises the returns in both developed and developing countries. If anything, the developed-developing gap slightly increases. Excluding part-time workers lowers the returns in developing countries when cohort fixed effects are included, thus also widening the developed-developing gap. Excluding self-employed workers does not substantially affect the returns. The developed-developing gap slightly increases. Finally, excluding public sector only slightly reduces the returns, and the gaps.

Weights. Results hold when country populations in 2017 are employed as weights, thus giving more weight to larger countries (row 9; N = 145; 122; 122).

Complementarities. Rows 10-13 examine if returns vary across education levels. According to UNESCO (2012), individuals finish high school after 12-13 years of education, thus 13 years is a reasonable cut-off. In developed countries, returns are slightly lower for more educated individuals (rows 10-11; 3.4*** vs. 3.2***; N = 143-122-122 in row 10, 124-98-98 in row 11). In developing countries, returns are higher for more educated individuals (2.1*** vs. 1.7*** in col. (1)). However, we lose about 20-25 countries because we do not have at least ten individuals for each experience-education bin. To remedy that issue, we use country population circa 2017 as weights (rows 12-13; N = 143-122-122 in row 12, 124-98-98 in row 13), making compositional changes due to smaller countries less consequential. Results are unchanged.[23]

Main Returns. In our simulations we use population-weighted education-specific

[21]Web Appx. Table A.9 shows that local returns are higher for lower-experience bins whereas Web Appx. Table A.12 shows that results hold for different combinations of local returns.

[22]Lagakos et al. (2018b) exclude: (i) female and part-time workers because potential experience is a better proxy of actual experience for male and full-time workers; (ii) self-employed individuals because their wages may also include the returns to the capital investments they make. In our case, I2D2 calculates their wage as the amount of salary taken from the business; and (iii) public sector workers because they receive nonwage compensation and their wages may not reflect the full payment for their labor.

[23]Results hold if we use 12 or 14 years or information about high school graduation (Web Appx. Table A.13).

returns based on the 0-25 bins. Returns are higher but the previously discussed differences are maintained, with the corresponding returns being 4.4*** and 4.2*** for developed countries and 2.0*** and 2.8*** for developing countries (rows 14-15; N = 143-122-122 and 124-98-98). These results hold if exclude female, part-time, self-employed and public sector workers (rows 16-17; N = 122-100-100 and 91-72-72).

4.4. Robustness Checks

Estimates of Returns. Web Appx. Section A.4 and Web Appx. Table A.14 show results hold if we use country-specific ages of entry in school or drop samples exhibiting age heaping.[24] Teenagers and children then disproportionately work in developing economies. We may thus mismeasure experience in developing countries. This could affect our results if we under-estimate the returns of developing countries, thus wrongly asserting how large the gap in the returns is between developed and developing countries. We indeed find that including potential teen labor experience (from age 15) or potential child labor experience (from age 13) raises the returns slightly more in developing countries – from 1.7 to 1.9-2.0 (see rows 7-8 of Web Appx. Table A.14) – than in developed countries – from 3.2 to 3.4 (ibid.).[25] The gap in the returns then either remains the same, at 1.5, or slightly decreases to 1.3 (ibid.). If we consider teen/child labor for developing countries only, the gap is 1.3-1.2. Also controlling for cohort effects, the gaps also remain high, at 1.5-1.3 and 1.7-1.4. Overall, the returns and the developed-developing gap remain essentially similar, at least enough not to change the main implications of our results.[26]

Results then generally hold if we (see Web Appx. Section A.4 and Web Appx. Table A.14): (i) Restrict the sample to post-2000 samples to minimize issues arising from ex-USSR countries; (ii) Use three- or seven-year bins; (iii) Keep workers for which the wage was reported for a period of at least a month since earnings may be mismeasured for workers paid hourly, daily or weekly; (iv) Include the wage of any secondary occupation (available for fewer countries); (v) Use mean wages, experience and education in the

[24] Results hold if we drop samples with a rough Whipple index. The index measures to what extent individuals disproportionately report their age as a round number ending in 0 or 5.

[25] For teen (child) labor, for individuals with at least 9 (7) years of education, experience is age - years of education - 9 (7). For individuals with less than 9 (7) years of education, experience is age - 15 (13).

[26] Web Appx. Figure A.4 replicates Figure 1 but add the respective wage-experience profiles of developed countries and developing countries when including teen labor ("TL" in the figure) and child labor ("CL").

household to account for intra-household optimization. This is particularly important for households where women do not work or for multi-generational or multi-family households; and (vi) Keep samples with at least 100 observations per experience bin.

Additionally, we focus on workers, which causes a selection problem in samples with skewed unemployment/non-labor participation (NLP) rates. In the context of low unemployment/NLP, non-workers may have specific unobservables. That is also true in contexts with high unemployment/NLP where competition for few jobs selects the "best". That is only an issue for us if unemployment/NLP is correlated with development. However, we find no such correlation and results hold if we (Web Appx. Section A.4 and Web Appx. Table A.14): (i) Add controls for selection, i.e. sector fixed effects, occupation fixed effects, an informal sector dummy, an urban dummy, and the square of education, to compare workers that are similar except in their experience level; (ii) Keep or drop samples with unemployment or NLP rates below the 25th percentile (7% and 35%, respectively) or 50th percentile (10% and 35%, respectively) in the sample; and (iii) Use the Heckman correction with the selection equation also including marital status and the number of children in the household.

Developing vs. Developed. The developed-developing gap holds after conducting the following checks (Web Appx. Section A.5 and Web Appx. Table A.15): (i) Add seven World Bank region fixed effects; (ii) Drop each developing region one by one or ex-Communist countries; (iii) Drop the top and bottom 10% outliers in the returns, i.e. countries that may have abnormally high or low returns, either because these returns are real or because of measurement error; (iv) Add country-level controls for factors generating cohort effects: whether a country had a Communist regime,[27] past child and adult mortality rates (including for HIV),[28] and past per capita GDP or population growth rates[29] for each country-decade from 1950 to 2010 (source: United Nations (2019)).

In addition, if agriculture exhibits lower returns to experience and given that developing countries have a higher share of their workers in agriculture (37% vs. 5%

[27] These include a dummy equal to one if the country ever had a Communist regime, the number of years the country has had a Communist regime, and the year the country transitioned to capitalism (source: Wikipedia (2019)). Since we are controlling for the country-specific mean year in the data, this also controls for how many years ago the country transitioned to capitalism.

[28] These include average child mortality rates (for 0-5 year-olds) and adult mortality rates (15-45) for each country-decade from 1950 to 2010 (source: United Nations (2019)) and average HIV infection rates for each country-decade from 1990 to 2010 (sources: World Bank (2018a); data unavailable before 1990).

[29] These include average annual per capita GDP growth rates (source: see footnote 15).

for developed countries), then their lower returns could be due to lack of structural change. For 111 countries with sectoral data, we obtain the wage-experience profiles of workers currently belonging to the agricultural sector (Ag) or the non-agricultural sector (Non-Ag).[30] A number of observations are provided in Web Appx. Fig. A.5. First, for both developed and developing countries, the Non-Ag profile is above the Ag profile. Second, the Non-Ag profile of developing countries is below the Ag profile of developed countries. Lastly, the gap in the profile for Ag appears to be similar to the gap in the profile for Non-Ag. Relatedly, the D-G gap in the Ag returns (1.5***) is similar to the gap in Non-Ag (1.6***) as well as the aggregate gap (1.5***). Therefore, structural change (or lack thereof) does not explain our patterns.[31]

Finally, standard errors (SE) in eq. (2) ignore the fact that the coefficients of the experience dummies may be imprecisely estimated in eq. (1). However, 75-92% out of the 145 x 7 = 1,015 coefficients have a p-value below 1%. Furthermore, the medians of the mean and max SEs across the seven coefficients in our sample are low, at 0.02.[32]

4.5. Returns to Education and Complementarities

Returns to Education. We use the coefficient of schooling as a proxy for the returns to education. Table 2 replicates our main Table 1 except that we use as our dependent variable the estimated returns to education. Row 1 shows that returns to education are not significantly different between developed and developing countries, whether one ignores cohort effects – $\approx$ 8.7-9.0*** – or attempt to control for them – $\approx$ 8.4-8.8*** – (N=145, 122, 122). Web Appx. Fig. A.3 also shows a statistically insignificant relation between returns to education and log per capita GDP (PPP) for the mean year in the data for each country. Rows 2-3 then show most of the returns in terms of monthly wages are driven by differences in hourly wages (row 2, N=131, 105, 105). Education increases the number of hours worked in developed countries, but the developed-developing gap is only significant when no cohort fixed effects are included (row 3, ditto).

Next, mean returns are lower for both developing and developed economies, and the developed-developing gap is positive and significant, if we restrict the sample to

[30] We do not know sectoral employment history. The returns are thus estimated using the current sector.

[31] More precisely, we obtain the following (population-weighted) returns to experience for Ag and Non-Ag: 1.2 and 2.0 for developing countries and 2.7 and 3.6 for developed countries (not shown).

[32] Results hold if we only use countries whose mean or max SE is below the median of the mean/max SE in the sample or bootstrapped SE 10,000 times (Web Appx. Section A.5 and Web Appx. Table A.15).

the type of workers studied by Lagakos et al. (2018b). However, this is only true if we consider monthly wages (row 4, N=123, 96, 96), not hourly wages (row 5, N=121, 93, 93). In row 4, the gap is also relatively small compared to the absolute values of the returns in both groups of countries. Indeed, the mean return to education for developed countries is only 20-25% higher than the mean return to education for developing countries (vs. 90-225% for experience based on the results of row 1 in Table 1).

The returns to education of developing countries slightly decrease and the returns to education of developed countries slightly increase when country populations in 2017 are employed as regression weights (row 6; N = 145; 122; 122). The developed-developing gap is significant in col. (1), but the difference remains small relative to the absolute values of the returns. Indeed, the mean return to education for developed countries is only 27-30% higher than the mean return to education for developing countries (vs. 100-150% for experience based on the results of row 9 in Table 1).

We find relatively higher returns for individuals with more than 13 years of education than for individuals with less than 13 years. When ignoring cohort effects and using population weights (col. (1)), these are 13.0*** vs 6.7*** in developed countries and 13.8*** vs. 6.8*** in developing countries (rows 9-10; see rows 7-8 for the equivalent returns when not using weights). If we try to account for cohort effects (col. (2)-(3)), the returns to education are similar, at 12.7-13.0*** vs. 6.6*** and 13.1-13.4*** vs. 6.8*** in developed and developing economies, respectively. If we exclude female, part-time, self-employed and public sector workers, results are similar (rows 11-12).[33]

Literature. How do our returns to education compare with existing estimates from the literature? Earlier studies such as Psacharopoulos and Patrinos (2018b) (henceforth, PP18) and Caselli et al. (2016a) (henceforth, CPR16) compile estimates from different studies. PP18 reports estimates of the returns for 72 countries during the same period as this study (1990-2016). Using population weights, the estimated PP18 average returns are 9.9 and 9.0 for developed countries (N = 5) and developing countries (67), respectively. We obtain respective returns of 10.3 and 7.9 in our data (145; row 6 of Table 2 Col. (1)). The correlation between our data and their data is about 0.6 (62; see Web

[33]These returns are not necessarily causal. They are nonetheless consistent with causal studies (Jedwab et al., 2020). Furthermore, if returns are over-estimated because better able individuals study longer, the causal returns would mean a lower relative contribution of education to economic development than what we obtain, reinforcing our result that experience significantly matters.

Appx. Fig. A.6). CPR16 add their own estimates from different studies to the estimates provided by PP18. The CPR16 database consists of 178 estimates defined c. 1995 or 2005. Using population weights, the estimated CPR16 average returns are about 9.0 for both developed observations (N = 48) and developing observations (130), respectively. The correlation between our data and their data is about 0.4 (117; see Web Appx. Fig. A.6). Comparability is likely limited because both PP18 and CPR16 rely on different studies that use different methodologies (e.g., 89 in CPR16) whereas we directly estimate our returns using a consistently harmonized global dataset and a consistent methodology.

4.6. High-Income vs. Middle-Income vs. Low-Income Countries

In this subsection, we show that, using our best specification and accounting for various issues, the relationship between returns to experience and economic development is monotonic. While the returns are twice higher in developed countries than in developing countries, among developing countries returns are only slightly higher in middle-income countries than in low-income countries, which explains why the relationship is not fully monotonic. Returns to experience thus only greatly increases as economies become developed, which suggests that returns to experience may proxy for an economy's ability to converge and catch up to high-income economies.

Graphical results. Figure 2 suggests that the relationship between returns to experience and economic development is U-shaped, with low-income countries (most of them in Africa) having higher returns than middle-income countries. We examine if this U-shape pattern holds across the various specifications investigated previously or whether it is a statistical artefact resulting from selective mortality raising the returns of poorer countries *and* transitions to capitalism having made experience more obsolete in ex-Communist countries which are now majoritarily middle-income countries.[34]

In Web Appx. Table A.16, we examine the Spearman rank-order correlation between the returns and log per capita GDP (PPP; constant 2011 USD; for the mean year in the data for each country). The baseline correlation is 0.38 (N = 145). Including decadal cohort fixed effects, using returns based on the 0-25 bins, and employing country populations (2017) as weights increases the value to 0.60 (specification 1). If

[34]Since most low-income countries are in sub-Saharan Africa and to ensure that our results are not driven by a lower quality of surveys from the region, we verify that the patterns that we obtain for sub-Saharan Africa in I2D2 are consistent with the patterns observed when using other global databases such as the *World Development Indicators* database of the World Bank (see Web Appx. Section A.1).

we additionally exclude female, part-time, self-employed and public sector workers, the value becomes 0.58 (specification 2). Thus, the relationship appears to be moderately monotonic.

Excluding countries in the top 5% in past child or adult mortality rate (averages in the 1950s-2010s) or HIV prevalence rate (1990s-2010s) increases the values for the two specifications to 0.63 and 0.60, respectively. If we also exclude ex-Communist countries, the correlations become 0.75 and 0.57, respectively, indicating a strongly monotonic relationship. The relationship is still not *fully* monotonic, which suggests non-linearities. These come from developing countries, not developed countries.

If we focus on specifications 1 and 2 and exclude ex-Communist and high-mortality countries, the correlations respectively increase to about 0.8 and 0.6 if we additionally exclude low-income countries (not shown). If we exclude high-income countries instead, the correlations respectively decrease to about 0.3 and 0 (ibid.). Thus, the relationship is barely monotonic among developing countries, which we discuss next.

Income Group-Specific Returns. We modify equation (2) to obtain the mean returns to experience for low-income countries, middle-income countries and high-income countries in 2017 according to the classification of the World Bank. As seen in Web Appx. Table A.17, with specification 1 or specification 2, returns are slightly higher for middle-income countries than for low-income countries (at 1.8-2.0 vs. 1.6-0.8), but not significantly so. Simultaneously excluding high-mortality/HIV countries and ex-Communist further increases the gap between low-income and middle-income countries. However, the difference is only significant in specification 2.

5. Variation in Returns to Work Experience Over Time

Returns to experience are available for 951 country-years for the time period 1990-2016. Using this data, we investigate using panel regressions how the returns vary with economic development, recessions and economic transitions as well as existing stocks of human capital. While estimates derived are not causal, the aim is to highlight novel stylized facts about how returns to experience vary across countries over time.

More precisely, for countries c and years t, we estimate the following model:

$$RetExp_{c,t} = \alpha + \beta \, \text{Var. of Interest}_{c,t} + \lambda_c + \theta_t + \mu_{c,t} \tag{3}$$

with Var. of Interest being the variable explored as a potential predictor of the returns to experience. We focus on 122 countries with returns available for at least two years. Using only the first year and last year available for each country allows us to estimate the long-difference effect of changes in the variable of interest on the returns.[35]

We also construct a five-year panel centered around the years 1994, 1999, 2004, 2009 and 2014.[36] Standard errors are clustered at the country level. One advantage of the five-year panel is that the sample is larger and the periodicity fixed. However, they only capture short-term effects and returns may be too "slow moving" with limited variation.

Our main analyses use returns to experience constructed using 0-25 bins, hence 25 years. In a panel framework limited to a period of 26 years (1990-2016), using fewer bins is warranted given that returns are mechanically more correlated over time. However, returns based on only one bin (0-5) are also limited as they are based on 5 years only. We choose an intermediate approach and study returns constructed using the 0-15 bins.[37]

5.1. Economic Development and Returns to Work Experience

In col. (1) of Panels A and C in 3, we report the long-difference and five-year correlations between the returns to experience and economic development proxied by a dummy variable equal to one if the country was "developed" (had reached high-income status) by year t, respectively. The correlations are quite high, at 1.03**-1.11**, and not that much lower than the baseline cross-sectional effect – 1.5*** – estimated in column (1) of row 1 in Table 1. In contrast, for the returns to education, the correlations are small and not significant (Web Appx. Table A.19), broadly consistent with the cross-sectional analysis.

In col. (2), we report the correlations between the returns to experience and two dummy variables that are equal to 1 if a country reached high-income status or middle-income status by year t respectively. The coefficient of the middle-income status dummy variable is positive but not significant. The coefficient of the high-income status dummy in Panel A is now larger. The statistically insignificant results for middle-income status are consistent with the weak results obtained from the cross-sectional

[35] Since there are countries for which the first year and last year are only separated by a few years, we use as weights the number of years between the two years.

[36] For each year (e.g., 2014), we use the year's return when available. If not, we use the mean return for the year before (2013) and/or after (2015). If still not available, we use the mean return for the two years before and after (2012, 2016). For 1994, if needed, we use three (1991) and four (1990) years before.

[37] Results generally hold if we use other combinations (not shown, but available upon request).

regressions. There is then no clear pattern between the returns to education and the income status of the country (Web Appx. Table A.19).[38]

Thus, developed economies may have features that increase the value of experience, hence workers accumulate more human capital at work in developed countries.

5.2. Economic Recessions and Returns to Work Experience

Is the wage growth of cohorts entering labor markets in turbulent times permanently affected? Since we focus on returns based on the 15 years after leaving school, we measure labor market turbulence in col. (3)-(5) as the share of years during their first five years of work experience with a per capita GDP growth rate (PPP; constant USD) below a particular threshold: below -1%, -3% and -5%. For individuals with 0-15 years of experience in 1990-2016, data on the country's growth rate is needed for each year from 1975 to 2001. In our data, one third of the country-years experienced a recession.[39]

The long-difference effects (Panel A) of recessions are negative on the returns. If we control for whether the country has reached high-income status by year t, in order to capture the independent effect of labor market turbulence 10-15 years ago rather than underdevelopment more generally, the effects remain unchanged (Panel B). The five-year difference effects are slightly lower, and not significant for -1% (Panel C). As expected, the effect are stronger and more significant for deeper recessions (col. (5) vs. col. (3)). More precisely, for each extra year of contraction above 5%, the share increases by 0.2 (since we consider five years). Consequently, returns might be 0.2*2.24 = 0.45 percentage points lower, given a mean return of 3.2% in that sample.

Could wages be lower after 15 years because recessions led to the unemployment of some individuals for some time, thus reducing their years of actual experience? The mean unemployment rate in the world is 10%. Assuming each deep recession year doubles the unemployment rate to say 20% for a full year, after one year average experience among individuals who were typically employed (the 100 - 10 = 90%) increases by (1 - 0.10/0.90) = 0.89 instead of 1. Thus, actual experience is 11% lower on average. Returns to experience are then lower by 0.45/3.2 = 14%. The numbers

[38] These countries are geographically dispersed. 18 countries reached high-income status. 10 of them are in Europe, 4 in Latin America and the Caribbean (LAC), 2 in Asia, 1 in the Middle-East and 1 in Africa. 19 countries reached middle-income status. 7 are in Africa, 6 in East Asia, 5 in South Asia and 1 in LAC.

[39] Among observations with a negative rate, -1%, -3% and -5% correspond to the 75th percentile, the median, and the mean in the sample, respectively.

are broadly consistent with the possibility that the effect of labor market turbulence is mostly due to missed experience for individuals who would have worked otherwise.

In Web Appx. Table A.18, we use the same econometric framework to study how the returns (based on 15 years) correlate with the mean unemployment rate (UR) or labor force participation rate (LFPR) during the cohorts' first five years of experience. We tend to find significant, negative correlations with UR or LFPR variables for youth (15-24) but not for the generally active population (15+) (cols. (1)-(4)). However, UR and LFPR being correlated and the sample being small, we cannot assess how much of the negative impact of recessions is coming from a higher UR and/or a lower LFPRh (cols. (5)-(8)).[40]

Alternatively, we can study whether recession experience has lower returns than non-recession experience. For each respondent, we separate their potential work experience into experience during recession years and experience in non-recession years, again using the -1%, -3% and -5% thresholds. We re-run the main regression (eq. (1)) using 5-year bins for each type of experience. We plot the estimated coefficients in Web Appx. Fig. 7(a), finding no wage growth effects of recession experience.

Finally, we also find significant negative effects of recessions on the returns to education (Web Appx. Table A.19). Once we account for the fact that the returns to education are on average three times higher than the returns to experienced based on the 0-15 bins, the effects of recessions on experience and education are broadly similar.[41]

5.3. Economic Transitions and Returns to Work Experience

40 countries had a communist regime at one point. We have information on the time when their transition out of communism began.[42] Since the transition involved structural or institutional changes that may have made pre-transition experience obsolete, we hypothesize that countries that recently transitioned out of communism should have lower returns than non-communist economies and this difference should

[40]Note that data (source: *World Development Indicators* of the World Bank) is available for fewer country-years than before since URs and LFPRs were not systematically measured before the 1990s.

[41]Kahn (2010) find large, negative wage effects of graduating in a bad economy in the United States whereas we focus on the global effects of recessions on the returns to experience, i.e. to what extent more experienced workers are paid more than less experienced workers. We do not study the effects on wage levels.

[42]We obtain this information from Wikipedia (2019) and the Wikipedia webpage of each country. For example, we use 1975 for China, 1986 for Vietnam, 1989 for Poland, 1991 for Russia, and 1992 for Albania.

attenuate over time as new cohorts accumulate post-transition experience.

Column (6) shows that the returns to experience are correlated with the number of years since the transition out of communism began. Ten years after the transition is initiated, returns are 10 * 0.08 = 0.8 percentage points higher, a large effect given the mean of 3.2%. This correlation holds if one controls for whether the country has achieved high-income status by year t (Panel B), suggesting the effect of transitioning out of communism is not purely due to economic development.

Figure 3(a) shows the effects of transitioning out of communism in a more flexible manner. To obtain these effects, we run panel regressions for all 951 country-years available in 1990-2016 (country fixed effects and year fixed effects included) and include dummies corresponding to different groupings of years since a transition. “3” includes 1-3 years, “6” includes 4-6 years, ..., and “27” includes 25-27 years. “30” (28-+) is the omitted category (standard errors clustered at the country level). The effects are generated for the returns based on the 0-15 bins but also for the returns based on the 0-25 bins and the 0-5 bin. As seen, countries that just began their transition start with much lower returns. Fast convergence is observed for groupings 6 to 12 (hence between 4 and 12 years after a transition). Returns continue converging after that but at a slower pace. Returns are still 1 percentage point lower after more than 25 years. As expected, returns adjust much faster when considering less experienced bins, showing how the patterns are driven by new cohorts accumulating post-communist experience. The results on fast convergence echo the results of Dauth et al. (2019) who study the determinants of wage convergence between East and West German workers. [43]

Alternatively, we can study whether communist experience has lower returns than post-communist experience. For each respondent in the 40 ex-communist countries, we separate their potential work experience into experience before the transition (incl.) and experience strictly after the transition. We re-run the main regression (eq. (1)) using 5-year bins for each type of experience. We plot the estimated coefficients in Figure 3(b). The results show that an individual with 20 years of post-communist experience earns about 50% more than an individual with no experience. For communist experience, the differential is at least -25%, implying that post-communist experience has negative

[43] We also find significant negative effects of transitioning out of communism on the returns to education (Appx. Table A.19). Again, once we account for the relatively higher returns to education, the effects of transitioning out of communism on experience and education are similar.

effects post-transition. The profile for post-communist experience is similar to the profile for the "average" (market-oriented) developing economy.[44]

5.4. Are Returns to Experience Decreasing with its Stocks?

While returns to education correlate negatively with the stock of education (e.g., Card and Lemieux, 2001; Psacharopoulos and Patrinos, 2018b), there is less evidence on the correlation between the returns to experience and the stock of experience. Table 4 replicates Table 3 with the exception that the variables of interest considered are measures of stocks of education and experience. For the long-difference specifications (col. (1) of Panels A-B), we indeed find a negative correlation between the returns to education and the mean number of years of education in the same year. However, the five-year specification does not show a statistically significant negative correlation (Panel C). In addition, developed countries do not have significantly lower returns to education despite the fact that workers are far more educated on average. In the simulation exercises below, we will thus ignore any possible feedback effect of increasing the quantity of schooling on the returns to education. The returns to experience are not particularly correlated with the mean number of years of experience (col. (2)), again suggesting the lack of a feedback effect.[45]

5.5. Are Experience and Education Substitutes?

Returns to experience may decrease with the stock of education or the returns to education, possibly indicating that work experience and education are substitutable. However, if education and experience are positively related or unrelated, this may imply that experience is important and the lack of it might not be compensated by investments in education. We find evidence in line with the latter. Indeed, across

[44] With most transitions taking place c. 1990 and the latest surveys taking place c. 2010, we do not have enough countries with a post-communist experience of 25 years or more. We also do not have enough observations with pre-communist experience in bin 35. We do not report estimates for these bins.

[45] The distinct long-difference results between education and experience warrants some consideration. First, experience may not have the same signaling role as education, and thus returns to experience may not decrease as much when the stock of experience increases. Second, education and experience may provide different skills for which the price elasticity of demand may also differ. Education systems may teach students skills that are not as valued by current labor markets. As the quantity of skills taught by education systems increases, prices may fall. Conversely, firms teach skills that are directly relevant for their operations and may also be updated to reflect new advancements in the field. Third, education systems focus on teaching hard basic skills. Firms also "teach" workers soft skills. If soft skills are deeply valued and scarce, increasing their quantity via more experience may not reduce their "price" as much.

the three panel specifications we do not find any correlation between the returns to experience and the mean number of years of education (col. (3)). We find, if anything, a positive correlation between the returns to experience and the returns of education (col. (4)) or its product with the mean number of years of education (col. (5)).[46]

6. Macroeconomic Impact

We now perform counterfactual experiments to further explore the relative importance of education and experience as factors of economic development. We require an accounting framework that tracks the accumulation of human capital and aggregates its returns across individuals. For this exercise, we assume that the measured differences in the returns mostly reflect differences in human capital accumulated in different countries, as in Lagakos et al. (2018b,a). However, Caselli and Ciccone (2019) argue that the estimated skill premia could reflect technological, institutional, organization and other differences across countries, in which case we over-estimate the contribution of human capital to economic development. Without further research, it is difficult to assess whether this disproportionately affects our interpretations of the education or experience premia, in developed countries or developing countries. In the rest of the analysis, we abstract from this issue and note that our analysis provides an upper bound of the contributions of both education and experience to economic development.

We also do not distinguish between human capital at work that is accumulated *actively* (via investment) or *passively* (via learning-by-doing). In the former case, we could imagine that less experienced workers accept initially lower wages in order to benefit from the training offered by their work environment (as, for example, for medical residents). Eventually, once their level of human capital increases, their wages also increase. We view human capital accumulated through experience as primarily a by-product of working, a form of learning-by-doing. One might ask whether this blurs the distinction between human capital and technology. We do not think so: indeed, early attempts to develop models of endogenous economic growth build on the idea that durable resources (such as knowledge, which is embodied in human capital) may

[46] Education and experience may not be substitutes for a number of reasons. One possibility is that both education and work experience teach skills that are not easily substitutable, in particular more theoretical skills vs. more applied skills that can only be learned on the job. Furthermore, education may teach hard skills vs. soft skills that one can only learn when working in a company. Soft skills may then become disproportionately important for productivity, and wages, to increase over time.

be generated as a by-product of operating a production technology, and that these resources could in future periods be used as inputs into the production technology: see Arrow (1962), Uzawa (1965) and Lucas (1988). For example, knowledge about how to operate a machine is distinct from the machine itself, and is embodied in a worker's human capital not in the machine. In the original formulation of Arrow (1962), the knowledge generated by production is proportional to output, in which case it would be no surprise to find that countries that produce output more efficiently also build human capital faster. That said, it is not known whether the production function parameters that produce output and those that produce knowledge are as tightly linked as such a formulation might suggest. The positive correlation between development and returns to experience suggests that such parameters are indeed linked, albeit with noise, suggesting that further work on this topic could be valuable for understanding the joint determinants of productivity in output and in learning-by-doing. Finally, our framework assumes that different levels of human capital are perfect substitutes.[47]

6.1. Accounting Framework

Each year t, $b_t = b_0 g_b^t$ agents are born. Agents of age a die with probability $\delta(a)$. The age structure of the model is a stationary distribution where the population of each age group rises over time by the factor g_b.

Schooling begins at age 6. Agents in school with schooling $s_{it} \geq 0$ proceed to $s_{it} + 1$ with probability $\pi_s(s_{it})$. Agents who leave school do not return.

Agents not in school work with probability $\pi_e(a_{it})$ where a_{it} is age. If they work, they generate earnings and accumulate experience. Earnings w_{it} of a working agent i at date t are $\log w_{it} = h_{it}$ where h_{it} is their human capital measured in units of the return it generates. While in school,

$$h_{it} = h_{i,t-1} + r_s(s_{it})$$

where $r_s(s_{it})$ is the return to schooling level s_{it}. When not in school,

[47] Our model assumes that workers of different schooling levels, or different human capital levels, are perfect substitutes even if their marginal contribution to output is different. If schooling groups are imperfect substitutes and the higher schooling groups are more plentiful in richer countries, then the Mincer returns may understate the importance of schooling to human capital in rich countries relative to in poorer countries (see Jones (2014, 2019) and Caselli and Ciccone (2019) for a discussion). That said, we would expect that, to the extent that different levels of schooling are poor substitutes, then the returns to schooling should not decline with the stock, for which the evidence in the previous Section is mixed. In particular, we found no such evidence in the case of human capital experience.

$$h_{it} = \begin{cases} h_{i,t-1} + r_e\left(s_{it}, p_{it}\right) & \text{with probability } \pi_e\left(a_{it}\right) \\ h_{i,t-1} & \text{otherwise} \end{cases}$$

where $r_e\left(s_{it}, p_{it}\right)$ is the return to experience, which may depend on schooling s_{it} and on potential experience $p_{it} \equiv a_{it} - s_{it}$.

Finally, GDP per person $pcGDP_t$ equals total earnings divided by the population.

We parameterize this framework for two countries: a representative developed country and a representative developing economy. Then we ask:

1. How much does output differ between the two economies?

2. What is the impact on the developing economy of changing the returns to education and/or experience and/or the schooling probabilities to those in the developed economy? We perform these experiments with three goals. One will be to see the potential long run impact on $pcGDP_t$. Another will be to examine the rate of transition. A third will be to gauge the impact on welfare.

6.2. Parameters

Once agents complete schooling (or reach 18 years of age, whichever is later), a share l_p of agents participate in the labor force. Those that participate face youth unemployment with probability u_y each year until they are 24. Above 24 they face unemployment each period with probability u, until they retire at age $R = 65$. We assume unemployment and participation are even across schooling and age groups.

Schooling returns $r_s\left(\cdot\right)$ have two values $\underline{r}_s$ and $\bar{r}_s$ such that:

$$r_s\left(s\right) = \begin{cases} \underline{r}_s & \text{if } s \leq 13 \\ \bar{r}_s & \text{if } s > 13 \end{cases},$$

reflecting the higher returns to college education ($\bar{r}_s > \underline{r}_s$). Experience returns $r_e\left(s, p\right)$ have three values:

$$r_e\left(s, p\right) = \begin{cases} \underline{r}_e & \text{if } s \leq 13 \text{ and } p \leq 25 \\ \bar{r}_e & \text{if } s > 13 \text{ and } p \leq 25 \\ 0 & \text{if } p > 25. \end{cases},$$

so that $r_e(s,p)$ flatten out with experience. If $\underline{r}_e < \bar{r}_e$, then the returns to experience also embody a college premium.

We require values of each of these parameters for a representative developing economy and a representative developed economy. We obtain the population growth rates g_b and the mortality functions $\delta(\cdot)$ from United Nations (2019), corresponding to the "More developed regions" and "Less developed regions". We use the medium variant forecasts over the 2020-2050 period, assuming that $\delta(a) = 1$ for $a \geq 99$.[48]

The return parameters are the average estimates for each group, weighted by population (see col. (1) of rows 9-10 in Table 2 and col. (1) of rows 14-15 in Table 1). For the developed economy, we use $\underline{r}_s$ = 6.7%, $\bar{r}_s$ = 13.0%, $\underline{r}_e$ = 4.4% and $\bar{r}_e$ = 4.2%. For the developing economy, we use $\underline{r}_s$ = 6.8%, $\bar{r}_s$ = 13.8%, $\underline{r}_e$ = 2.0% and $\bar{r}_e$ = 2.8%.

We set the schooling transition probabilities $\pi_s(\cdot)$ to match the schooling distribution in developed and developing economies (I2D2).[49] We assume agents may only accumulate up to 25 years of schooling as some countries only record schooling up to 25. Finally, we set the employment probabilities $\pi_e(\cdot)$ using participation, youth unemployment and adult unemployment rate averages reported by World Bank (2018a).

See Table 5 for a summary of the values of the parameters we used. See Web Appx. Section A.6 for details of the parameterization of the accounting framework.

6.3. Main Quantitative Findings

A typical developing economy has 24% of the GDP per capita of a typical developed economy (World Bank, 2018a). In the simulations, we find a value of 48.5%. The gap between 48.5 and 100 is 68% of the gap between 24 and 100. Thus, in our accounting model, differences in education, experience and the returns thereof, plus demographic and labor market differences, account for two thirds of the income gap.[50] Demographic and labor market differences are small, however, with the exception of labor market participation. Assume instead that demographic and labor market factors are the same as in the developed economy, allowing only differences in the stock of schooling and the returns to human capital. Then, we find that relative $pcGDP$ is 53.5 percent, accounting

[48] See Web Appx. Fig. 8(a) for the mortality distributions.

[49] See Web Appx. Fig. 8(b) for the distribution of schooling we use, based on the I2D2 data (1990-2016).

[50] We compare GDP per capita in levels. An alternative approach would be to compare GDP per capita in log levels. In that case, the gap is of 51%. In any case, the main point of our inquiry in this section is to compare the relative contribution of education and experience, so the absolute metric is not important.

for 61 percent of the income gap. Estimates in the literature range from one third or less (Hall and Jones, 1999; Bils and Klenow, 2000; Caselli, 2005) up to four fifths (Jones, 2014), but recent work by Hendricks and Schoellman (2018) finds that human capital accounts for 62 percent of the income gap. Lagakos et al. (2018a) find a value of 74% when estimating returns to education and experience among immigrants in the US. Thus, our results are broadly consistent with the recent literature.

What is the impact of education and experience *separately*? Assume that demographic and labor market factors are the same in the developing economy as in the developed economy, but that the returns to experience are the same, so that the only difference is in the quantity and returns to schooling. In this case, GDP is 75.6%, leaving 33.9% of the output gap unaccounted for. Instead suppose that demographic and labor market factors are again the same, but that the quantity and returns to education are the same, so that the only difference is in the returns to experience. Now GDP is 75.2%, leaving 34.4% of the output gap unaccounted for. Thus, separately, schooling and experience each account for about a third of the income gap.

Figure 4 displays $pcGDP_t$ in the developing economy after various reforms that might impact the schooling distribution and/or the returns to schooling and experience. First, in the NW panel, we increase the quantity of schooling, the returns to education and the returns to experience in the developing economy to the levels of the developed economy. Relative $pcGDP_t$ rises steadily for about 50 years before slowing and settling around 87 percent. Output per worker converges to 92 percent of that in the developed economy (not shown) – closer, because it takes account of the fact that participation is lower in the developing economy, but still some distance away.

The NE panel assumes the schooling distribution converges to that in the developed economy. This raises income per head to 69.4 percent. Part of this is attributable to the *experience college premium*. If we set $\bar{r}_e$ equal to $\underline{r}_e$ in the developing economy after transition (eliminating the premium), the impact of increasing education is lower, raising income to 65.2 percent of the developed economy. About a quarter of the jump from increasing schooling is due to the experience college premium.

This experiment assumed that the returns to schooling do not respond to increases in the quantity. We repeat the experiment of increasing the distribution of schooling to that in the developed economy, while also changing the schooling return parameters to match those in the developed economy – which are lower. See the SW panel. Changing the returns has less impact than changing the quantity of schooling alone, increasing output to 67.7 percent of the developed economy. Again, a portion of this is due to the experience premium. If we remove the premium, $pcGDP$ only rises to 63.6 percent.

The SE panel shows what happens if we increase the returns to experience only. This increases $pcGDP$ to 66.4 percent. This is similar to the impact of increasing the quantity of education. The panel also compares the impact from changing the returns to experience to changing the quantity of education (NE panel): the impact on income of changing the returns to experience is faster. This is notable as significant reform to the schooling system is likely costly and slow. On the other hand, if reforms that improve the returns to experience are institutional, costs may be lower.

Robustness. Web Appx. Section A.7 shows that our quantitative results hold when we perform a number of robustness experiments with different parameter values. For example, the results are robust to alterations in demographics, retirement ages, labor market conditions or sets of returns. Furthermore, the findings are unchanged if specific types of workers or countries are excluded, more prominence is given to youth unemployment, experience is allowed to be accumulated before age 18, human capital spillovers are accounted for, or the sample is divided into three income groups (low-, middle- and high-income countries). Web Appx. Section A.8 discusses the long-run welfare impacts of reforms. These impacts depend on the chosen discount rate, especially as reforms to experience have a faster impact than reforms to education. The same section then describes how our results can shed light on the long-run impact of reforms to the retirement age (since they affect the period of time over which the returns to experience or education pay off) or reforms that increase youth employment.

Finally, if human capital accumulation is not entirely a by-product of production (i.e. some investment in time is required) then the time spent by workers at work is reduced by the amount of time spent investing in human capital – let us call this “training.” If training is spread over one’s working life, then our estimates of the gap are not biased. However, as suggested Ben-Porath (1967), training is likely concentrated in a worker’s early years. This means that workers’ earnings in their early years are higher than measured, so that the experience slope is flatter. If workers in developed economies spend more time training than workers in developing economies, then this may lead estimates of the gap to be biased upwards. However, Web Appx. Fig. 7(b) shows that the number of hours worked does not significantly increases with experience, whether in developed or developing countries. Thus, any training that could differentially affect the returns in developed vs. developing countries would be at work.

To see whether the differences in the experience premium might be accounted for by differences in hours spent training, we draw on recent data from *OECD.Stat* (OECD, 2021). The data contain information on 33 developed economies and 4 developing economies.[51] Let us assume that all this time was compensated, and that none of it involved training that was performed simultaneously with production. Assuming the data are reasonably representative of developed and developing economies, we can use them to explore the impact of any adjustment of hours to account for time spent in formal or informal training on our measured gaps in the returns. To do this, first we obtain an estimate of the share of time that workers spend in training. Then, given that the Ben-Porath framework has human capital accumulation concentrated in the early years, we explore different scenarios for the years in which this training is concentrated.

First, in developed economies 59% of workers report spending time formally and/or informally training, compared to 31% in developing economies. On the other hand, when they do train, workers train slightly more in developing economies than in developed economies, 154 hours compared to 120 hours. This implies that a typical worker obtains 71 hours of training per year in developed economies, compared to 48 in developing economies. According to I2D2 data, workers in developed economies work 43 hours per week on average compared to 50 in developing economies. Assuming three weeks of time off, we get that workers in developed economies on average train for 3.4% of their working time, compared to 2.0% in developing economies.[52]

Now, suppose that this training is entirely concentrated among the least-experienced workers. This is an extreme assumption perhaps, but it does serve to verify whether our results might be sensitive to the potential issue described above.

Suppose these workers are in the lowest two experience bins, i.e. 0-4 and 5-9. In

[51] Colombia, Costa Rica, Mexico and Turkey

[52] Recall that we estimate returns separately for workers with and without college. College-educated workers do receive slightly more training than their less-educated counterparts. However, if we focus on the college-educated we get training ratios of 3.5% and 2.2% for developed and developing countries, respectively. Since the differences are very small, we abstract from them for clarity.

this case, the coefficients on the other bins in Figure 1 are over-estimated relative to bin 0-4. The coefficients on workers in the 5-9 year bin are not over-estimated relative to bin 0-4, however, since both groups train. There are 8 bins so, abstracting from mortality, training is concentrated among one quarter of the workers. This implies that workers in the 0-4 and 5-9 experience bins spend 13% of their time training in developed economies, compared to 8% in developing economies. What does this imply for the returns? According to our benchmark estimates, the gap in experience returns between developed and developing economies was 2.4% for workers without college, or 1.4% percent for workers with college. If we adjust the returns in Figure 1 based on the above scenario and recompute the gap, it declines to 2.2% for workers without college and 1.2% for workers with college. These are declines of 8.3% and 14.3% respectively. Thus, while the magnitude of our estimated gaps are somewhat sensitive to assumptions regarding worker training early in their careers, the difference is small. See Web Appx. Table A.11.

Suppose instead that all training is performed by workers in the lowest experience bin, i.e. 0-4. In this extreme case, the coefficients on the other bins in Fig. 1 are over-estimated relative to bin 0-4, including the 5-9 bin. There are 8 bins so, abstracting from mortality, training is concentrated among one eighth of the workers. This implies that workers in the 0-4 experience bin spend 25% of their time training in developed economies, compared to 15% in developing economies. If we recompute the gap, it declines to 2.2% for workers without college and 1.2% for workers with college. These are declines of 25% and 35.7% respectively. Thus, even under a scenario where all training is complete within 4 years, a significant gap in returns remains.

7. Conclusion

In this paper, we provide additional global evidence that experience matters.

First, we studied wage-experience profiles and obtained returns to experience, and education, using data from 1,084 household surveys and census samples across 145 countries. Across many specifications, we found that returns to experience are strongly correlated with economic development and that workers in developed countries may accumulate twice more human capital at work than workers in developing countries.

Second, exploiting the fact that we were able to estimate returns to experience for more than 100 countries and multiple years of data during the period 1990-

2016, we employed panel regressions to investigate how changes in the returns to experience over time correlated with several important factors. Returns to experience are positively correlated with economic development and are lower for individuals that experienced a recession in the initial years of their career. Economies that transitioned out of communism made past experience obsolete and thus exhibited lower returns to experience. Returns to experience had no correlation with initial stocks of experience or education. In particular, the latter two results suggest that experience may not have decreasing returns and may not be easily substituted by more education.

Third, our accounting framework showed that the contribution of experience to human capital and economic development is as important as the contribution of education itself. Indeed, the long run impact is similar whether developing countries achieve the returns to experience or attain the same distribution of education as developed economies. However, raising returns to experience has a faster impact.

Finally, returns to experience only greatly increase as economies become developed. This suggests that returns to experience might proxy for an economy's ability to converge and catch up to high-income economies.

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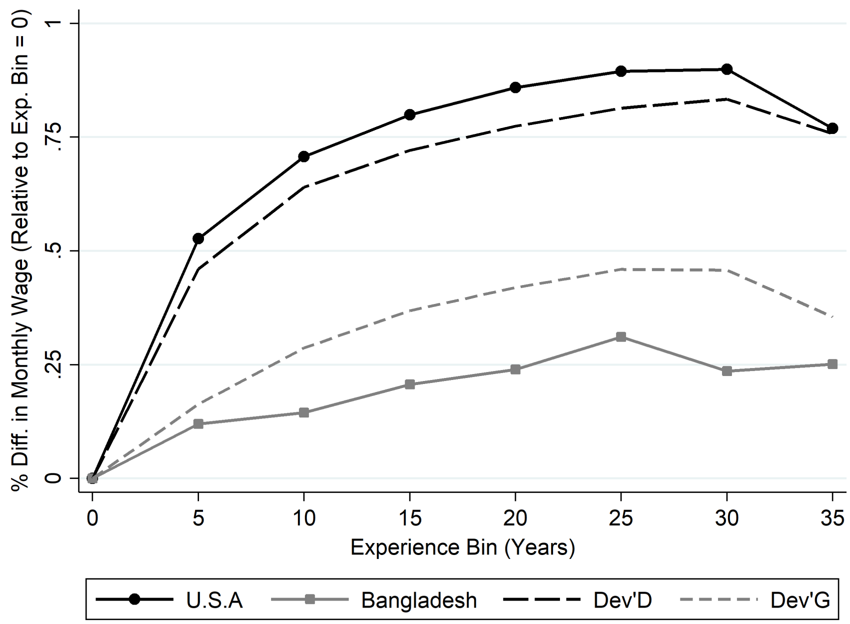
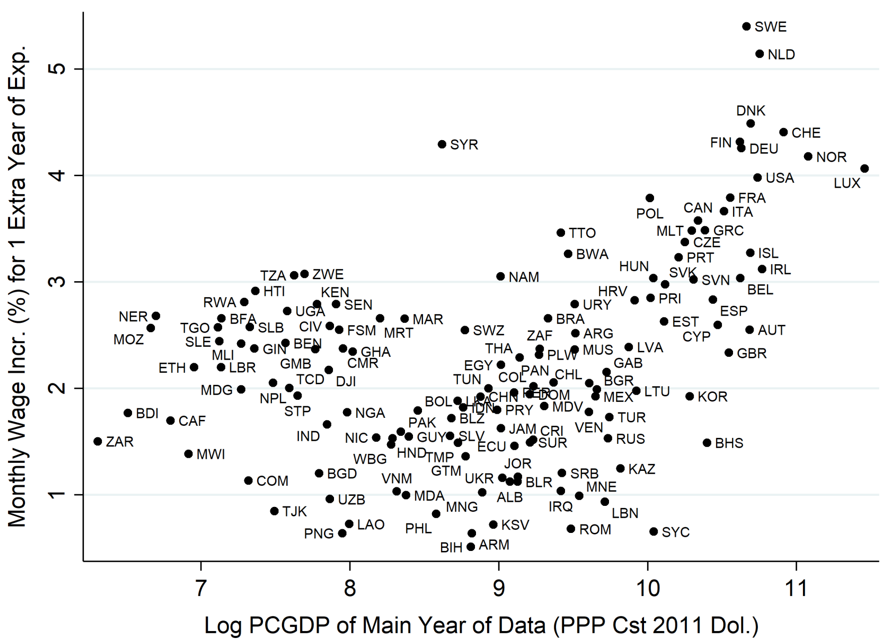
Figure 1: Wage-Experience Profiles for Developed vs. Developing Countries



Notes: This figure shows the average wage differential for the seven experience bins for the U.S., Bangladesh, developed countries (Dev'D) and developing countries (Dev'G) (using population ca. 2017 as weights). The 0 experience bin is the omitted group. Only samples from 1990 to 2016 are used.

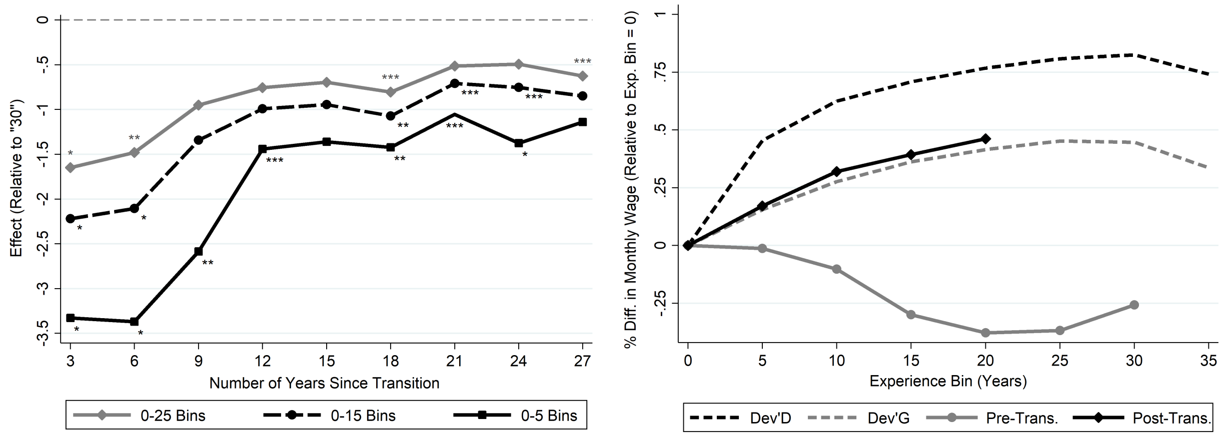
Figure 2: Estimated Returns to Experience and Log Per Capita GDP



Notes: This figure plots the relationship between the estimated returns to experience and log per capita GDP (PPP; constant 2011 USD; for the mean year in the data for each country). The sample consists of 138 countries (145 countries - 7 countries in the bottom 5% in estimated returns).

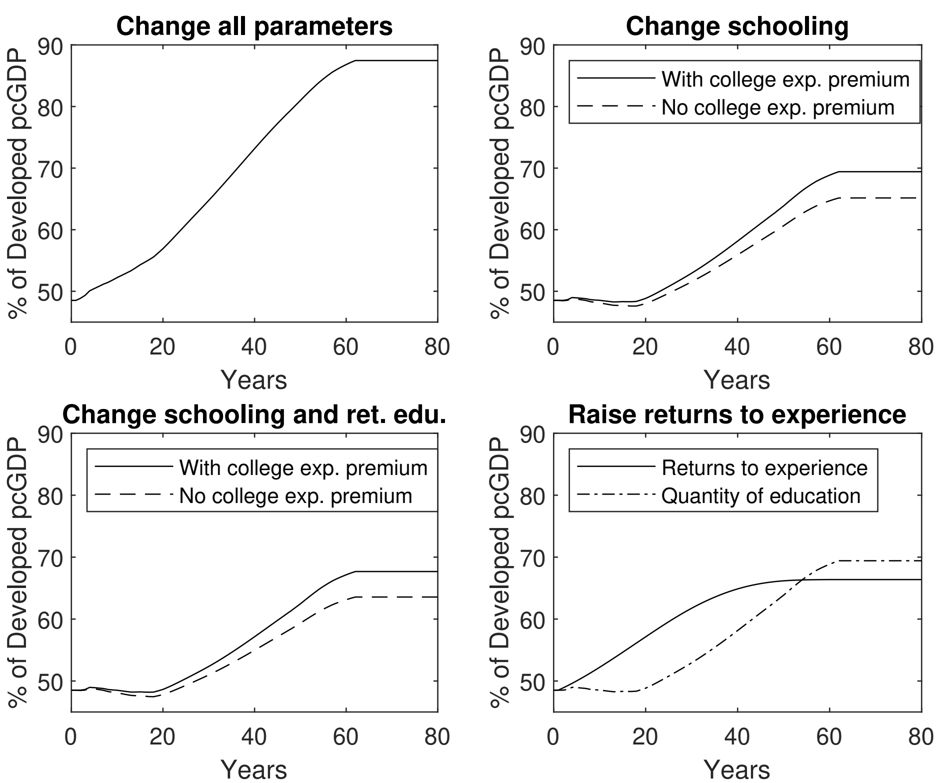
Figure 3: Effect of the Number of Years Since Transition from Communism

(a) Overall Returns to Exp. and Communism **(b)** Communist vs. Post-Communist Experience



Note: Subfig. 3(a) shows the effects of the number of years since the country transitioned out of communism on the returns to experience (estimated for the 0-25, 0-15 and 0-5 bins). These results are obtained through panel regression estimations for 951 country-years available for the period 1990-2016 (145 country fixed effects and 27 year fixed effects included). The specification includes dummy variables corresponding to different groupings of years. The groupings are as follows: "3" includes 1-3 years, "6" includes 4-6 years, ..., and "27" includes 25-27 years. "30" (28-+) is the omitted category. Robust SEs clustered at the country level. Subfig. 3(b) shows for 40 ex-communist countries the (pop.-weighted) wage-experience profiles for communist and post-communist experience separately. The figure also shows the (pop.-weighted) profiles that we obtained for developed and developing countries.

Figure 4: Counterfactual Experiments, Income Levels



Notes: Per capita GDP (pcGDP) in the developing economy is measured relative to the developed economy. The dashed lines in the NE and SW panels assume that there is no experience premium to college education. The dot-dashed line in the SE panel ("Quantity of education")) is the same as the path representing the reform to schooling in the NE panel ("With college exp. premium").

Table 1: Returns to Work Experience by Development Status

Dependent Variable:	Estimated Returns to Potential Work Experience								
Return Specification:	(1) No Cohort FE			(2) Decadal Cohort FE			(3) Events Cohort FE		
2 Development Groups:	G	D - G	D	G	D - G	D	G	D - G	D
1. Baseline	1.7***	1.5***	3.2***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
2. Log Hourly Wage	1.8***	1.3***	3.1***	0.8***	1.8***	2.6***	0.4**	2.0***	2.4***
3. Log Hours Worked	0.0	0.3***	0.3***	0.3***	0.0	0.3***	0.4***	-0.1	0.3***
4. 0-25 Exp. Bins Only	2.0***	1.8***	3.8***	1.3***	2.1***	3.4***	1.1***	2.1***	3.2***
5. 0-15 Exp. Bins Only	2.4***	2.4***	4.8***	1.7***	2.7***	4.4***	1.4***	2.8***	4.1***
6. 5-35 Exp. Bins Only	1.5***	1.1***	2.6***	0.9***	1.3***	2.2***	0.6***	1.4***	2.0***
7. Lagakos et al 2018 (m)	1.9***	1.6***	3.5***	0.9***	2.1***	3.1***	0.6***	2.2***	2.7***
8. Lagakos et al 2018 (h)	1.9***	1.5***	3.4***	0.9***	2.1***	3.0***	0.6***	2.1***	2.6***
9. Cntry Pop. 2017 as Wgts	1.8***	1.8***	3.6***	1.5***	1.5***	3.0***	1.1***	1.7***	2.8***
10. Yrs of Educ. $\leq$13	1.7***	1.7***	3.4***	1.4***	1.6***	3.1***	1.4***	1.6***	3.0***
11. Yrs of Educ. $>$13	2.1***	1.2***	3.2***	1.7***	1.2***	3.0***	1.5***	1.2***	2.7***
12. Yrs of Educ. $\leq$13 & Wgts	1.7***	2.0***	3.7***	1.8***	1.5***	3.3***	1.7***	1.7***	3.4***
13. Yrs of Educ. $>$13 & Wgts	2.4***	1.0***	3.5***	2.2***	1.1***	3.3***	1.9***	1.2***	3.1***
14. 0-25, Educ. $\leq$13 & Wgts	2.0***	2.4***	4.4***	2.2***	1.8***	3.9***	2.0***	2.0***	4.1***
15. 0-25, Educ. $>$13 & Wgts	2.8***	1.4***	4.2***	2.5***	1.4***	3.9***	2.2***	1.5***	3.7***
16. Row 14, Lagakos et al '18	2.2***	2.2***	4.4***	2.2***	1.7***	3.9***	2.3***	1.6***	3.9***
17. Row 15, Lagakos et al '18	2.9***	1.6***	4.5***	2.7***	1.3***	4.0***	2.4***	1.3***	3.7***

Notes: This table shows the constant, i.e. the mean return for developing countries ("*G*"), and the coefficient of the developed country dummy, i.e. the difference between the mean returns of developed countries and developing countries ("*D-G*"). The mean return for developed countries ("*D*") is obtained by adding the constant and the coefficient of the developed country dummy. See text for details for each row and each column (N for row 1 = 145; 12; 122). Robust SEs: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Returns to Education by Development Status

Dependent Variable:	Estimated Returns to Education								
Return Specification:	(1) No Cohort FE			(2) Decadal Cohort FE			(3) Events Cohort FE		
2 Development Groups:	G	D-G	D	G	D-G	D	G	D-G	D
1. Baseline	8.7***	0.3	9.0***	8.4***	0.3	8.8***	8.4***	0.3	8.6***
2. Log Hourly Wage	8.4***	0.4	8.8***	7.9***	0.8	8.6***	7.8***	0.6	8.5***
3. Log Hours Worked	0.1	0.4**	0.5***	0.2*	0.3	0.5***	0.2**	0.3	0.5***
4. Lagakos et al 2018 (m)	7.0***	1.5***	8.5***	6.5***	1.6***	8.1***	6.5***	1.5***	7.9***
5. Lagakos et al 2018 (h)	7.7***	0.6	8.4***	7.3***	0.7	8.0***	7.2***	0.6	7.9***
6. Cntry Pop. 2017 as Wgts	7.9***	2.4*	10.3***	7.8***	2.1	9.9***	7.7***	2.1	9.8***
7. Yrs of Educ. ≤13	7.2***	-1.1*	6.2***	7.2***	-0.8	6.4***	7.2***	-0.8	6.40***
8. Yrs of Educ. >13	15.8***	-3.1*	12.8***	15.8***	-3.9**	11.9***	15.5***	-4.0**	11.6***
9. Yrs of Educ. ≤13 & Wgts	6.8***	-0.1	6.7***	6.8***	-0.2	6.6***	6.8***	-0.2	6.6***
10. Yrs of Educ. >13 & Wgts	13.8***	-0.7	13.0***	13.4***	-0.4	13.0***	13.1***	-0.4	12.7***
11. Row 9 Lagakos et al 18	5.4***	0.6	6.0***	5.2***	0.8	6.0***	5.2***	0.8	5.9***
12. Row 10 Lagakos et al 18	15.1***	-3.2***	11.8***	14.4***	-3.1***	11.3***	14.2***	-3.3***	11.0***

Notes: The dependent variable is the estimated return to education, i.e. the coefficient of the number of years of education.

Table 3: Development, Recessions, Transitions and Returns to Work Experience

Dep. Var.:	Estimated Returns to Potential Work Experience (0-15 Bins) of Country c in Year t						
	(1)	(2)		(3)	(4)	(5)	(6)
Var. of Interest:	High-Income	High-Income	Middle-Income	Share 0-5 Years Exp. with Growth ≤ -1%	≤ -3%	≤ -5%	Years Since Transition
Panel A:	*Long-Difference Panel Regression (N = 244; 226 in (3)-(5))*						
Var. of Interest c, t	1.11**	1.63***	0.47	-1.32**	-1.68***	-2.24***	0.08***
	[0.45]	[0.61]	[0.41]	[0.50]	[0.52]	[0.78]	[0.02]
Panel B:	*Long-Diff. Panel Regression, Ctrl for High-Income Dummy (N = 244; 226 in (3)-(5))*						
Var. of Interest c, t				-1.31***	-1.64***	-2.05**	0.07***
				[0.48]	[0.51]	[0.79]	[0.02]
High-Income c, t				1.06***	1.00***	0.83**	0.97**
				[0.31]	[0.36]	[0.41]	[0.41]
Panel C:	*Five-Year Panel Regression (N = 420; 390 in (3)-(5))*						
Var. of Interest c, t	1.03**	1.11*	0.08	-0.96	-1.15*	-1.52*	0.07**
	[0.52]	[0.64]	[0.39]	[0.60]	[0.63]	[0.88]	[0.03]
Country FE, Year FE	Y	Y		Y	Y	Y	Y

Note: This table uses panel regressions to explore how returns to experience correlate with various country-level factors. These include development status, recessions, and duration (no. of years) post communism. The sample consists of 122 countries with returns available for several years. Panels A-B: First and last years of data only (weighted by the number of years between the first year and last year). Panel C: Five-year panel for $t = \{1994$ (1990-1996), 1999 (1997-2001), 2004 (2002-2006), 2009 (2007-2011), 2014 (2012-2016)$\}$. Robust SEs (clustered at the country level in Panel C): * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Stocks of and Returns to Education and Work Experience

Dep. Var.:	Estimated Returns to Education and Experience of Country c in Year t				
	Col. (1): Education	Col. (2)-(5): Potential Work Experience (0-15 Bins)			
	(1)	(2)	(3)	(4)	(5)
Var. of Interest:	Mean Years Education	Mean Years Experience	Mean Years Education	Returns to Education	Education (Years x Returns)
Panel A:	*Long-Difference Panel Regression (N = 244)*				
Var. of Interest c, t	-1.23***	0.13	-0.08	0.11***	0.01***
	[0.41]	[0.08]	[0.10]	[0.03]	[0.00]
Panel B:	*Long-Difference Panel Regression, Control for High-Income Dummy (N = 244)*				
Var. of Interest c, t	-1.23***	0.12	-0.08	0.11***	0.01***
	[0.41]	[0.08]	[0.10]	[0.03]	[0.00]
High-Income c, t	0.36	1.06**	1.10**	1.06**	1.08**
	[0.84]	[0.41]	[0.45]	[0.45]	[0.45]
Panel C:	*Five-Year Panel Regression (N = 420)*				
Var. of Interest c, t	-0.12	0.07	-0.02	0.12**	0.01**
	[0.46]	[0.09]	[0.10]	[0.05]	[0.01]
Country FE, Year FE	Y	Y	Y	Y	Y

Note: This table uses panel regressions to explore how returns to education and experience correlate with various country-level factors. These include a country's mean num. of years of education, mean num. of years of experience and/or return to education. The sample consists of 122 countries with returns available for several years. Panels A-B: First and last years of data only (weighted by the num. of years between the first year and last year). Panel C: Five-year panel for t = {1994 (1990-1996), 1999 (1997-2001), 2004 (2002-2006), 2009 (2007-2011), 2014 (2012-2016)}. Robust SEs (clust. at the country level in Panel C).

Table 5: Parameters Used For Quantitative Experiments

Control Parameters	Parameter	Developed	Developing	High (H)	Middle (M)	Low (L)
Population growth rate	g_b	0.2%	0.8%	0.2%	0.6%	2.2%
Mortality function	$\delta(\cdot)$	See text	See text	See text	See text	See text
Labor force participation	l_p	84.0%	77.1%	84.0%	75.7%	89.6%
Youth unemployment	u_y	13.7%	13.0%	13.7%	13.8%	6.3%
Adult unemployment	u	4.9%	3.7%	4.9%	3.8%	2.5%
Retirement age	R	65	65	65	65	65
Schooling	–	See text	See text	See text	See text	See text
Mortality	$\delta(\cdot)$	See text	See text	See text	See text	See text
Return Parameters	Parameter	Developed	Developing	High (H)	Middle (M)	Low (L)
Ret. to exp., before college	$\underline{r}_e$	4.4%	2.0%	4.4%	2.1%	1.8%
Ret. to exp., college +	$\bar{r}_e$	4.2%	2.8%	4.2%	2.8%	2.8%
Ret. to educ., before college	$\underline{r}_s$	6.7%	6.8%	6.7%	8.7%	5.0%
Ret. to educ., college +	$\bar{r}_s$	13.0%	13.8%	13.0%	12.8%	14.6%

Notes: This table summarizes the parameters used for the quantitative experiments.