FOR ONLINE PUBLICATION: APPENDIX

Human Capital Accumulation at Work:
Estimates for the World and Implications for Development

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A.1 Quality of the I2D2 Database

We use returns for 1,084 household surveys and census samples (1,073 surveys and 11 censuses) across 951 country-years and 145 countries for the period 1990-2016. Our main analysis uses data on the following variables: wages, age and education (as well as gender). To assess the quality of our data, we examine to what extent the I2D2 data generate patterns that are aligned with those observed in other global databases. One particular concern is that data quality is lower for sub-Saharan African (SSA) countries. We thus also examine whether these patterns specifically align for SSA.

Average Wages. As shown by eq. (1) in the main text, the country-level returns are estimated for each country one by one. In I2D2, wages are reported in current prices and in the local currency unit (LCU) used by each survey/country-year-sample. Since we systematically include country-year-sample fixed effects in eq. (1) (the θ), this absorbs variations in currencies and prices – which can therefore be ignored as we de facto compare individuals with more experience vs. less experience *within* the same country-year-sample. Therefore, the returns to experience and education can be estimated without having to first correct for currency changes and inflation/deflation across samples within countries.

However, to compare average wages in I2D2 and per capita GDP from other sources (we use the *World Development Indicators* database of the World Bank), we express all wages in the same LCU, then use the GDP deflator data to express wages in constant prices (ibid.; we use 2010), and finally use exchange rate data (ibid.) to convert them to USD. With 1,084 samples and numerous currency changes – some surveys also report wages in hundreds or thousands, which necessitates corrections –, harmonizing the data is a necessarily difficult task. Nevertheless, for 681 surveys/country-year-samples for which log per capita GDP is available the same year (also in 2010 constant prices), we find a very strong correlation of about 0.9 between log wages and log per capita GDP.[1]

The correlation is 0.86 for developed countries and 0.71 for developing countries. Indeed, developing countries have experienced more currency changes and inflationary episodes than developed countries post-1990, complicating the harmonization process of their wage data. While we did our best to track changes, there are still anomalies. The correlation is higher for sub-Saharan Africa (0.78) than for developing countries overall. Finally, the summary statistics for the two variables, the four groups of countries, and the 681 samples are shown below in Web Appx. Table A.1.

Table A.1: Log Mean Yearly Earnings for Different Groups of Countries

Group of Countries	Variable (2010 cst USD)	Samples	Mean	SD	Min	Max
All	Log pcGDP (WDI)	681	8.27	1.33	5.27	11.42
All	Log Mean Yearly Earnings (I2D2)	681	8.27	1.19	5.64	11.23
Developed (as of 2017)	Log pcGDP (WDI)	152	10.54	0.29	9.42	11.42
Developed (as of 2017)	Log Mean Yearly Earnings (I2D2)	152	10.28	0.59	6.27	11.23
Developing (as of 2017)	Log pcGDP (WDI)	529	7.80	0.92	5.27	9.92
Developing (as of 2017)	Log Mean Yearly Earnings (I2D2)	529	7.85	0.79	5.64	10.52
Sub-Saharan Africa	Log pcGDP (WDI)	94	7.38	1.24	5.27	9.06
Sub-Saharan Africa	Log Mean Yearly Earnings (I2D2)	94	7.72	0.98	5.64	10.25

Wage Variance. To study whether I2D2 generates patterns that broadly make sense in terms of wage variance, we consider three wage variance measures that bypass the harmonization issues highlighted above: the 90/10 log earnings ratio, the 50/10 log earnings ratio (lower tail inequality) and the 90/50 log earnings ratio (upper-tail inequality). We obtain the (pop.-weighted) means of these measures for different groups of countries. Web Appx. Table below A.2 shows that the log earnings ratios are not dramatically different between developed countries, developing countries, and SSA countries. However, and as expected, wage variance, hence inequality, is slightly higher in developing countries than in developed countries. It is also slightly higher in sub-Saharan African countries than in developing countries overall. Finally, inequality (90/10) is driven by upper tail inequality (90/50).

Age Structure. It is also important to verify that the I2D2 data generate patterns that are broadly consistent in terms of age structure. For each country-year-sample, we obtain the mean age in the data (considering all individuals from 0 to 99). We use the age structure data from the *World Population Prospects* database of United Nations (UN) to obtain the mean age for the same country-years. We compare the age structures for 1,036 samples for which the UN data is also available. The correlation between the I2D2 and the UN data is 0.94, 0.89, 0.92 and 0.91 for all countries, developed countries only, developing countries only, and sub-Saharan African countries only, respectively. Web Appx. Table

[1]We use population weights since the average returns obtained for developed countries and developing countries were also estimated using population weights. Indeed, discrepancies for larger countries are more consequential for our analysis.

A.3 below shows that the summary statistics are very similar between I2D2 and the UN, although the UN data is often interpolated and/or extrapolated given that it disproportionately relies on census data - censuses are infrequent in many developing countries during the 1990-2016 period.

Table A.2: Wage Variance Measures for Different Groups of Countries

Group of Countries	Measure	Samples	Mean	SD	Min	Max
All	90/10	1,083	1.33	0.16	1.07	3.98
Developed	90/10	201	1.29	0.07	1.12	1.44
Developing	90/10	882	1.34	0.17	1.07	3.98
Sub-Saharan Africa	90/10	155	1.46	0.23	1.15	3.72
All	90/50	1,083	1.13	0.06	1.00	2.63
Developed	90/50	201	1.10	0.02	1.06	1.15
Developing	90/50	882	1.13	0.06	1.00	2.63
Sub-Saharan Africa	90/50	155	1.18	0.08	1.06	2.63
All	50/10	1,083	1.18	0.09	1.00	2.69
Developed	50/10	201	1.17	0.06	1.05	1.31
Developing	50/10	882	1.18	0.09	1.00	2.69
Sub-Saharan Africa	50/10	155	1.23	0.12	1.00	2.69

Table A.3: Mean Age for Different Groups of Countries

Group of Countries	Source	Samples	Mean	SD	Min	Max
World	I2D2	1,036	31	6	18	56
	UN	1,036	29	5	19	43
Developed	I2D2	199	41	3	29	46
	UN	199	40	2	29	43
Developing	I2D2	837	30	5	18	56
	UN	837	28	4	19	42
sub-Saharan Africa	I2D2	158	24	3	18	36
	UN	158	23	3	19	35

Education. It is also important to verify that the I2D2 data generate patterns that are broadly consistent in terms of educational attainment. For the comparison, we rely on the *Barro-Lee* [BL] *Educational Attainment Database* (Barro and Lee, 2013). The BL database reports for many country-years the *Average Years of Schooling Attained* for individuals aged 15+ as well as for individuals aged 25+. For our main sample, we use the I2D2 database to obtain the same measures.

For 888 I2D2 samples with a corresponding observation in the BL database, Web Appx. Table A.4 below shows the summary statistics of the two variables. The numbers are broadly comparable between I2D2 and BL. For 15+ individuals, the correlation between I2D2 and BL is 0.88, 0.87, 0.79 and 0.88 for all countries, developed countries, developing countries, and sub-Saharan African countries, respectively. For 25+ individuals, the corresponding correlations are 0.89, 0.89, 0.82, and 0.87. Since many individuals in the world still study after age 15, we believe the 25+ measures are better measures of global educational attainment. The correlation is not that much weaker in developing countries than in developed countries, and very high in sub-Saharan Africa.

Self-Employment. For one of the main robustness checks, we exclude self-employed individuals as in Lagakos et al. (2018). We use the data from the *World Development Indicators* database of the World Bank (WB), which in turn rely on estimates from the International Labor Organization (ILO). One issue with the WB-ILO data is that some estimates come from censuses or surveys whereas other estimates are what they call "modelled", which in this case means interpolated or extrapolated in some specific ways that are not explained in detail by WB-ILO. WB-ILO is thus less accurate than our data. However, since no other global sources of self-employment data exist, we use WB-ILO.

Table A.4: Mean Years of Education for Different Groups of Countries

Group of Countries	Mean Yrs of Educ.	Samples	Mean	SD	Min	Max
All	15+ (I2D2)	888	7.8	2.2	1.9	13.8
	15+ (Barro-Lee)	888	7.4	2.4	0.9	13.2
	25+ (I2D2)	888	7.5	2.4	1.4	13.9
	25+ (Barro-Lee)	888	7.0	2.6	0.8	13.4
Developed	15+ (I2D2)	202	11.8	1.2	8.4	13.8
	15+ (Barro-Lee)	202	11.3	1.3	7.0	13.2
	25+ (I2D2)	202	11.9	1.3	8.2	13.9
	25+ (Barro-Lee)	202	11.4	1.4	6.6	13.4
Developing	15+ (I2D2)	686	7.3	1.7	1.9	13.5
	15+ (Barro-Lee)	686	6.8	1.9	0.9	12.8
	25+ (I2D2)	686	6.9	1.9	1.4	13.6
	25+ (Barro-Lee)	686	6.4	2.2	0.8	13.1
Sub-Saharan Africa	15+ (I2D2)	106	7.1	1.8	1.9	10.4
	15+ (Barro-Lee)	106	6.6	2.4	0.9	9.7
	25+ (I2D2)	106	6.7	2.0	1.4	9.5
	25+ (Barro-Lee)	106	6.2	2.4	0.8	9.4

Web Appx. Table A.5 below shows the summary statistics for 966 I2D2 samples for which we have corresponding data in WB-ILO. Differences can be observed for developing countries. Likewise, the correlation is 0.75, 0.90, 0.68 and 0.86 for all countries, developed countries, developing countries and sub-Saharan African countries, respectively. The lower correlation for developing countries than for developed countries or sub-Saharan African countries is, in our view, not surprising. Self-employment shares changed little during the period in developed countries – where they remained low – and sub-Saharan African countries – where they remained high. Self-employment shares changed more significantly over time in more developed developing countries. Since the WB-ILO estimates are often interpolated/extrapolated, discrepancies are more likely for this group of countries.

Table A.5: Self-Employment Shares for Different Groups of Countries

Group of Countries	Variable	Samples	Mean	SD	Min	Max
All countries	Self-Empl. Share (WB-ILO)	966	0.51	0.25	0.02	0.96
All countries	Self-Empl. Share (I2D2)	966	0.34	0.16	0.00	1.00
Developed	Self-Empl. Share (WB-ILO)	203	0.15	0.07	0.07	0.37
Developed	Self-Empl. Share (I2D2)	203	0.14	0.07	0.00	0.37
Developing	Self-Empl. Share (WB-ILO)	763	0.56	0.23	0.02	0.96
Developing	Self-Empl. Share (I2D2)	763	0.37	0.15	0.00	1.00
Sub-Saharan Africa	Self-Empl. Share (WB-ILO)	142	0.67	0.31	0.16	0.96
Sub-Saharan Africa	Self-Empl. Share (I2D2)	142	0.39	0.24	0.00	0.86

Mincerian R2s. Finally, we examine the (adjusted) R-squared (R2) that we obtain for each country.[2] These "Mincerian" R2s capture to what extent wages are explained by the Mincerian control variables,

[2] The R2 are adjusted for the country-year-sample fixed effects.

hence education, experience and gender. As can be seen in Web Appx. Table A.6 below, the R2s are higher on average in developing countries than in developed countries, with the R2s being in-between the two for sub-Saharan African countries. That might not be surprising if the number of years of education more strongly predict wages in developing countries than in developed countries. Indeed, in developed countries, the unobserved "quality" of schooling, in particular of college education (e.g., which university one went to), may also strongly explain wage differences across individuals.

Table A.6: Mincerian R-Squared for the 145 Countries

Group of Countries	Variable	Countries	Mean	SD	Min	Max
All Countries	Adj. R2	145	0.41	0.19	0.03	0.99
Developed Countries	Adj. R2	38	0.25	0.10	0.08	0.94
Developing Countries	Adj. R2	107	0.44	0.19	0.03	0.99
Sub-Saharan Africa	Adj. R2	39	0.34	0.23	0.09	0.87

A.2 Details on the Experience-Time-Cohort Problem

The Experience-Time-Cohort Problem. As Heckman and Robb (1985, p.137) show, the literature considers earnings W of individuals i as a function of schooling s, work experience e, age a, time t (e.g., the survey is from 2008) and cohort c (e.g., individual i is born in 1982). For the sake of simplicity, we consider a linear function and the number of years of experience instead of experience bins:

$$W_i = \alpha + \alpha_s s + \alpha_e e + \alpha_a a + \alpha_t t + \alpha_c c + \epsilon_i \tag{A.2.1}$$

Wages increase with schooling ($\alpha_s > 0$) and work experience ($\alpha_e > 0$). Age could have an effect that is independent of the effect of work experience. As Heckman and Robb (1985, p.137) explain, "age may be a direct determinant of earnings through maturation and other physiological effects". In that case, wages increase with age ($\alpha_a > 0$). However, employers could also discriminate against older workers ($\alpha_a < 0$). There are also time effects. In contexts where the economy is growing (declining), time effects will be positive (negative), and thus $\alpha_t > 0$ ($\alpha_t < 0$). Finally, there could be cohort effects. For example, Heckman and Robb (p.138 1985) explain that "workers reared in the Depression may be pessimistic or risk averse while workers reared in the 1950s may be overly optimistic". We could also imagine that people born earlier did not have access to a good health infrastructure in countries where modern health systems were established later on. In that case, and if past health investments matter for productivity, wages will increase with the year of birth/cohort ($\alpha_c > 0$).

Without retrospective data on individual employment, experience tends to be estimated as age minus schooling ($e_i = a_i - s_i$). Time is then equal to age plus the year of birth ($t = a_i + c_i$). Thus, one cannot simultaneously include schooling, experience, age, time fixed effects and cohort fixed effects in the same estimation. In that case, and not including age and cohort fixed effects, we de facto estimate:

$$W_i = \alpha + (\alpha_t + \alpha_c) * t + (\alpha_s + \alpha_a - \alpha_c) * s + (\alpha_e + \alpha_a - \alpha_c) * e + \epsilon_i \tag{A.2.2}$$

In other words, the coefficient of experience (and schooling) captures the age and cohort effects.

Distinguishing Experience Effects and Age Effects. One cannot distinguish the effects unless one has separate data on age and past employment. However, if one considers experience as *life experience* rather than work experience per se, one may be interested in $\alpha_e + \alpha_a$. Obviously, there is still an issue if employers discriminate relatively more against older (or younger) workers. Also, since we are mostly interested in the difference between developed and developing countries, that is only an issue for us if richer countries discriminate more (or less) against older (or younger) workers than poorer countries. Without country-level data on age-based discrimination, we abstract from this issue in our analysis and acknowledge that our experience effects may capture age affects.

Distinguishing Experience Effects and Cohort Effects. As can be seen in equation A.2.2, the coefficient of experience captures the cohort effects. In particular, if later cohorts benefit from say new technologies raising productivity, we expect positive cohort effects ($\alpha_c > 0$). In that case, the estimated effect of experience (+ age) will be lower than the true effect ($\alpha_e + \alpha_a - \alpha_c < \alpha_e + \alpha_a$), and the returns are downward-biased. Conversely, if there is fast population growth and cohort size negatively affects wages, we expect negative cohort effects ($\alpha_c < 0$) and the returns to be upward-biased. Again, that is only an issue for us if richer countries have different cohort effects than poorer countries.

Specific Related Issues in our Sample of 145 Countries. Since we focus on workers aged 18-67 in samples from 1990-2016, we study individuals born between 1923 and 1998. Without controls for cohort effects, various factors may affect our results. First, investments in human capital and/or new technologies may lead to positive cohort effects ($\alpha_c > 0$), where later cohorts have better unobservable abilities over time. Returns are then downward-biased. The question is whether this is more true in developed countries or in developing countries.[3] Second, faster population growth in poorer countries could have reduced their cohort effects. Indeed, if cohort size negatively affects wages, one could expect fast population growth to reduce wages over time ($\alpha_c < 0$). In that case, the returns of poorer countries are upward-biased. Third, there may be selection effects due to very high child and adult mortality rates in the past in poorer countries (or in countries with major pandemics such as HIV). If "survivors" from these times were positively selected, older workers still alive in the data may be intrinsically more productive. In that case, cohort effects may end up negative ($\alpha_c < 0$), and the returns of poorer countries are upward-biased. Finally, the experience of older cohorts may be less valuable ceteris paribus than the experience of younger cohorts in countries that have experienced a dramatic change in their economic system, for example in the ex-USSR. Given a same level of experience, older cohorts will be paid less than younger cohorts, so cohort effects are positive ($\alpha_c > 0$). Therefore, the returns of these countries may be downward-biased.

A.3 Robustness Checks for the Cohort Effects

This section shows results hold if we use different approaches to capture cohort effects. Remember that the individuals in our full sample are born between 1923 and 1998.

No Cohort FE. Row 1 of Appendix Table A.8 shows the "no cohort FE" results when restricting the sample to countries with at least 3 years (Col. (1); N = 104), 5 years (Col. (2); N = 80) or 8 years of data (Col. (2); N = 55). We lose too many countries when using countries with more than eight years of data.

Decadal Cohort FE. In the main paper, we use decadal cohort fixed effects (1920s, ..., 1990s) for

[3] Developed countries have grown relatively fast during the 1923-1998 period, since they became "developed". However, life expectancy has dramatically improved in developing countries even when per capita incomes did not. Since increases in life expectancy reflects major health improvements, and since health is a major determinant of productivity, one could expect productivity to have dramatically increased across cohorts over time in developing countries.

countries with at least two years of data. Row 2 in Appx. Table A.8 replicates these results when using countries with at least three, five or eight years of data (N = 104; 79; 55).

Decadal Cohort FE: Issue due to the Periodicity of the Surveys. 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 fixed effects (1920s, ..., 1990s). However, the decadal cohort effects are identified only if the repeated cross-sections are fewer than ten years apart. In our sample of 939 surveys in 122 countries with at least two years of data, the median, mean, 75th percentile, 90th percentile and 95th percentile number of years between two surveys is actually low, at 1, 1.6, 1, 4 and 6, respectively.

Cases where there is a gap of more than 10 years between surveys occur in earlier decades that have fewer surveys. The 1920s effect is not identified for 8 countries and the 1930s effect is also not identified for 8 countries. Given we focus on post-1990 surveys, this issue only affects a few older individuals in the earliest survey of 12 countries (some countries appearing in both lists, 12 < 8+8).

In addition, using returns based on the bins 0 to 25 ("25-29"), as we do several times, eliminates the issue. Indeed, these returns exclude individuals with 30-49 years of experience (49 comes from 67 – 18 = 49), hence individuals born in the 1920s-1930s. For example, for Namibia, we have a survey in 1993 and then another survey in 2008. The 18-67 y.o. in 1993 were born in 1926-1975 and the 18-67 y.o. in 2008 were born in 1941-1990. We thus do not identify the 1920s and 1930s effects for Namibia. However, since experience starts at age 18 in our analysis, individuals in the 1993 survey who were born in 1926-1939 – and for which the 1920s and 1930s effects are not identified – had 36-49 years of experience, thus more experience than 29 years. Lastly, we find an almost perfect correlation of 0.995 between the returns based on all bins and the returns based on the bins 0-25 (N = 122).

Alternatively, our results hold when excluding the 12 countries for which there is a potential issue or excluding the 7 countries with problematical surveys. In the latter case and for the 5 countries that we therefore "save", the correlation with the baseline returns is 0.985.

Web Appx Table A.10 shows the returns for G and D and their difference when: (i) Excluding the 12 countries with a problematical survey (col. (2)); (ii) Excluding problematical surveys and only keeping countries with at least two years of data (col. (3)); and (iv) Using bins 0-25 (col. (4)).

Bi-Decadal or Semi-Decadal Cohort FE. Logically, coarser cohort fixed effects – bi-decadal cohort fixed effects (e.g., 1980s-1990s) – should produce results relatively more in line with the "no cohort FE" results than more refined cohort fixed effects – semi-decadal cohort fixed effects (e.g., 1980-1984, 1985-1989, 1990-1994 and 1995-1999). Row 3 of Appendix Table A.8 (N = 104; 79; 55) shows that bi-decadal cohort fixed effects indeed produce results in line with the "no cohort FE" results (row 1). Row 4 then shows that 5-year cohort fixed effects preserves the difference between developed and developing countries (1.6***-1.7***, N = 104; 79; 55). However, estimated returns are lower across all countries, since collinearity increases as one uses more and more refined cohort fixed effects. Indeed, with 5-year experience bins, including 5-year cohort fixed effects may ask too much of the data.

Events Cohort FE for Younger Workers Only. For the important events cohort fixed effects, we included country-specific period dummies equal to one if the person was aged between 18 and 67 during the defined period(s). However, people could be shaped by events taking place during the first decades or years after leaving high school. Results hold if we instead include country-specific period dummies equal to one if the person was aged between 18 and 40 or between 18 and 30 during the defined period(s) (see rows 6-7, N = 104; 79; 55).

Events Cohort FE and Growth Rates. One could argue that important events do not capture more normal periods of economic growth and economic decline, hence the need to also control for the economy faced by the individual during her work years. In addition to the country-specific period dummies equal to one if the individual was aged between 18 and 67 during the period(s), we thus also control for the country's average growth rate of per capita GDP (PPP, constant 1990 dollars) for those years during which the individual was aged between 18 and 67 (row 8, N = 1104; 79; 55).[4]

Events Cohort FE and Growth Rates for Children. Individuals may also be shaped by important events, and the state of the economy, during their childhood. Row 9 replicates the results of row 8 when we also include country-specific period dummies equal to one if the person was aged between 0 and 17 during the period(s) and the country's average growth rate of per capita GDP (PPP, constant 1990 dollars) for those years during which the individual was aged between 0 and 17. Estimated returns are lower across both groups of countries, but the difference between developed countries and developing countries is now slightly higher (1.8***-2.2***, N = 104; 79; 55).

Combining Decadal, Events Cohort FE and Growth Rates. Decadal cohort FE are more flexible than events cohort FE since decadal cohort FE simply posit that people born in the same decade have similar wage growth patterns ceteris paribus. Row 10 shows that results somewhat hold if we combine both approaches (N = 104; 79; 55). Returns are lower for both developing and developed countries, but the difference is preserved and returns increase as we rely on countries with more years of data. Indeed, with 8 cohort fixed effects and 11.5 period fixed effects on average, this method should work better for larger samples. Row 11 then shows that the difference is also preserved when adding as a control the average growth rate faced by each individual between ages 18 and 67.

Lagakos et al. (2018)'s HLT Approach. We use the algorithm developed by Lagakos et al. (2018) to implement their approach for our sample of 145 countries. 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%. We show in rows 12-15 the results for countries with at least 3, 5 or 8 different years of data (N = 95, 73, 53). Overall, this method increases returns for all countries, and slightly decreases the gap between developing countries and developed countries to 1.0***-1.2***, depending on the specification. However, results remain relatively similar to the baseline results.

A.4 Robustness Checks for the Regressions Estimating the Returns

Row 1 of Appendix Table A.14 replicates the baseline results (N = 104; 79; 55).

Excluding Selected Types of Workers. Lagakos et al. (2018) exclude female workers, part-time workers, self-employed workers and public sector workers. Rows 2-5 of Appendix Table A.14 show results hold if we drop each type of workers at a time: female workers in row 2 (N = 144, 122, 122),

[4]The main source for GDP is Bolt and van Zanden (2014) who update Maddison (2008)'s data set. The data show per capita GDP in constant 1990 international $ (i.e. PPPs). We extend the data to 2017 using the levels in the data in 2010 and annual per capita GDP growth rates reported by World Bank (2018) for the period 2000-2017 (constant 2011 international $). Note that we use the Maddison (2008) data set as our baseline data set for the per capita GDP data, because it is the only data set with available per capita GDP for as far back as 1950.

part-time workers in row 3 (N = 130, 103, 103), self-employed workers in row 4 (N = 142, 118, 119), and public sector workers in row 5 (N = 141, 117, 117).

Measurement of Experience. For all countries, we used 6 years as the age of entry into primary school. However, in some countries, children start school at the age of 5 whereas in other countries they start at age 7. We read the Wikipedia webpage "Education in country X" of each country and adjusted the age of entry to recalculate experience accordingly. When doing so, results are unchanged (row 6; N = 104; 79; 55). Next, we show results hold if we include potential teen labor from age 15 (row 7; N = 104; 79; 55) or potential child labor from age 13 (row 8; N = 104; 79; 55).[5]

Age may also be mis-measured in some countries. For each survey, we construct the Whipple Index that measures to what extent individuals disproportionately report their age as a round number ending in 0 or 5. In rows 9-11, we show results hold if we drop samples with a very rough ($>$ 175; N = 125, 102, 102), rough ($>$ 150; N = 113, 91, 91) or moderately rough ($>$ 125; N = 61, 40, 40) index.

We focus on samples from 1990-2016. However, several countries transitioned from a command economy to a market economy during the 1990s, so their measure of relevant experience may be mismeasured. Row 12 shows results hold if we restrict the analysis to samples from 2000-2016 (N = 139, 113, 113). Interestingly, the returns are not significantly different from the baseline results (row 1; not shown), thus suggesting that returns did not dramatically change over time on average.

Finally, results somewhat hold if we categorize experience into 3-year bins (row 13; N = 144, 122, 122) or 7-year bins (row 14; N = 145, 122, 122). We use 5-year bins to mimic Lagakos et al. (2018) but also because it allows us to plot wage-experience profiles and the specification is more flexible than a quadratic Mincerian specification. Interestingly, the returns, and the R2 (not shown), are higher when using more refined experience bins, which confirms that using a coarser specification would hide useful information about how wages vary with experience across countries.

Measurement of Wages. Row 15 shows results hold if we keep workers for which the wage was reported for a period of at least a month (e.g., monthly, semi-annually or annually) since the monthly wage may be mis-measured for workers paid hourly, daily or weekly (N = 123, 103, 103). Row 16 shows results hold if we include the monthly wage of any secondary occupation (N = 145, 122, 122). This information is available for few countries, hence our focus on the main occupation in our analysis. Next, we use mean wages, experience and education at the household-level in case there is intra-household optimization. Row 17 shows results hold when doing so (N = 143, 120, 120).

Sample Size. We restrict our analysis to samples with at least 10 observations in each bin. However, we verify results hold if we raise this threshold to 100 (row 18, N = 137, 113, 113). Other thresholds (e.g., 20, 50 and 500) return similar results (not shown, but available upon request).

Selection Bias due to Unemployment or Non-Labor Force Participation (NLFP). Our regressions only include workers, thus causing a selection problem in samples with disproportionately high, or low, unemployment/NLFP rates. First, that is only an issue for us if unemployment/NLFP is correlated

[5]For teen labor (row 7), for individuals with at least 9 years of education, experience is now defined as age - years of education - 9. For individuals with less than 9 years of education, experience is defined as age - 15, thus assuming that potential work experience before age 15 is irrelevant. Likewise, for child labor (row 8), for individuals with at least 7 years of education, experience is now defined as age - years of education - 7. For individuals with less than 7 years of education, experience is defined as age - 13, thus assuming that potential work experience before age 13 is irrelevant.

with development. For each country, we thus obtain the mean unemployment rate and the mean NFLP rate across all available years (using as weights the number of observations in each sample). We then regress these rates on log per capita GDP (PPP, constant 2011 international $) for the country-specific "mean" year in the data.[6] No relationship is found for unemployment (*unemp.* = 4.13 + 0.63 *lpcgdp*; R2 = 0.01; N = 145) and NLFP (*NLFP* = 22.63** + 1.32 *lpcgdp*; R2 = 0.01; N = 145). Indeed, poor countries do not offer unemployment benefits, which may force most people to work in order to survive. Conversely, rich countries have more dynamic economies, which may reduce unemployment, but they also offer unemployment benefits and other subsidies, thus raising the reservation wage of non-workers. Second, the I2D2 database does not include data on individual ability, an important individual characteristic to explain unemployment/NLFP. However, we verify results hold if we add 3 sector fixed effects (agriculture, industry, services), 10 occupation fixed effects (which controls for whether the individual's occupation is cognitive or manual), an urban dummy, a male dummy, and the square of education, to compare workers that are relatively similar except in their experience level. Doing so, we risk over-controlling. Indeed, part of the returns could be the choice of a specific sector/occupation/location. Nonetheless, estimated returns are surprisingly unchanged (row 19; N = 110, 92, 92). Third, rows 20-23 of Appx. Table A.14 show results hold if we keep, or drop, samples with low or high unemployment, i.e. samples with unemployment rates below or above the 25th percentile in the sample (7%, rows 20-21, N = 91-69 and 100-73) or the median in the sample (10%, rows 22-23, N = 118-95 and 71-49). Likewise, rows 24-25 show results hold if we keep, or drop, samples with low or high NLFP, i.e. samples with NLFP rates below or above the median in the sample which also happens to be the 25th percentile in the sample (35%, N = 100-120 and 85-64). Finally, we attempt to correct for selection bias using the Heckman correction method. The selection equation includes the variables of equation 1 and a female dummy and as external variables marital status dummies (married, non-married, divorced, widowed or single) and the number of children and its square. Results hold (row 26, N = 128, 104, 103). Obviously, these results should be taken with caution since marital status and the number of children may not be good "instruments" for selection.

A.5 Robustness Checks for the Group-Specific Returns

Row 1 of Appendix Table A.15 replicates the baseline results.

Region Fixed Effects. Row 2 shows that results hold if we include 7 World Bank region fixed effects (N = 145, 122, 122): East Asia & Pacific, Europe & Central Asia, Latin America & Caribbean, Middle East & North Africa, North America, South Asia and Sub-Saharan Africa.

Excluding Selected Regions. Results hold if we drop each developing region one by one, whether East Asia & Pacific (row 3, N = 131, 122, 122), Latin America & Caribbean (row 4, N = 119, 99, 99), Middle East & North Africa (row 5, N = 134, 114, 114), South Asia (row 6, N = 138, 116, 116) or Sub-Saharan Africa (row 7, N = 106, 93, 93), or ex-Communist countries (row 8, N = 105, 84, 84).

Excluding Outliers. Row 9 shows results hold if we drop the top and bottom 10% outliers in the returns (N = 131, 110, 110), i.e. countries that may have abnormally high or low returns, either because these

[6] For countries with only one sample, it is the year of the sample. For countries with multiple samples, we obtain the mean year in the data using as weights the number of observations in each sample, thus giving more weight to larger samples.

returns are real or because of measurement error. One such example is Syria (SYR) in Figure 3.

Ex-Post Country-Level Controls. In rows 10-15, we add country-level controls for factors that may be driving cohort effects, in addition to the country-specific mean sample year in the data:[7] (i) We add 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 for the three variables: Wikipedia). Since we are controlling for the country-specific mean year in the data, this controls for how many years ago the country transitioned. Results are unchanged (row 10, N = 145-122). (ii) We control for the average child mortality rates (for 0-5 year-olds) and adult mortality rates (for 15-45 year-olds) for each country-decade from 1950 to 2010 (source: United Nations (2019)). Results are unchanged (row 11, N = 143, 121, 121). (iii) Results hold if we control for the average HIV infection rates for each country-decade from 1990 to 2010 (row 12, N = 108, 92, 92) (sources: World Bank (2018)). HIV data is not available before 1990. (iv) We control for the average annual per capita GDP growth rate for each country-decade from 1950 to 2010. Results are unchanged (row 13, N = 119, 108, 108).[8] (v) We control for the average annual population growth rate for each country-decade from 1950 to 2010 (source: United Nations (2019)). Results are unchanged (row 14, N = 144, 121, 121). (vi) Finally, results hold if we control for all factors mentioned in (i)-(v), although we lose a high number of observations when doing so (row 15, N = 95, 86, 86). Note that we do not report the average estimated returns for developing countries and developed countries because the inclusion of the controls changes the interpretation of the constant. However, what matters is that the difference between developing countries and developed countries is preserved.

Standard Errors. Standard errors in equation 2 do not account for the fact that the coefficients of the seven experience dummies may be imprecisely estimated in equation 1. However, because of the large data sets that we use for each country, coefficients are precisely estimated in almost all regressions estimating the returns. For example, 929 out of the 145 countries x 7 bins = 1,015 coefficients when ignoring cohort effects – i.e., 92% of the sample – have a p-value below 1%. This share remains high, at 79% and 75%, when including cohort FE or events FE. Next, p-values only test if coefficients are significantly different from 0. However, it could be that the coefficients of various country-bins are not significantly different from 0 while being precisely estimated. So what matters is that the absolute values of the standard errors are low. For the 1,015 coefficients, the 25th percentile, median, mean and 75th percentile standard errors are 0.01, 0.02, 0.03 and 0.05, respectively. These are very low values relative to the coefficients (the corresponding values are 0.23, 0.38, 0.41 and 0.58). Alternatively, we can test whether the results hold if we use countries whose mean, or even maximal, standard error across the seven coefficients is below the median mean standard error (0.02) or the median maximal standard error (0.02) across the 145 countries. As can be seen in rows 16-17, results hold (N = 73-61 and 73-61 respectively). Note that results were also unchanged when focusing on samples with 100 (or more) observations per bin (row 18 of Appx. Table A.14). Finally, results hold if we use standard

[7]For countries with only one sample, it is the year of the sample. For countries with multiple samples, we obtain the mean year in the data using as weights the number of observations in each sample, thus giving more weight to larger samples.

[8]The main source for GDP is Bolt and van Zanden (2014) who update Maddison (2008)'s data set. The data show per capita GDP in constant 1990 international $ (i.e. PPPs). We extend the data to 2017 using the levels in the data in 2010 and annual per capita GDP growth rates reported by World Bank (2018) for the period 2000-2017 (constant 2011 international $).

errors bootstrapped 10,000 times (row 18, N = 145, 122, 122) or more (not shown).

A.6 Parameterization Details

Here we discuss some details of the parameterization of the accounting framework. We calibrate the economy to match a representative developed economy and a representative developing economy.

In each case we require values of population growth rates g_b, mortality profiles $\delta(\cdot)$, unemployment rates u_y and u, retirement ages R and return parameters $\underline{r}_s$, $\bar{r}_s$, $\underline{r}_e$ and $\bar{r}_e$, as well as the employment probabilities $\pi_e(\cdot)$ schooling transition probabilities $\pi_s(\cdot)$. We obtain g_b and $\delta(\cdot)$ 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. The return parameters are the average estimates for each group, weighted by population. We set the schooling transition probabilities $\pi_s(\cdot)$ to match the schooling distribution in developed and developing economies, obtained from the I2D2 data. Finally, we set the employment probabilities $\pi_e(\cdot)$ using participation, youth unemployment rates and adult unemployment rate averages reported circa 2017 by World Bank (2020).

We begin with the mortality function $\delta(\cdot)$. United Nations (2019) reports $\delta(\cdot)$ only for ages zero, 1, 5 and for five year intervals henceforth. As a result, we need to interpolate $\delta(\cdot)$ for other ages. We develop a smooth function $\delta(\cdot)$ by computing the step function implied by taking the UN's reported values of δ and assuming the unreported years equal the nearest lowest value (e.g. $\delta(2) = \delta(1)$), and then smoothing the step function with the Hodrick-Prescott filter. We assume that there is some $\bar{a}$ such that $\delta(a) = 1$ for $a \geq \bar{a}$. We set $\bar{a} = 99$. See Appendix Figure 8(a) for the mortality distributions.

We also match the distribution of schooling. See Appendix Figure 8(b) for the distribution of schooling we use, based on the I2D2 data (1990-2016). In transition between educational systems, we set $\pi_s(s)$ so that the share of agents in the cohort rising from schooling s to $s+1$ equals that in the developed economy (unless there are not enough such agents because the number with schooling s was too small, in which case we assume they all move to $s+1$). We assume that agents may only accumulate up to 25 years of schooling because some countries only record schooling up to 25 years.

See Table 5 for a summary of the values of the parameters we used.

A.7 Sensitivity Checks

We performed a number of robustness experiments with different parameter values to see whether the results of our counterfactual experiments varied much. Table $A.22$ displays this information in tableform. It reports the ratio of $pcGDP$ in the developing economy compared to the developed economy (1) before reforms, (2) after all reforms, (3) after increasing schooling only, and (4) after increasing the returns to experience only. It also reports the ratio of $pcGDP$ in experiment (4) divided by $pcGDP$ in experiment (3) y years after reforms which gives a sense of how quickly reforms that affect the returns to experience impact aggregate income relative to reforms that increase schooling.

Robustness Checks. Row A of Panel A represents the benchmark results reported in Section 6.3.. Table $A.22$ shows results hold if we: (B) Assume that the developing economy has the same demographics as the developed economy; (C) Use a lower retirement age (60) in developing countries, closer to the statutory age there;[9] (D) Give developing countries the labor market conditions of developed

[9] See https://en.wikipedia.org/wiki/Retirement_age, last checked 12/13/2019.

countries; (E-F) Assume that returns are computed using decadal cohort effects and events cohort effects, respectively; (G) Use returns estimated when excluding female, part-time, self-employed and public sector workers; (H) Use the raw unweighted average return values rather than average returns weighted by population; (I) Exclude ex-Communist countries and countries with past mortality/HIV rates above the 99th percentile in the data; (J) Combine rows E (decadal cohort fixed effects), G (excluding selected types of workers) and I (excluding selected countries); (K) Use returns to experience estimated for the 0-35 bins instead of 0-25; (L) Give 18-24 year-old individuals the returns for the 0-5 bin, thus making youth unemployment more consequential (see Appx. Section A.9 for details).; (M-N) Allow for experience to be accumulated from age 15 or 13; (O) Assume that unemployment requires workfare, so that workers are able to accumulate some minimal experience. The return in the developed economy to unqualified manual labor is 4%, and in the developing economy it is 1.5 % (estimate from Islam et al. (2019)). This is an additional boost to experience overall, even if a small one, and to reforms to experience, since the return to manual labor is higher in the developed economy; (P) Endow all agents with the same (average) level of schooling (see Appx. Section A.9 for details);[10] and (Q) Allow for human capital *spillovers* that increase output but are not reflected in private returns to human capital (see Appx. Section A.9 for details).

In most cases, Table $A.22$ shows that results are similar. The developing economy is generally around 50 percent of the developed economy initially ((1)). The full set of reforms brings it close to full convergence ((2)). Finally, reforms to schooling ((3)) and reforms to the returns to experience ((4)) have a roughly similar long-run impact, although the impact of reforms to experience occurs sooner.

Three Income Groups. We do not simulate the model for each country one by one in order to maintain tractability. For robustness, we simulate the model for three groups of countries, i.e. for low-, middle- and high-income countries. We first estimate for each income-college group mean returns to experience (for the 0-25 bins) and mean returns to education. However, the returns of low- and middle-income countries may be disproportionately affected by selective mortality and transitions out of communism, respectively. To obtain more reliable estimates of the returns, one could exclude ex-Communist and high-mortality/HIV countries. But returns for the college+ group are only available for 1 low-income country when excluding such countries (using the 99th percentile to exclude as few countries as possible) *and* including decadal cohort fixed effects (since we need countries to have at least two years of data) *and* excluding female, part-time, self-employed and public sector workers. Indeed, few individuals have at least 13 years of education in low-income countries. Since we need at least 10 observations for each experience-education bin, we lose too many low-income countries. To circumvent this issue, we distinguish low- and middle-income countries based on their World Bank classification not in 2017 but in the mean year in the country's data (the group of high-income countries is based on 2017 and thus unchanged). Doing so allows us to increase the number of countries for this income-experience-education group to 6 (17 for the "before college" group).[11]

[10] In this case, schooling has a slightly greater impact than reforms to experience, due to the skewness of the schooling distribution in developing economies. The fact that many agents in developing economies have little or no education means that the transition to an educated workforce is slower than one might infer from the average level of schooling.

[11] For the less reliable benchmark specification, we get 38 and 50 countries, respectively. However, even with that many more countries, results are similar (see Table A.21 for the parameters and returns used).

We obtain similar results as before (Panel B of Table A.22). With the benchmark specification, $pcGDP$ in the middle-income (M) economy and the low-income (L) economy is 55.5% and 39.2% of $pcGDP$ in the high-income (H) economy (col. (1)). With the more complete specification of row J in Panel A (decadal FE + excluding selected types of workers and countries), these numbers become 38.4% and 44.6%. The full set of reforms brings the two economies close to full convergence (col. (2)). However, since the low-income economy starts at a lower level, the reforms have a disproportionately stronger impact there. For both groups, reforms to schooling and reforms to the returns to experience have a roughly similar impact, although the impact of reforms to experience materializes sooner.

A.8 Welfare and Applications

Welfare. The full set of reforms represents in the long run a roughly 50 percent increase in aggregate income per capita in the developing economy. However, this 50 percent long-run increase is not an accurate indicator of their *welfare* impact, as reforms impact $pcGDP$ slowly – see Fig. 5. To get a back-of-the-envelope calculation, suppose all output is consumed (or, equivalently, a constant share). Assume the economy is composed of a number of infinitely-lived representative agents whose welfare equals the discounted sum of log consumption - as is standard in the growth literature.[12] Then, given a discount rate, we can compute the share C of steady state consumption in the developing economy that we could give an agent in each period in order to make her would make such an agent indifferent between remaining in the steady state and embarking on the transition path of the reforms. We refer to C as the compensating variation. Notice that, since this is a share of consumption in each period, for reasonable discount rates the potential welfare gains are enormous.

With a discount rate of 4 percent, the full set of reforms yields $C = 22.9$ percent. Changing schooling quantity and returns yields $C = 7.5$ percent. Changing the returns to experience doubles C to 16.3 percent, because reforms to experience have faster impact.

Next, the experiments above give us a sense of the general impact on developing country economies of reforms that might affect the returns to experience, relative to those that increase schooling. However, since there is variation around the world in some of the parameters concerned, we use the accounting model to see to what extent our findings could be sensitive to this variation. The results described below also allow us to shed light on how the relative impact of experience may, or may not, vary across economic and institutional contexts and with various government policies.

Retirement Age. Recent policy discussions have concerned either the raising of the retirement age (e.g. France, Italy, Russia) or the lowering thereof (e.g. Poland). In Table $A.23$, we report the relative impact of reforms to schooling vs. reforms to experience returns, and compare them to the benchmark results (row A). In row B we repeat our experiments assuming that the retirement age has been raised from 65 to 70 in the developing economy. In row C we assume the retirement age is lowered to 60. The results are not very different. Indeed, changes in the retirement age do not affect the accumulation of experience, just the period of time over which the returns to experience (or to schooling) pay off. The changes in the retirement age affect labor market participation, but this appears to affect the earnings due to schooling and earnings due to experience to a similar degree in the long run. Lowering the

[12] Alternatively we could assume that the social planner is endowed with this utility function.

retirement age does imply that the returns to reforming experience drop off more quickly, however, as the agents who gain from the new higher returns retire sooner.

Population Growth. Row D asks what would be the relative impact of reforms in a developing country with high population growth. Instead of the baseline growth rate of 0.8%, we assume $g_b = 2.2\%$, the average forecast for Sub-Saharan Africa. In row E we ask what happens when $g_b = -0.6\%$ (Japan). Population growth does not appear to make much difference, except that the relative benefits of the experience reforms dwindle faster when population growth is rapid. This is because the educated young are a larger share of the workforce, so their impact is disproportionately large, whereas the experienced will be a correspondingly smaller share of the workforce

Labor Market Conditions. Results are sensitive to the performance of the labor market. In row F, we assume that the reforming economy experiences labor market stagnation similar to that in Southern Europe. In particular, we assume the average youth unemployment rate across Greece, Italy, Portugal and Spain according to World Bank (2020), which is 36 percent, and the adult rate, which is 12.6% (instead of 13.0% and 3.7%, respectively, in the baseline). Row G instead assumes statistics from a developing country that is experiencing labor market stagnation (South Africa), where youth unemployment rates are 53.3 percent and adult rates are 23.6 percent. Finally, row H looks at a developing economy where labor market participation is lower, assuming $l_p = 55.2$ percent, the average across developing economies in the Middle East and North Africa (instead of 77.1% in the baseline). In these contexts, reforms to experience have less impact relative to reforms to schooling. Indeed, the long run impact of reforms to experience is now less, as workers accumulate less experience over their lifetimes.

A.9 Robustness for the Accounting Framework

Youth Returns. Row L of Table $A.22$ considers the fact that the empirical section finds that returns to experience are particularly high the first 5 years or so. We repeat the experiments assuming that this holds in the accounting model as well. This implies that

$$r_e(s,p) = \begin{cases} \underline{r}_e^* & \text{if } s \leq 13 \text{ and } p \leq 5 \\ \bar{r}_e^* & \text{if } s > 13 \text{ and } p \leq 5 \\ \underline{r}_e & \text{if } s \leq 13 \text{ and } 5 < p \leq 25 \\ \bar{r}_e & \text{if } s > 13 \text{ and } 5 < p \leq 25 \\ 0 & \text{if } p > 25. \end{cases},$$

For individuals with at least 5 years of experience, we use the same returns as before. But for individuals with less than years of experience, we set $\underline{r}_e^* = 3.2\%$ and $\bar{r}_e^* = 3.4\%$ in the developing economy, and $\underline{r}_e^* = 7.5\%$ and $\bar{r}_e^* = 6.6\%$ in the developed economy, in accordance with our estimates.

Average Schooling. Row P of Table $A.22$ assumes that everyone has the same schooling, equal to the average (8 for the developing economy and 13 for the developed economy). We perform this last experiment because computing the transition dynamics in the economy where there is a nondegenerate distribution of schooling is considerably more cumbersome than assuming, for example, that agents all share the same (mean) level of schooling. In principle one might worry that results using such a simple framework could be distorted, because they might be dominated by the dynamics of transitioning from nobody having college to everyone having college. Table $A.22$ shows that the model where everyone has the same schooling behaves differently. The impact of reforms to schooling and to experience returns is almost the same in both the short run and the long run, however this time reforms to schooling have larger long run impact at all horizons. Thus, the slower impact of education reforms we find in the benchmark economy is not seen if we assume everyone has the same education – likely because it is the skewness, not just the average, of the distribution of education that matters. For example, in the developing economy 16 percent of adults do not have any schooling at all, whereas this number is negligible for the developed economy. As a result of this skewness, increasing schooling in the developing economy is a slow process. Nonetheless, the contribution of work experience to economic development remains very high, and close to the contribution of education itself.

Spillovers. Finally, Row N assumes that there are spillovers, in that human capital of h_{it} generates a return of $h_{it}(1+B)$, with the portion $h_{it}B$ being distributed to other agents (and thus not forming part of the private retuns to human capital measured earlier). B is chosen so as to account for the full 28 percent development gap mentioned earlier (see below). There is a precedent in the literature for the idea that spillovers from human capital might affect aggregate productivity – see Bils and Klenow (2000) for a survey. For these purposes we assume that aggregate productivity is a function of the stock of human capital. Thus, the impact of human capital is its direct effect (as before) plus a spillover. We assume the spillover is linear so that if an agent has human capital h_t, then the contribution to aggregate income is $h_t(1+\beta)$ for $\beta \geq 0$. As before if an agent is not working then there is no spillover. Key to this exercise will be the value of β, the impact parameter of human capital on growth. Since there is little guidance on the value of this parameter (Bils and Klenow (2000) argue that estimates are likely to be biased upwards), we assume β is such that in the baseline economy differences in human capital account for the entirety of differences in income per capita between the developed and developing economies. This provides an upper bound on the possible impact of spillovers on our results. We find that a value of $\beta = 0.89$ matches the developing economy income per capita of 0.28 relative to the developed economy income. This is fairly large, although it is hard to say whether it is realistic or not without independent confirmation.[13] The point is not to provide an estimate of this number, however, it is to test the qualitative robustness of our findings to the possibility of spillovers, and in this regard looking at a large number is appropriate. Row Q of Table $A.22$ shows that the overall results are very similar to those in the text where there are no spillovers ($\beta = 0$). The presence of spillovers implies that the reformed developing economy cannot approach the developed economy as closely as before, only 82.1 percent. This reflects the added burden that higher mortality has on the economy's ability to accumulate human capital through experience when there are spillovers. Similarly, increasing schooling and increasing experience have less impact than before, raising income per capita up to 50.4 and 51.4 percent of that in the developed economy respectively. As before, however, the two are comparable in magnitude, and the transition is faster when changing returns

[13]Bils and Klenow (2000) estimate a spillover parameter of around 0.77.

to experience than when changing the quantity of schooling.

A.10 Welfare comparisons

Suppose that, as is common in the growth literature, there is $[0, 1]$ continuum of dynasties. In period $t = 0$ each dynasty has mass one, and the mass of agents in each dynasty increases each year by a factor γ. Assume that each dynasty is identical in terms of their distribution over education and age, and that their utility is defined over the aggregate consumpiton of the dynasty multiplied by the number of agents as in King et al. (1988). The dynastic utility function is then

$$\sum_{t=0}^{\infty} (1+r)^{-t} g_b^t u(c_t).$$

We assume as is standard in the growth and business cycle literature that $u(\cdot) = \log(\cdot)$.

Suppose c_0 is the steady state consumption level in the developing economy, and that $c_{i,t}$ is the level of consumption at date t in the developing country after some sort of reform. Then, define C as the proportionate increase in c_0 each year that would make the agents indifferent between staying in the unreformed steady state and reforming education and/or experience returns, transitioning gradually to a new reformed steady state. We can interpret C as the "true" welfare benefit of initiating reforms at date $t = 0$. Alternatively, C is also an indicator of the minimum expected discounted cost that might deter reforms from being welfare improving. We can define C implicitly via the equation:

$$\sum_{t=0}^{\infty} (1+r)^{-t} g_b^t \log\left[c_0(1+C)\right] = \sum_{t=0}^{\infty} (1+r)^{-t} g_b^t \log c_1.$$

Algebraic manipulation yields the expression:

$$C = \exp\left\{\left(1 - \frac{g_b}{1+r}\right)\left[\sum_{t=0}^{\infty} (1+r)^{-t} g_b^t \log \frac{c_{1t}}{c_0}\right]\right\} - 1$$

Using this expression, we can compute the value of C for the case of (1) the full complex of reforms, (2) reforms that increase schooling, and (3) reforms that increase the returns to experience.

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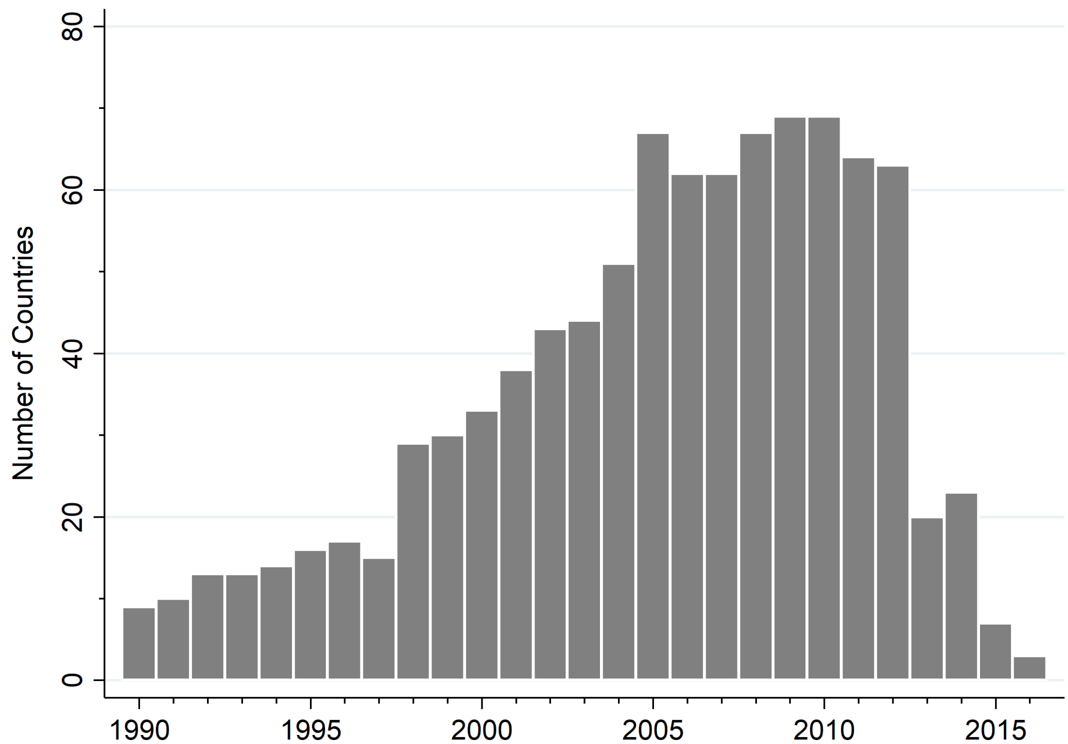
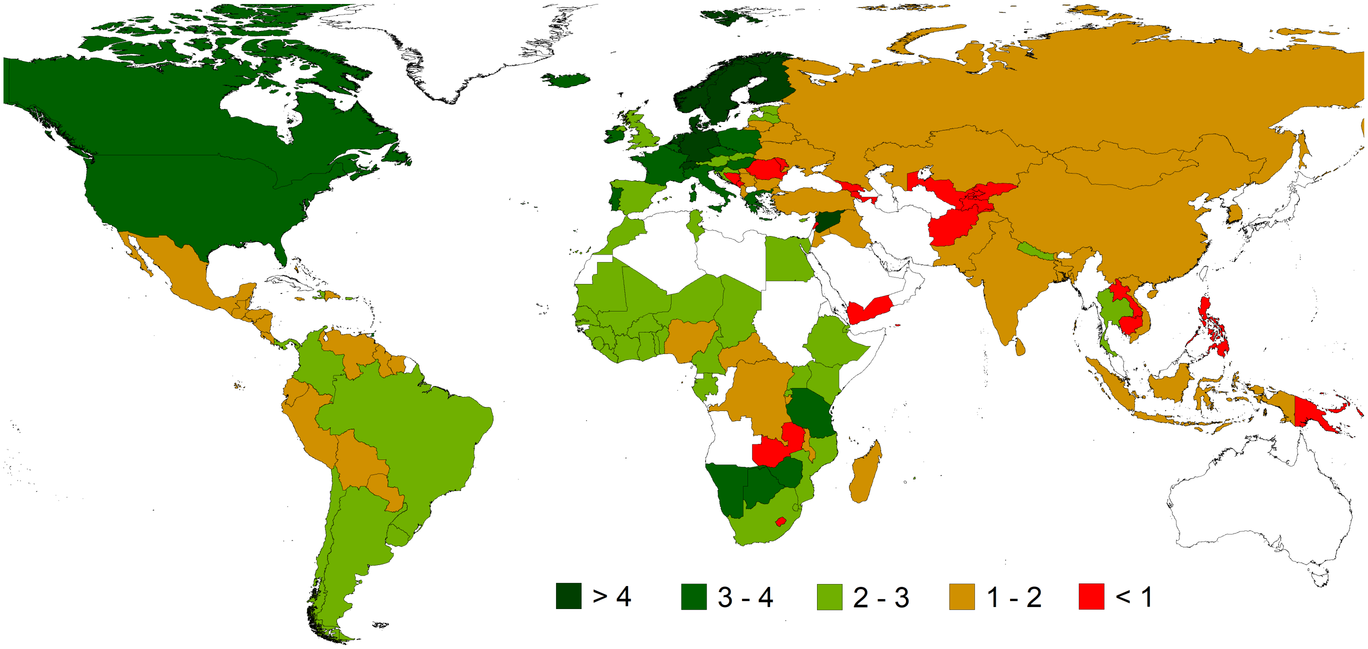
Figure A.1: Distribution of Countries with Available Data over the Number of Years



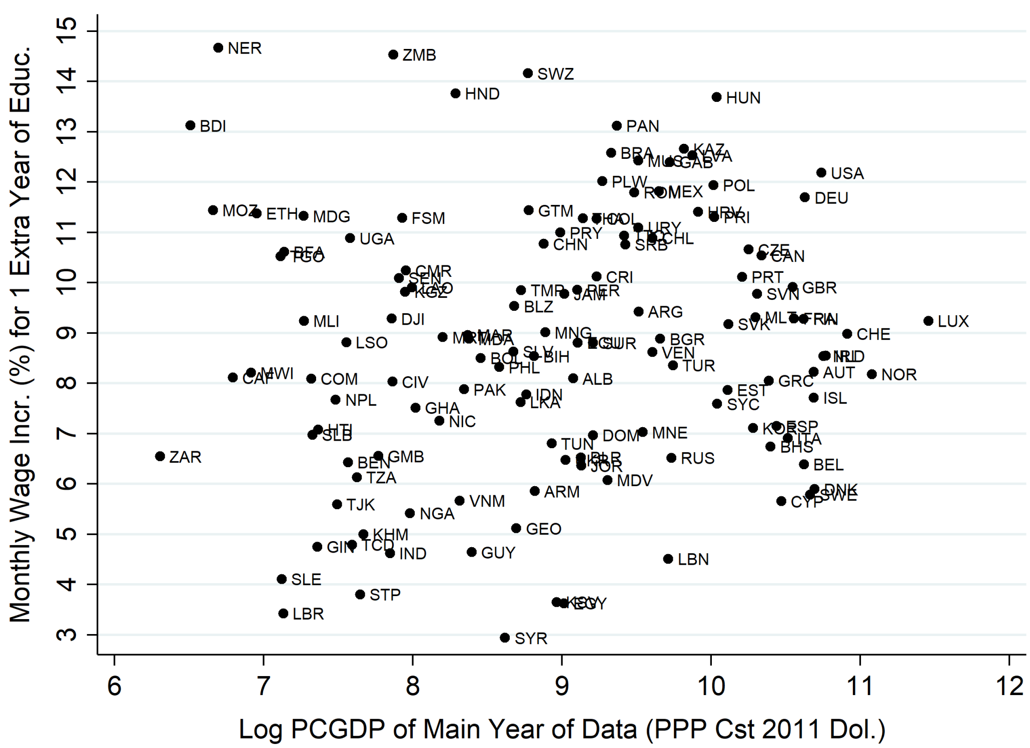
Note: This figure shows the number of countries with available data for each year from 1990-2016.

Figure A.2: Estimated Returns to Work Experience for the World



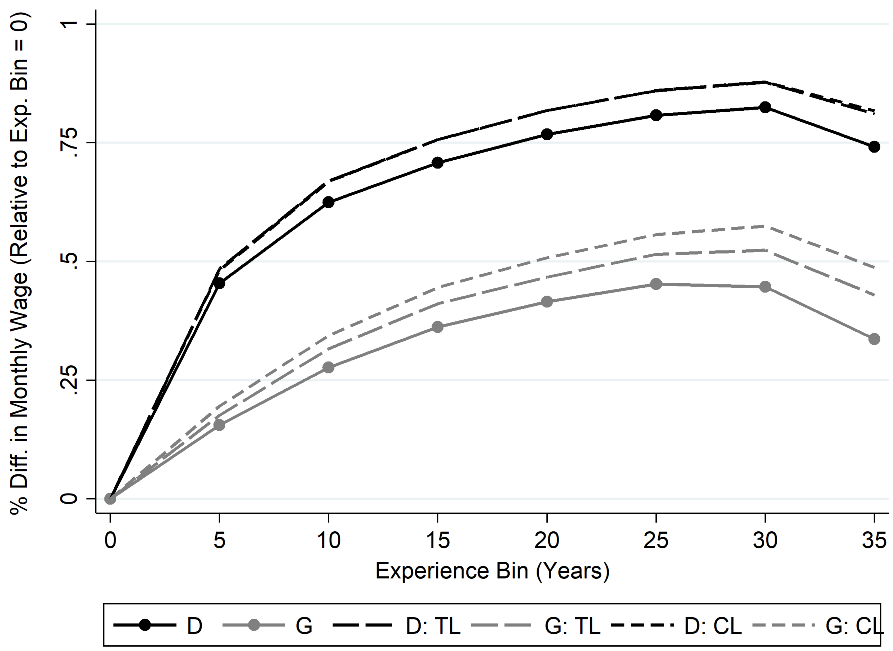
Notes: This figure shows the estimated returns to potential work experience for each of the 145 countries in our sample.

Figure A.3: Estimated Returns to Education & pcGDP



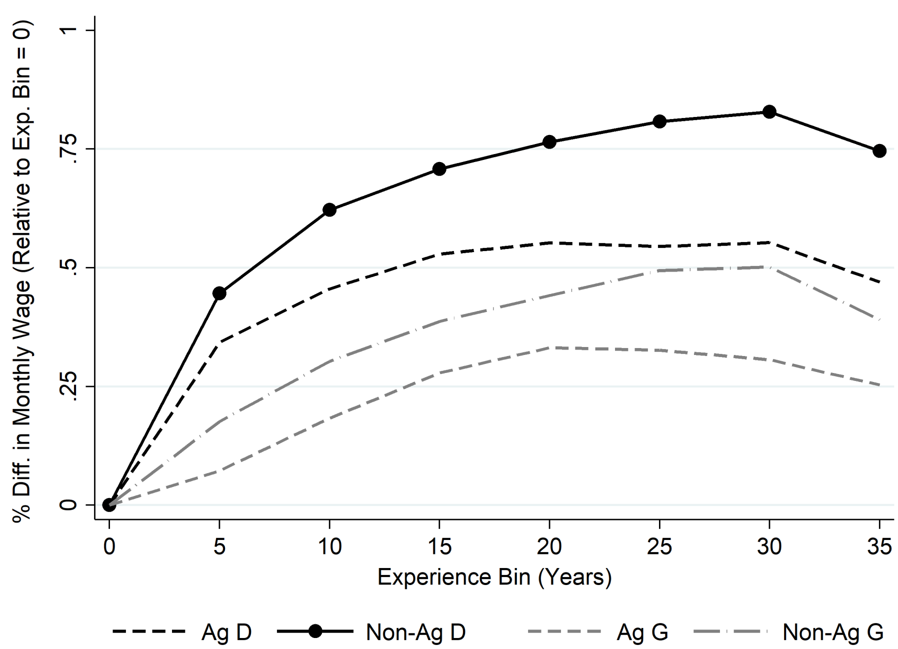
Notes: Figure A.3 plots the relationship between the estimated returns to education (i.e., the coefficient of schooling) and log per capita GDP (PPP; constant 2011 USD; for the mean year in the data for each country). The sample consists of 131 countries (145 countries - 14 countries in the top and bottom 5% in estimated returns).

Figure A.4: Estimated Returns to Education & Child Labor



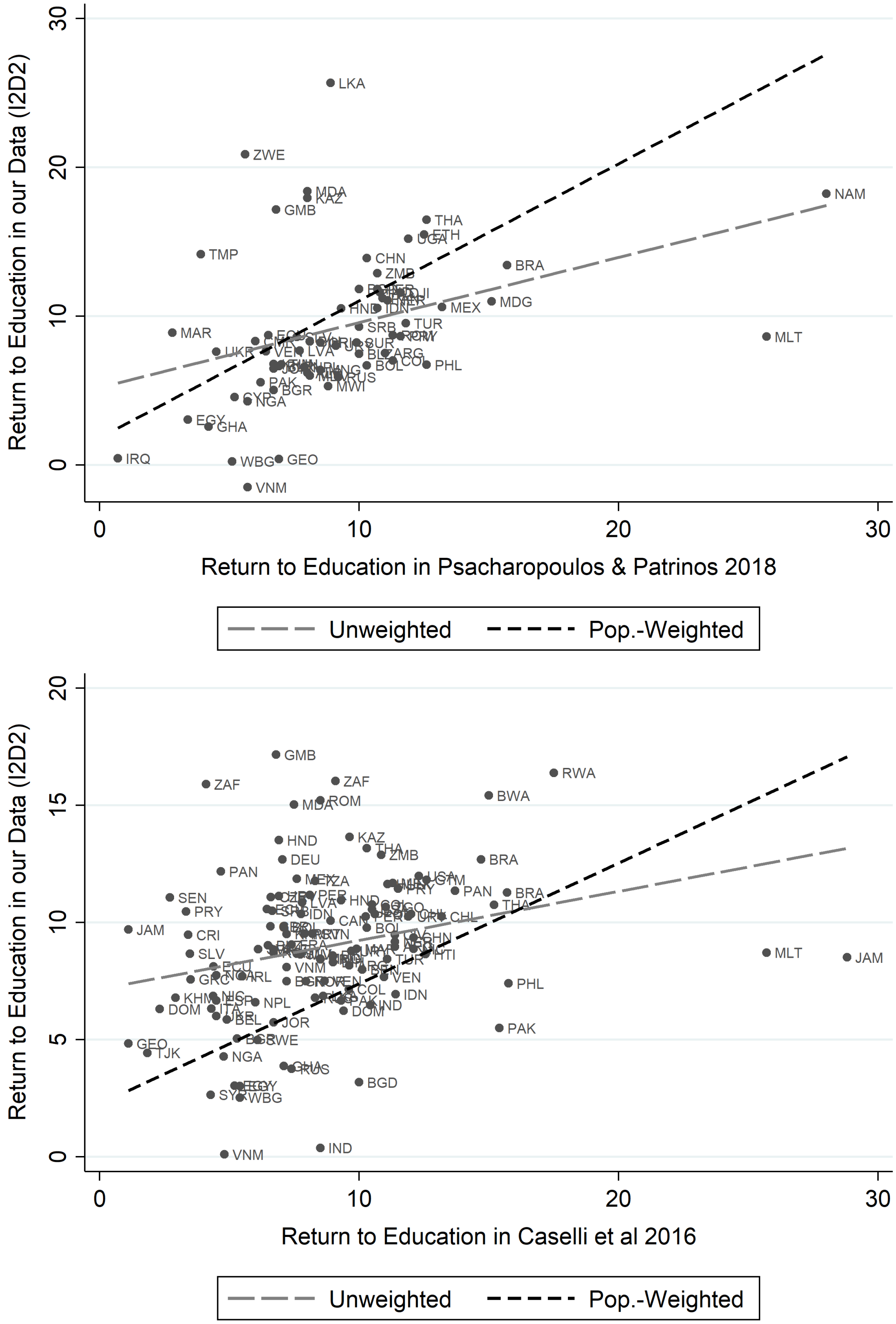
Notes: Figure A.4 shows the average wage differential for 7 experience bins for developed countries (D) and developing countries (G) (using pop. c. 2017 as weights). The 0 exp. bin is the omitted group. Only samples from 1990 to 2016 are used. TL: We include potential teen labor experience from age 15. CL: We include potential teen labor experience from age 13.

Figure A.5: Returns to Experience in Agriculture vs. Non-Agriculture



Notes: This figure shows the (pop.-weighted) wage-experience profiles for the agricultural sector (Ag) and the non-agricultural sector (Non-Ag). The sample consists of 111 countries with sectoral data in I2D2.

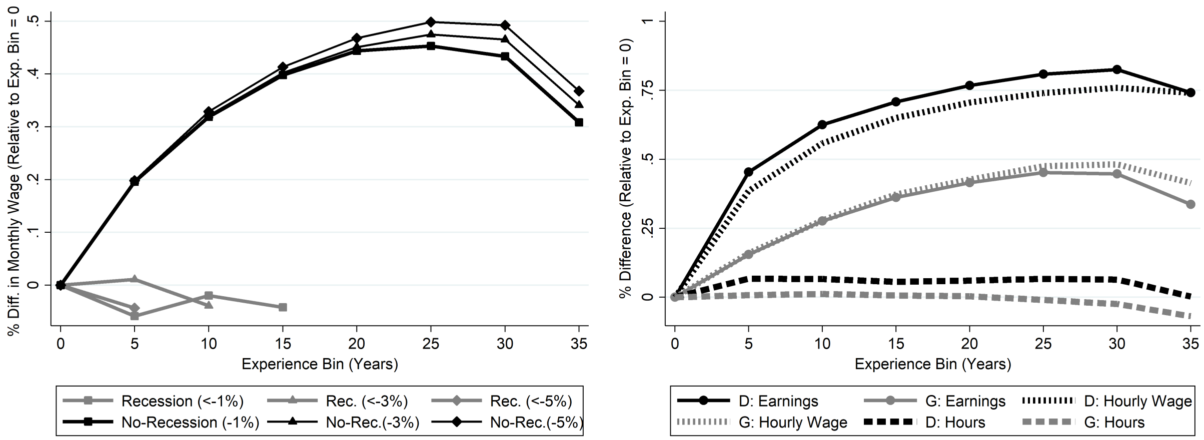
Figure A.6: Returns to Education in I2D2 vs. Other Studies



Notes: The top figure shows for 72 countries during the period 1990-2016 how the returns to education compare between our data and the data from Psacharopoulos and Patrinos (2018). The top figure shows for 178 country-years during the period 1990-2016 how the returns to education compare between our data and the data from Caselli et al. (2016).

Figure A.7: Returns to Recession Experience and Hours Worked

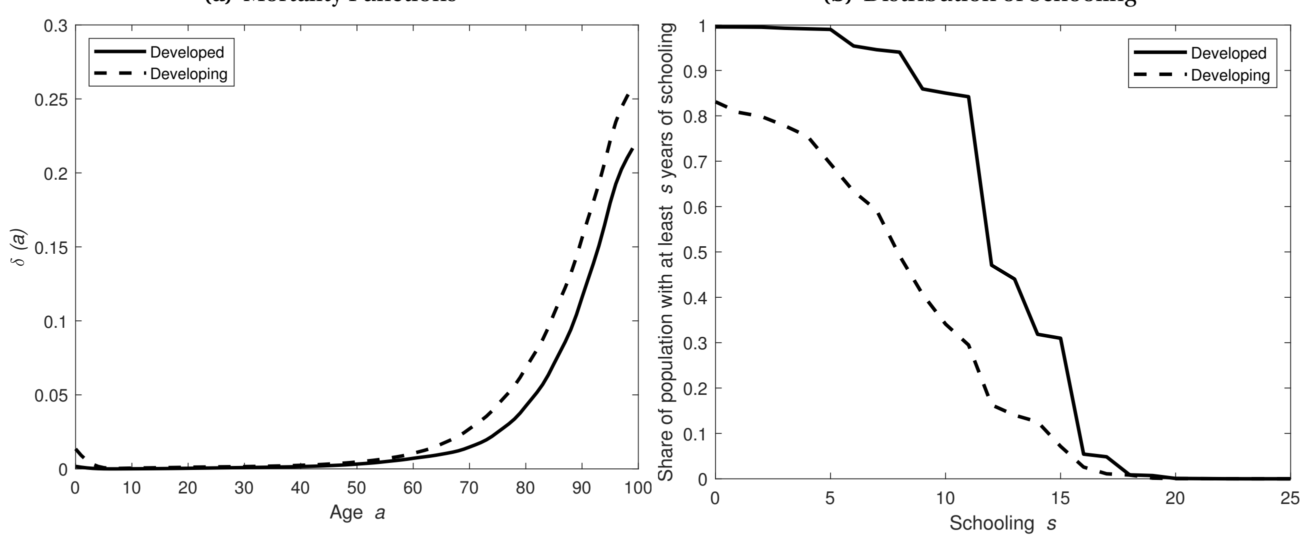
(a) Rec. Experience vs. Non-Recession Exp. **(b)** Decomposition of the Earnings-Experience Profiles



Notes: Subfigure 7(a) shows the (pop.-weighted) wage-experience profiles for recession experience and non-recession experience separately. Recession years are defined as years with a growth rate of national per capita GDP (PPP; constant 2011 USD) below -1%, -3% or -5%. For the -1% threshold, we do not have enough countries with at least 20 years of recession experience. For the -3% threshold, we do not have enough countries with at least 15 years of recession experience. For the -5% threshold, we do not have enough countries with at least 10 years of recession experience. Subfigure 7(b) shows the (pop.-weighted) wage-experience profiles for (log) total earnings, (log) hourly wages and (log) hours worked.

Figure A.8: Mortality Functions and Distribution of Schooling

(a) Mortality Functions **(b)** Distribution of Schooling



Notes: Subfigure 8(a): $\delta(a)$ is the probability that an agent of age a does not survive to age a+1. Values are drawn from United Nations (2019), corresponding to the "More developed regions" and "Less developed regions". We assume $\delta(a) = 1\%$ for $a \geq$ 99%. Subfigure 8(b): The distribution assumes a maximum of 25 years of education.

Table A.7: Estimated Returns for the 145 Countries (Average in 1990-2016)

Country:	Estimated Returns to Experience (%)			Estimated Returns to Education (%)		
Cohort FE:	None	Decadal	Event	None	Decadal	Event
AFG	0.2			0.2		
ALB	1.1	0.4	0.9	8.1	8	8.1
ARG	2.5	2.2	1.9	9.4	9.3	9.1
ARM	0.6	0.7	0.6	5.9	6	5.9
AUT	2.6	2.3	2.2	8.2	8.2	8
BHS	1.5			6.7		
BGD	1.2	0.7	-0.2	-1.2	-1.4	-1.5
BLR	1.1	1.1	0.8	6.5	6.5	6.3
BEL	3	2.3	2.1	6.4	6	5.9
BLZ	1.7	1.2	1.4	9.5	9.5	9.5
BEN	2.4	1.7	1.2	6.4	6.3	6.3
BOL	1.8	1.8	1.7	8.5	8.5	8.5
BIH	0.5			8.5		
BWA	3.3			15.8		
BRA	2.7	1.8	1.6	12.6	12.4	12.4
BGR	2	1.7	1.5	8.9	8.9	8.8
BFA	2.7	2.8	2.8	10.6	10.6	10.6
BDI	1.8			13.1		
KHM	-0.7	-0.2	-0.4	5	5	5
CMR	2.4	1.9	1.8	10.2	10.2	10.2
CAN	3.6	2.9	2.6	10.5	9.9	9.7
CAF	1.7			8.1		
TCD	2	0.4	-0.1	4.8	4.5	4.4
CHL	2	1	0.7	10.9	10.6	10.5
CHN	1.9	2.1	1.8	10.8	10.7	10.6
COL	2	0.4	-1	11.3	10.8	10.6
COM	1.1	-0.3	0.1	8.1	7.9	8
ZAR	1.5	-0.1	0.5	6.5	6.4	6.5
CRI	1.5	1	0.8	10.1	10	9.9
CIV	2.6	2	1.5	8	7.9	7.7
HRV	2.8	2.2	1.8	11.4	11	10.9
CYP	2.6			5.7		
CZE	3.4	3.2	2.8	10.7	10.7	10.4
DNK	4.5	3.8	3.7	5.9	5.7	5.7
DJI	2.2	2.2	2.6	9.3	9.2	9.3
DOM	1.9	1	0.7	7	6.7	6.7
ECU	1.5	1	0.9	8.8	8.6	8.6
EGY	2.2	1.7	1.3	3.6	3.5	3.4
SLV	1.6	1.1	1.1	8.6	8.5	8.5
EST	2.6	2.3	1.5	7.9	7.9	7.5
SWZ	2.5			14.2		
ETH	2.2	1.1	-0.2	11.4	11.1	10.9
FIN	4.3	3.7	3.4	9.3	8.9	8.7
FRA	3.8	3.1	3.1	9.3	8.7	8.8
GAB	2.2			12.4		
GMB	2.4	1.8	2	6.6	6.5	6.5
GEO	-0.6	-1.3	-2	5.1	4.9	4.7
DEU	4.3	4	3.8	11.7	11.7	11.6
GHA	2.3	-3.8	-1.8	7.5	6.8	7
GRC	3.5	3.2	3	8.1	7.8	7.7
GTM	1.4	1	1.1	11.4	11.4	11.4
GIN	2.4	1.9	1.4	4.8	4.6	4.5
GUY	1.5	1.3	1.9	4.6	4.6	4.6
HTI	2.9	4	3.4	7.1	7.6	7.5
HND	1.5	1.7	1.6	13.8	13.8	13.8
HUN	3	2.6	2.1	13.7	13.5	13.3
ISL	3.3	2.5	2.5	7.7	7.2	7.2
IND	1.7	1.4	1.2	4.6	4.5	4.4
IDN	1.8	1.7	1.7	7.8	7.7	7.7
IRQ	1	0.9	1.1	1.7	1.7	1.7
IRL	3.1	2.7	2.1	8.5	8.4	8.2
ITA	3.7	3.4	3.4	6.9	6.8	6.7
JAM	1.6	0.4	0.6	9.8	9.5	9.5
JOR	1.2	0.4	0.6	6.4	6	6.1
KAZ	1.2	0.9	0.9	12.7	12.4	12.4
KEN	2.8			15.1		
KOR	1.9	1.6	1.5	7.1	6.8	6.7
KSV	0.7	-0.2	-0.2	3.7	3.5	3.5
KGZ	-1.6	-1.5	-1.8	9.8	9.8	9.8
LAO	0.7	0.8	1.1	9.9	9.9	10
LVA	2.4	1.6	0.8	12.5	12.2	11.8

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Table A.7: Estimated Returns for the 145 Countries (Average in 1990-2016)

Country:	Estimated Returns to Experience (%)			Estimated Returns to Education (%)		
Cohort FE:	None	Decadal	Event	None	Decadal	Event
LBN	0.9			4.5		
LSO	0.4			8.8		
LBR	2.2			3.4		
LTU	2	-0.4	-1.8	0.3	-0.2	-0.5
LUX	4.1	3.3	3.2	9.2	8.9	8.8
MDG	2	1	1.7	11.3	11.3	11.4
MWI	1.4	-0.2	-1.3	8.2	8.1	8.1
MDV	1.8	1.5	0.9	6.1	6.1	6.1
MLI	2.4	2.7	2.6	9.2	9.3	9.3
MLT	3.5	3	2.3	9.3	9	8.7
MRT	2.7	-1.2	1.2	8.9	8.5	8.7
MUS	2.4	1.8	1.5	12.4	12.2	12.2
MEX	1.9	1.7	1.6	11.8	11.7	11.7
FSM	2.6			11.3		
MDA	1	0	0.9	8.9	8.5	9
MNG	1	0.8	0.4	9	9	8.9
MNE	1	0.6	0.1	7	6.8	6.6
MAR	2.7	2.1	2.1	9	8.8	8.8
MOZ	2.6	1.5	0.7	11.4	11.2	11
NAM	3.1	1.4	0.1	17.8	17.2	17.1
NPL	2.1	0.7	-3.5	7.7	7.5	7.4
NLD	5.1	4.3	4.4	8.5	8.2	8.1
NIC	1.5	1	1	7.3	7.2	7.2
NER	2.7	1.9	1.6	14.7	14.6	14.6
NGA	1.8	1.6	1	5.4	5.4	5.4
NOR	4.2	3.8	3.6	8.2	8.1	8
PAK	1.6	0.6	-1	7.9	7.7	7.6
PLW	2.3			12		
PAN	2.1	1.9	2	13.1	13	13
PNG	0.6			15.1		
PRY	1.8	1.3	1.2	11	10.9	10.9
PER	2	1.6	1.3	9.9	9.7	9.6
PHL	0.8	-0.3	-1.7	8.3	8	7.8
POL	3.8	3	2.5	11.9	11.4	11
PRT	3.2	2.8	2.6	10.1	9.9	9.9
PRI	2.9	1.8	2.6	11.3	10.5	11.1
ROM	0.7	1.4	1.8	11.8	12.2	12.3
RUS	1.5	1.8	1.9	6.5	6.3	6.4
RWA	2.8	1.2	0.2	14.9	14.6	14.4
STP	1.9	1.2	0.7	3.8	3.7	3.7
SEN	2.8			10.1		
SRB	1.2	0.9	0.6	10.8	10.5	10.5
SYC	0.7			7.6		
SLE	2.4	-0.3	1.4	4.1	3.4	3.8
SVK	3	2.9	2.8	9.2	9.3	9.1
SVN	3	2.7	2.7	9.8	9.4	9.2
SLB	2.6			7		
ZAF	2.4	1.3	0.3	15.2	15	14.8
ESP	2.8	2.5	2.3	7.1	6.9	6.7
LKA	1.9	1.4	1.4	7.6	7.6	7.6
SUR	1.5			8.8		
SWE	5.4	4.8	4.5	5.8	5.6	5.4
CHE	4.4	3.4	3.8	9	8.5	8.7
SYR	4.3			2.9		
TJK	0.8	0.3	0.4	5.6	5.4	5.4
TZA	3.1	1.7	0.3	6.1	5.8	5.5
THA	2.3	2	1.7	11.3	11.1	11
TMP	1.5	1.4	0	9.9	9.8	9.6
TGO	2.6	1.7	0.6	10.5	10.3	10.2
TTO	3.5			10.9		
TUN	2			6.8		
TUR	1.7	1.6	1	8.4	8.2	8
UGA	2.7	2.2	2	10.9	10.8	10.8
UKR	1.2	0.8	0.9	6.5	6.5	6.5
GBR	2.3	1.6	1.8	9.9	9.6	9.7
USA	4	3.3	3	12.2	11.7	11.6
URY	2.8	2.7	2.7	11.1	11	11
UZB	1	1.5	0.8	0.5	0.5	0.5
VEN	1.8	1.4	1.4	8.6	8.5	8.5
VNM	1	0.7	0.3	5.7	5.5	5.3
WBG	1.5	0.8	0.8	2.5	2.2	2.2
YEM	-0.8	-1.7	-2.7	2.6	2.4	2.3
ZMB	0.3	0	-0.7	14.5	14.5	14.5
ZWE	3.1	2	-1.2	20.4	20.1	19.7

Table A.8: Robustness Checks Related to the Cohort Effects

Dependent Variable:	Estimated Returns to Potential Work Experience								
Sample of Countries:	(1) $\geq$ 3 Yrs of Data			(2) $\geq$ 5 Yrs of Data			(3) $\geq$ 8 Yrs of Data		
Development Status:	G	D-G	D	G	D-G	D	G	D-G	D
1. Baseline	1.6***	1.7***	3.3***	1.6***	1.7***	3.3***	1.7***	1.7***	3.4***
2. 10-Year of Birth Cohort FE	1.0***	1.7***	2.8***	1.1***	1.7***	2.8***	1.2***	1.6***	2.8***
3. 20-Year of Birth Cohort FE	1.5***	1.7***	3.2***	1.4***	1.7***	3.1***	1.5***	1.7***	3.1***
4. 5-Year of Birth Cohort FE	0.5**	1.7***	2.3***	0.5***	1.6***	2.1***	0.5*	1.6***	2.1***
5. Events Cohort FE 18-67	0.7***	1.8***	2.5***	0.9***	1.6***	2.5***	0.9***	1.6***	2.6***
6. Events Cohort FE 18-40	1.0***	1.8***	2.8***	1.0***	1.8***	2.8***	1.1***	1.8***	2.9***
7. Events Cohort FE 18-30	1.0***	1.8***	2.8***	1.0***	1.8***	2.8***	1.1***	1.8***	2.9***
8. Events FE & Growth 18-67	0.7***	1.7***	2.4***	0.8***	1.6***	2.4***	1.0***	1.4***	2.4***
9. Regression 8, Also Incl. 0-17	0.1	2.2***	2.4***	0.6**	1.8***	2.4***	0.6**	1.8***	2.4***
10. Combining Regr. 2 & 5	0.3*	1.9***	2.3***	0.6***	1.7***	2.3***	0.6**	1.7***	2.3***
11. Combining Regr. 2 & 8	0.3	1.9***	2.2***	0.6***	1.6***	2.2***	0.7***	1.5***	2.2***
12. HLT: 5 Yrs, depr. = 0%	2.8***	1.1***	3.9***	2.8***	1.1***	3.9***	2.9***	1.1***	4.0***
13. HLT: 5 Yrs, depr. = 1%	2.1***	1.0***	3.1***	2.1***	1.0***	3.0***	2.2***	1.0***	3.1***
14. HLT: 10 Yrs, depr. = 0%	2.4***	1.2***	3.7***	2.4***	1.2***	3.6***	2.5***	1.2***	3.7***
15. HLT: 10 Yrs, depr. = 1%	1.6***	1.2***	2.8***	1.6***	1.1***	2.7***	1.6***	1.2***	2.8***

Notes: Obs. in rows 1-8 = 104 in Col. (1); 80 in Col. (2); 55 in Col. (3). Obs. in rows 9-12 = 95 in Col. (1); 73 in Col. (2); 53 in Col. (3). 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. Developed countries are high-income countries in 2017 according to the classification of the World Bank. Row 1: Baseline regressions. Rows 2-4: Decadal cohort FE (e.g., for the 1990s), bi-decadal cohort FE, and semi-decadal cohort FE (e.g., for 1990-1994 and 1995-1999) are included in the regressions estimating the country returns, respectively. Rows 5-7: For each country, we construct periods based on important historical years. We then include in the regressions estimating the country returns multiple country-specific period dummies equal to one if the individual was aged between 18 and 67, between 18 and 40 or between 18 and 30 during the period(s). Row 8: In addition to the country-specific period dummies equal to one if the individual was aged between 18 and 67 during the period(s), we control for the country's average growth rate of per capita GDP (PPP, constant 1990 dollars) for those years during which the individual was aged between 18 and 67. The source for per capita GDP data is Maddison (2008), which was updated by Bolt and van Zanden (2014). Row 9: This regression replicates row 8 except we now also include multiple country-specific period dummies equal to one if the individual was aged between 0 and 17 during the period(s) as well as the country's average growth rate of per capita GDP for those years during which the individual was aged between 0 and 17. Row 10: We include both decadal cohort FE (see row 2) and country-specific period dummies constructed based on important years (see row 5). Row 11: This regression replicates row 10 except we now also include the country's average growth rate of per capita GDP for those years during which the individual was aged between 18 and 67. Rows 12-15: We use the main approach of Lagakos et al. (2018), which is an adaptation of the method used by Heckman, Lochner and Taber (1998). In Col. (1), we restrict the analysis to countries with at least 3, instead of 2, years of data, because this method only works for countries with at least 3 years of data. We consider 5 or 10 as the number of years at the end of the life cycle for which there are no experience effects and 0% or 1% as the depreciation rate of human capital at the end of the life cycle.

Table A.9: Returns to Experience for More Experienced vs. Less Experienced Workers

Dependent Variable:	Estimated Returns to Potential Work Experience								
Return Specification:	(1) No Cohort FE			(2) Decadal Cohort FE			(3) Events Cohort FE		
Development Status:	G	D-G	D	G	D-G	D	G	D-G	D
1. Baseline: 0-35 Bins	1.7***	1.5***	3.2***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
2. Exp. Bin = 5 Only	3.1***	3.8***	6.9***	2.2***	4.2***	6.4***	2.0***	4.2***	6.2***
3. Exp. Bin = 10 Only	1.8***	1.1***	2.8***	1.2***	0.9***	2.1***	0.6***	1.2***	1.8***
4. Exp. Bin = 15 Only	1.3***	-0.1	1.2***	0.5**	0.4	0.9***	0.3*	0.3	0.5**
5. Exp. Bin = 20 Only	1.1***	0.1	1.2***	0.4***	0.0	0.4***	-0.0	0.3	0.3
6. Exp. Bin = 25 Only	0.9***	-0.3	0.7***	0.1	0.0	0.1	0.0	-0.2	-0.1
7. Exp. Bin = 30 Only	-0.1	0.4**	0.3**	-0.8***	0.5***	-0.3**	-1.1***	0.7***	-0.4**
8. Exp. Bin = 35 Only	-1.6***	0.7**	-0.8***	-2.0***	1.0***	-1.0***	-1.9***	0.7*	-1.2***

Notes: Obs. = 145 in Col. (1); 122 in Col. (2); 122 in Col. (3). This table is constructed like Table 1 (see notes under Table 1 for details). Row 1: This row replicates the baseline results where returns are constructed using all seven experience bins from "5" to "35". Rows 2-8: Local returns are shown for each experience bin one by one. For example, the returns in row 3 should be interpreted as the average percentage increase in wages for each extra year of experience when going from "5" to "10" years of experience.

Table A.10: Returns to Experience with Decadal FE: Issue Related to the Periodicity of the Surveys

Test:	(1) Baseline with Decacal Fixed Effects (FE)	(2) Excl. 12 Countries with Problematical I2D2 Samples	(3) Excl. 12 Problematical I2D2 Samples	(4) Returns Based on the 0-25 Bins
G	1.1***	1.0***	1.0***	1.3***
	[0.1]	[0.1]	[0.1]	[0.1]
D	2.8***	2.8***	2.8***	3.4***
	[0.2]	[0.2]	[0.2]	[0.2]
D-G	1.7***	1.8***	1.8***	2.1***
	[0.2]	[0.2]	[0.2]	[0.2]
Observations	122	110	115	122
Decadal FE	Y	Y	Y	Y

Notes: Col. (1): Baseline results from row 1 of Table 1 Col. (2). Col. (2): We exclude 12 countries with a problematical survey as a result of which the 1920s effect and/or 1930s effect is not identified. Col. (3): We exclude the 12 problematical surveys. 5 countries then do not need to be excluded. Col. (4): We use the returns constructed the bins 0-25 only.

Table A.11: Formal and/or Informal Training and Returns to Experience

Panel A: Training Bin 0-4 and 5-9	dev'D		dev'G		D-G Gap		
Parameter (B-P = Ben-Porath)	Baseline	B-P	Baseline	B-P	Baseline	B-P	% decline
Ret. to exp., before college	4.4	4.1	2.0	1.9	2.4	2.2	8.3
Ret. to exp., college+	4.2	3.9	2.8	2.7	1.4	1.2	14.3

Panel B: Training Bin 0-4 Only	dev'D		dev'G		D-G Gap		
Parameter (B-P = Ben-Porath)	Baseline	B-P	Baseline	B-P	Baseline	B-P	% decline
Ret. to exp., before college	4.4	3.5	2.0	1.7	2.4	1.8	25.0
Ret. to exp., college+	4.2	3.3	2.8	2.4	1.4	0.9	35.7

Notes: This table compares returns to experience and the gap in returns between developed economies and developing economies in the benchmark estimation compared to a specification where starting earnings are biased downwards because of time spent actively accumulating human capital in the early years of workers' careers (as opposed to producing). "B-P" refers to Ben-Porath. "Training bin" refers to the experience bins where training is assumed to be concentrated. "% decline" measures the share of the returns that is possibly due to training. See the text for a detailed explanation of the two scenarios.

Table A.12: Returns to Experience for Different Combinations of the Local Returns

Dependent Variable:	Estimated Returns to Potential Work Experience								
Return Specification:	(1) No Cohort FE			(2) Decadal Cohort FE			(3) Events Cohort FE		
Development Status:	G	D-G	D	G	D-G	D	G	D-G	D
1. Baseline: 0-35 Exp. Bins	1.7***	1.5***	3.2***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
2. 0-30 Exp. Bins Only	1.9***	1.6***	3.5***	1.2***	1.9***	3.1***	0.9***	1.9***	2.8***
3. 0-25 Exp. Bins Only	2.0***	1.8***	3.8***	1.3***	2.1***	3.4***	1.0***	2.1***	3.2***
4. 0-20 Exp. Bins Only	2.2***	2.1***	4.3***	1.5***	2.3***	3.8***	1.2***	2.4***	3.6***
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. 0-10 Exp. Bins Only	2.7***	3.0***	5.7***	1.9***	3.2***	5.2***	1.6***	3.3***	4.9***
7. 0-5 Exp. Bin Only	3.1***	3.8***	6.9***	2.2***	4.2***	6.4***	2.0***	4.2***	6.2***

Notes: Obs. = 145 in Col. (1); 122 in Col. (2); 122 in Col. (3). This table is constructed like Table 1 (see notes under Table 1 for details). Row 1 replicates the baseline results where returns are constructed using all seven experience bins from "5" to "35". Rows 2-7: Returns are constructed sequentially dropping more and more higher-experience bins: "35", "30", "25", "20", "15", and "10".

Table A.13: Returns to Experience for Different Levels of Education

Dependent Variable:	Estimated Returns to Potential Work Experience								
First-Stage Specification:	(1) No Cohort FE			(2) Decadal Cohort FE			(3) Events Cohort FE		
Development Status:	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. $\leq$ 12 Yrs Educ.	1.7***	1.7***	3.4***	1.5***	1.6***	3.1***	1.4***	1.6***	3.0***
3. $\leq$ 13 Yrs Educ.	1.7***	1.7***	3.4***	1.4***	1.6***	3.1***	1.4***	1.6***	3.0***
4. $\leq$ 14 Yrs Educ.	1.7***	1.6***	3.3***	1.4***	1.6***	3.1***	1.4***	1.6***	3.0***
5. $\leq$ High School	1.6***	1.7***	3.3***	1.4***	1.7***	3.1***	1.4***	1.6***	3.0***
6. $>$ 12 Yrs Educ.	2.1***	1.2***	3.4***	1.8***	1.3***	3.2***	1.6***	1.5***	3.0***
7. $>$ 13 Yrs Educ.	2.1***	1.2***	3.2***	1.7***	1.2***	3.0***	1.5***	1.2***	2.7***
8. $>$ 14 Yrs Educ.	2.1***	0.8***	2.8***	1.8***	1.0***	2.7***	1.5***	1.0***	2.5***
9. $>$ High School	2.1***	1.2***	3.2***	1.7***	1.3***	3.0***	1.4***	1.3***	2.7***
10. $\leq$ 12 Yrs Educ. & Wgts	1.6***	2.0***	3.6***	1.8***	1.4***	3.3***	1.7***	1.7***	3.4***
11. $\leq$ 13 Yrs Educ. & Wgts	1.7***	2.0***	3.7***	1.8***	1.5***	3.3***	1.7***	1.7***	3.4***
12. $\leq$ 14 Yrs Educ. & Wgts	1.7***	2.0***	3.7***	1.8***	1.5***	3.3***	1.6***	1.6***	3.3***
13. $\leq$ High School & Wgts	1.5***	2.1***	3.5***	1.7***	1.4***	3.1***	1.6***	1.5***	3.1***
14. $>$ 12 Yrs Educ. & Wgts	2.5***	1.2***	3.6***	2.3***	1.1***	3.4***	2.1***	1.2***	3.3***
15. $>$ 13 Yrs Educ. & Wgts	2.4***	1.0***	3.5***	2.2***	1.1***	3.3***	1.9***	1.2***	3.1***
16. $>$ 14 Yrs Educ. & Wgts	2.4***	1.1***	3.5***	2.2***	1.2***	3.4***	1.9***	1.3***	3.2***
17. $>$ High School & Wgts	2.4***	1.2***	3.7***	2.2***	0.9***	3.1***	1.9***	0.9***	2.8***

Notes: Obs. = 145 in Col. (1); 122 in Col. (2); 122 in Col. (3). This table is constructed like Table 1 (see notes under Table 1 for details). Row 1 replicates the baseline results. Rows 2-5: Returns are shown for individuals with less than 12, 13, or 14 years of education, or individuals who have not completed high school. Rows 6-9: Returns are shown for individuals with more than 12, 13, or 14 years of education, or individuals who have completed high school. Rows 10-13: These rows replicate rows 2-5 except we use as weights country populations circa 2017. Rows 14-17: These rows replicate rows 6-9 except we use as weights country populations circa 2017.

Table A.14: Robustness Checks for the Regressions Estimating the Returns

Dependent Variable:	Estimated Returns to Potential Work Experience								
First-Stage Specification:	(1) No Cohort FE			(2) Decadal Cohort FE			(3) Events Cohort FE		
Development Status:	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. Drop Female Work.	1.9***	1.7***	3.6***	1.3***	1.9***	3.2***	1.1***	1.9***	3.0***
3. Drop Part-Time Work.	1.7***	1.5***	3.2***	0.9***	1.9***	2.8***	0.6***	2.0***	2.6***
4. Drop Self-Empl. Work.	1.8***	1.6***	3.4***	1.0***	1.8***	2.8***	0.6***	2.0***	2.6***
5. Drop Publ. Sect. Work.	1.7***	1.3***	3.1***	1.0***	1.7***	2.8***	0.7***	1.7***	2.4***
6. Country-Spec. Age Entry	1.7***	1.4***	3.1***	1.0***	1.7***	2.7***	0.7***	1.7***	2.4***
7. Incl. Teen Labor ($\geq$ 15 y.o.)	1.9***	1.5***	3.4***	1.3***	1.7***	3.0***	0.9***	1.9***	2.8***
8. Incl. Child Labor ($\geq$ 13 y.o.)	2.0***	1.3***	3.4***	1.5***	1.5***	3.0***	1.2***	1.7***	2.8***
9. Drop Age Heap. $>$ 175	1.8***	1.5***	3.3***	1.3***	1.6***	2.9***	1.0***	1.7***	2.7***
10. Drop Age Heap. $>$ 150	1.7***	1.5***	3.2***	1.1***	1.8***	2.9***	0.5	2.2***	2.7***
11. Drop Age Heap. $>$ 125	1.2***	2.2***	3.4***	0.8***	2.3***	3.1***	0.7**	2.2***	2.9***
12. Post-2000 Samples	1.8***	1.4***	3.2***	0.9***	1.9***	2.8***	0.6***	1.9***	2.5***
13. 3-Year Exp. Bins	2.0***	2.3***	4.3***	1.4***	2.6***	4.0***	1.6***	2.6***	4.2***
14. 7-Year Exp. Bins	1.5***	1.0***	2.5***	0.8***	1.1***	1.8***	1.0***	1.0***	2.0***
15. Wage Info. $\geq$ Monthly	1.8***	1.5***	3.3***	1.0***	1.7***	2.8***	0.7***	1.9***	2.5***
16. Incl. Secondary Job	1.8***	1.4***	3.2***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
17. Agg. Household Level	1.7***	1.3***	3.0***	0.8***	1.5***	2.3***	0.8***	1.9***	2.7***
18. Bin Size $\geq$ 100	1.8***	1.5***	3.3***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
19. Individual Controls	1.6***	1.5***	3.0***	1.3***	1.6***	2.9***	1.1***	1.5***	2.6***
20. Drop Unempl. $<$7%	1.7***	1.6***	3.3***	1.1***	1.7***	2.9***	0.9***	1.8***	2.7***
21. Drop Unempl. $\geq$7%	1.6***	1.6***	3.2***	1.1***	1.5***	2.6***	0.9***	1.4***	2.3***
22. Drop Unempl. $<$10%	1.7***	1.5***	3.1***	1.1***	1.7***	2.8***	0.7***	1.8***	2.6***
23. Drop Unempl. $\geq$10%	1.6***	1.6***	3.3***	1.1***	1.5***	2.5***	0.8***	1.4***	2.2***
24. Drop Non-Labor $<$35%	1.7***	1.5***	3.2***	1.1***	1.7***	2.8***	0.8***	1.7***	2.5***
25. Drop Non-Labor $\geq$35%	1.6***	1.5***	3.2***	1.1***	1.2***	2.4***	0.9***	1.0**	1.9***
26. Heckman Correction	1.9***	1.1***	3.0***	1.2***	1.2***	2.4***	0.8***	1.1***	2.0***

Notes: This table is constructed like Table 1 (see notes under Table 1 for details). Row 1 replicates the baseline results. Rows 2-26: Robustness checks in rows 2-26 and the number of countries available for each are described in Appendix Section A.4.

Table A.15: Robustness Checks for the Group-Specific Returns

Dependent Variable:	Estimated Returns to Potential Work Experience								
Return Specification:	(1) No Cohort FE			(2) Decadal Cohort FE			(3) Events Cohort FE		
Development Status:	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. WB Region FE	1.7***	1.7***	3.4***	1.0***	1.8***	2.8***	0.8***	1.7***	2.5***
3. No EAP Region	1.8***	1.5***	3.3***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
4. No LAC Region	1.7***	1.6***	3.3***	0.9***	1.9***	2.9***	0.6***	2.0***	2.6***
5. No MENA Region	1.7***	1.5***	3.2***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
6. No SAR Region	1.8***	1.5***	3.2***	1.1***	1.7***	2.8***	0.8***	1.7***	2.6***
7. No SSA Region	1.5***	1.8***	3.3***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
8. No Ex-Communist	2.0***	1.3***	3.3***	1.3***	1.7***	3.0***	1.0***	1.9***	2.8***
9. Drop Bottom/Top 10% Ret.	2.0***	1.3***	3.3***	1.2***	1.6***	2.8***	0.9***	1.6***	2.6***
10. Ctrls Communism	–	1.4***	–	–	1.7***	–	–	1.7***	–
11. Ctrls Mort. Rates	–	1.6***	–	–	1.6***		–	1.3***	–
12. Ctrls HIV Rates	–	1.7***	–	–	1.9***	–	–	1.6***	–
13. Ctrls PCGDP Growth	–	1.5***	–	–	1.7***	–	–	1.8***	–
14. Ctrls Pop Growth	–	1.7***	–	–	1.4***	–	–	1.4***	–
15. Ctrls All	–	1.5***	–	–	1.2**	–	–	1.3**	–
16. Mean SE <50th Pctile	1.6***	1.7***	3.4***	1.1***	1.7***	2.8***	0.8***	1.7***	2.5***
17. Max SE <50th Pctile	1.6***	1.8***	3.4***	1.1***	1.7***	2.8***	0.8***	1.7***	2.6***
18. Boostrapped SE	1.7***	1.5***	3.2***	1.1***	1.7***	2.8***	0.8***	1.8***	2.6***
19. $0.25 \leq$ Mincerian R2 ≤ 0.5	1.9***	1.4***	3.3***	1.3***1.5***	2.7***	0.9***	1.7***2.5***		

Notes: This table is constructed like Table 1 (see notes under Table 1 for details). Row 1 replicates the baseline results. Rows 2-18: Robustness checks in rows 2-18 are described in the main text and in Appendix Section A.5.

Table A.16: Spearman Rank-Order Corr. for the Returns to Exp.-Income Relationship

	Spearman Rank-Order Correlation			Number of Countries		
Return Spec.:	No Cohort FE	Decadal Cohort FE	Events Cohort FE	No Cohort FE	Decadal Cohort FE	Events Cohort FE
1. Baseline	0.38	0.52	0.55	145	122	122
2. 0-25 Exp. Bins Only	0.38	0.52	0.55	145	122	122
3. Lagakos et al ’18 (m)	0.40	0.63	0.60	124	101	101
4. Cntry Pop. ’17 as Wgts	0.56	0.60	0.64	145	122	122
5. 0-25 & Wgts	0.59	0.60	0.62	145	122	122
6. 0-25 & Wgts & Lagakos et al ’18	0.62	0.58	0.46	124	101	101
Panel A: **Specification 1 (Row 5)**						
7. Row 5 & No Communist	0.71	0.69	0.67	105	84	84
8. Row 5 & Mort. < 99th Pctile	0.60	0.60	0.63	140	120	120
9. Row 5 & Mort. < 95th Pctile	0.63	0.63	0.65	128	110	110
10. Row 5 & Mort. < 90th Pctile	0.71	0.65	0.65	117	102	102
11. Row 5 & Both (99th Pctile)	0.72	0.70	0.68	100	82	82
12. Row 5 & Both (95th Pctile)	0.75	0.75	0.73	91	74	74
13. Row 5 & Both (90th Pctile)	0.81	0.78	0.75	83	69	69
Panel B: **Specification 2 (Row 6)**						
14. Row 6 & No Communist	0.69	0.55	0.37	90	71	71
15. Row 6 & Mort. < 99th Pctile	0.62	0.57	0.45	120	100	100
16. Row 6 & Mort. < 95th Pctile	0.67	0.60	0.47	110	94	94
17. Row 6 & Mort. < 90th Pctile	0.75	0.61	0.48	100	87	87
18. Row 6 & Both (99th Pctile)	0.69	0.54	0.36	86	70	70
19. Row 6 & Both (95th Pctile)	0.74	0.57	0.39	79	66	66
20. Row 6 & Both (90th Pctile)	0.78	0.57	0.40	72	62	62

Notes: This table shows the Spearman rank-order correlation between the estimated returns to experience and log per capita GDP (PPP; cst 2011 USD; for the mean year in the data for each country). Rows 1-6: See the description of Table 1 for details. Rows 7-13: Returns based on the 0-25 bins and country populations (2017) employed as weights. Rows 14-20: Returns based on the 0-25 bins and excluding female, part-time, self-employed or public sector workers and country populations (2017) employed as weights. “No communist”: We exclude ex-Communist countries. “Mort. < X Pctile”: We exclude countries whose average child (0-5) mortality rate or average adult (15-45) mortality rate in the 1950s-2010s was above the Xth percentile in the sample as well as countries whose mean HIV prevalence rate in the 1990s-2010s was above the Xth percentile in the sample. “Both (Xth Pctile)”: We drop ex-Communist countries and countries with disproportionately high mortality rates (1950s-2010s) or HIV prevalence rates (1990s-2010s).

Table A.17: Returns to Experience by Income Group: Low vs. Middle-Income Countries

Specification:	Baseline	Col. (2)-(5): Specification 1: Decadal FE & 0-25 & Cntry Pop. Wgts				Col. (6)-(9): Specification 2: Decadal FE & 0-25 & Wgts & Lagakos et al 2018			
Countries:			Excluding Ex-Communist & Mort. < Xth Pctile				Excluding Ex-Communist & Mort. < Xth Pctile		
Xth Pctile:			99	95	90		99	95	90
Panel A: 2 Inc. Groups	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
G	1.7***	1.8***	1.6***	1.6***	1.6***	1.9***	1.7***	1.7***	1.7***
	[0.1]	[0.2]	[0.1]	[0.1]	[0.1]	[0.2]	[0.2]	[0.2]	[0.2]
D	3.2***	3.7***	3.7***	3.7***	3.7***	3.8***	3.8***	3.8***	3.8***
	[0.2]	[0.2]	[0.2]	[0.3]	[0.3]	[0.2]	[0.2]	[0.2]	[0.2]
D-G	1.5***	1.8***	2.0***	2.1***	2.1***	1.9***	2.1***	2.1***	2.1***
	[0.2]	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]	[0.3]
Observations	145	122	82	74	69	101	70	66	62
R-squared	0.3	0.4	0.6	0.6	0.6	0.4	0.5	0.5	0.5
Panel B: 3 Inc. Groups	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Low-Income	2.2***	1.6***	1.4***	1.2**	0.8	0.8	-0.2	-0.3	-0.7
	[0.1]	[0.3]	[0.3]	[0.1]	[0.5]	[0.2]	[0.1]	[1.2]	[0.2]
Middle-Income	1.6***	1.8***	1.6***	1.6***	1.6***	2.0***	1.9***	1.8***	1.8***
	[0.1]	[0.2]	[0.5]	[0.6]	[0.1]	[0.7]	[0.2]	[0.2]	[0.2]
High-Income	3.2***	3.7***	3.7***	3.7***	3.7***	3.8***	3.8***	3.8***	3.8***
	[0.2]	[0.2]	[0.1]	[0.3]	[0.3]	[0.2]	[1.0]	[0.2]	[1.5]
Middle - Low	-0.7***	0.2	0.2	0.5	0.8	1.2	2.1**	2.2*	2.5*
	[0.2]	[0.4]	[0.5]	[0.6]	[0.5]	[0.8]	[1.0]	[1.2]	[1.5]
Observations	145	122	82	74	69	101	70	66	62
R-squared	0.4	0.4	0.6	0.6	0.6	0.4	0.6	0.6	0.6

Notes: Panel A shows for various specifications the mean returns to experience for developing countries and developed countries. Developed countries are high-income countries in 2017. Panel B shows for various specifications the mean returns to experience for low-income countries, middle-income countries and high-income countries in 2017. Col. (2)-(5) (Specification 1): We include decadal cohort fixed effects, restrict the analysis to the 0-25 exp. bins, and employ country pop. (2017) as weights. Col. (6)-(9) (Specification 2): We also exclude female, part-time, self-employed or public sectors workers. Col. (3)-(5) and (7)-(9): We exclude ex-Communist countries and countries with disproportionately high mortality rates (1950s-2010s) or HIV prevalence rates (1990s-2010s) (see the notes of Appx. Table A.16 for details).

Table A.18: Development, Recessions and Returns to Work Experience

Dep. Var.:	Estimated Returns to Potential Work Experience (0-15 Bins) of Country c in Year t						
Ages for Unemp. and/or LFP	15+	15-24	15+	15-24	15-24		15-24
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A:	*Long-Difference Panel Regression*						
Unemp. Rate 0-5 Yrs Exp.$_{c,t}$	2.44	-4.43*			-4.33		-4.74
	[6.12]	[2.47]			[2.57]		[3.03]
LFP Rate 0-5 Yrs Exp.$_{c,t}$			-3.34	-7.31**	-1.13		2.91
			[3.83]	[2.73]	[3.93]		[5.56]
Sh. 0-5 Yrs Exp. Growth $\leq$ -5$_{c,t}$						-2.24***	-2.86
						[0.78]	[2.53]
Obs.	138	76	154	142	76	226	72
Panel B:	*Long-Diff. Panel Regression, Ctrl for High-Income Dummy*						
Unemp. Rate 0-5 Yrs Exp.$_{c,t}$	1.57	-5.01**			-5.03*		-5.98**
	[6.53]	[2.29]			[2.43]		[2.56]
LFP Rate 0-5 Yrs Exp.$_{c,t}$			-2.18	-6.16**	0.12		2.94
			[3.77]	[2.71]	[3.78]		[4.90]
High-Income$_{c,t}$	1.06	1.47***	1.54***	1.46***	1.48***	0.83**	1.69**
	[0.63]	[0.45]	[0.50]	[0.43]	[0.47]	[0.41]	[0.73]
Sh. 0-5 Yrs Exp. Growth $\leq$ -5$_{c,t}$						-2.05**	0.86
						[0.79]	[2.86]
Obs.	130	76	154	142	76	226	72
Panel C:	*Five-Year Panel Regression*						
Unemp. Rate 0-5 Yrs Exp.$_{c,t}$	2.15	-2.53			-2.83		-2.85
	[4.20]	[1.63]			[1.77]		[1.78]
LFP Rate 0-5 Yrs Exp.$_{c,t}$			-0.16	-2.81*	-4.80***		-4.7**
			[2.23]	[1.63]	[1.79]		[1.88]
Sh. 0-5 Yrs Exp. Growth $\leq$ -5$_{c,t}$						-1.52*	-0.25
						[0.88]	[1.08]
Obs.	323	237	340	314	235	420	222
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 related to economic recessions. These include the mean unemployment rate (Unemp.) and the mean labor force participation rate (LFP) during the respondents' first five years of work experience, whether for 15-+ year-olds or 15-24 year-olds only. We use 15-24 because this is the only specific age bracket for which the *World Development Indicators* database of the World Bank reports the data. The baseline 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).

Table A.19: Development, Recessions, Transitions and Returns to Education

Dep. Var.:	Estimated Returns to Education 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 $\leq$ -1%	$\leq$ -3%	$\leq$ -5%	Years Since Transition
Panel A:	*Long-Difference Panel Regression (N = 244; 226 in (3)-(5))*						
Var. of Interest c, t	0.43	-0.29	-0.64	-5.97***	-7.11***	-6.79**	0.20***
	[0.86]	[1.90]	[1.49]	[2.26]	[2.21]	[3.28]	[0.08]
Panel B:	*Long-Diff. Panel Regression, Ctrl for High-Income Dummy (N = 244; 226 in (3)-(5))*						
Var. of Interest c, t				-5.97**	-7.10***	-6.85**	0.20***
				[2.27]	[2.22]	[3.30]	[0.08]
High-Income c, t				0.51	0.22	-0.24	0.07
				[1.50]	[1.34]	[1.00]	[0.99]
Panel C:	*Five-Year Panel Regression (N = 420; 390 in (3)-(5))*						
Var. of Interest c, t	0.54	-0.43	-0.90	-3.87***	-3.25*	-2.26	0.29***
	[1.00]	[1.85]	[1.52]	[1.46]	[1.69]	[1.89]	[0.10]
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 A.20: % of Steady State DevG Cntry pcGDP that Equals the Discounted Welfare Gain from Reforms

r (%)	(1) All Reforms	(2) Schooling	(3) Exp. Ret.
2	39.5	16.3	23.6
4	22.9	7.5	16.3
6	15.0	3.7	11.9
8	10.6	2.0	9.1
10	8.0	1.1	7.2
15	4.7	0.4	4.4
25	2.4	0.2	2.2
50	0.8	0.1	0.7

Notes: Percentage of steady state developing country pcGDP that equals the discounted welfare gain from reforms. This can also be interpreted as an indicator of the magnitude of reform costs that would be sufficient to deter the developed economy from reforming.

Table A.21: Parameters Used For Quantitative Experiments

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

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

Table A.22: Results of the Benchmark and Robustness Experiments

Experiment	Relative Per Capita GDP, % (1) No Reforms	(2) All Reforms	(3) Qty. Edu.	(4) Ret. Exp.	(4) Ret. Exp. / (3) Qty. Edu. Ratio after y Years $y = 25$	50	100
Panel A:	Developing (G) Economy Relative to the Developed (D) Economy						
A. Benchmark	48.5	87.5	67.7	66.4	1.18	1.06	0.98
B. Same Demog. as D	48.5	88.5	68.0	66.7	1.18	1.07	0.98
C. Retirement= 60 in G	44.2	78.6	61.2	60.0	1.20	1.02	0.98
D. Same Lab. Mkt. as D	53.5	98.7	74.8	75.2	1.20	1.09	1.01
E. Decadal Cohort FE	52.4	88.0	71.1	66.5	1.13	1.00	0.93
F. Events Cohort FE	59.8	87.9	67.7	79.3	1.27	1.25	1.17
G. Lagakos et al 2018	41.4	87.2	67.1	56.1	1.10	0.91	0.84
H. Unweighted	56.7	88.0	69.3	75.0	1.21	1.15	1.08
I. Excl. Comm.,Mort.¿99p	52.2	88.4	83.9	65.5	1.07	0.87	0.78
J. Combining E, G & I	39.9	88.0	71.5	52.1	1.03	0.80	0.73
K. 0-35 Exp. Bins	51.7	88.5	72.0	66.8	1.14	1.00	0.93
L. Youth Returns	48.5	87.5	67.7	66.4	1.18	1.06	0.98
M. Incl. Teen Labor	46.9	87.5	70.9	59.1	1.11	0.93	0.86
N. Incl. Child Labor	47.2	87.5	71.7	57.5	1.08	0.88	0.80
O. Workfare Program	48.0	87.4	66.2	68.4	1.21	1.11	1.03
P. Avg. Schooling	46.3	87.7	62.6	66.7	1.13	1.09	1.07
Q. Spillovers	28.4	82.1	50.8	50.1	1.40	1.14	0.98
Panel B:	Low-Income (L) and Middle-Income (M) vs. High-Income (H)						
Benchmark M to H	55.5	85.6	67.8	75.1	1.20	1.15	1.11
Benchmark L to H	39.2	91.0	69.0	57.9	1.13	0.90	0.84
Row J M to H	38.4	86.2	71.4	49.5	0.99	0.75	0.69
Row J L to H	44.6	91.2	75.0	66.3	1.18	0.95	0.88

Notes: Panel A: Col. (1) reports pcGDP in the developing economy compared to the developed economy without reforms. Col. (2) reports the long-run impact of reforms that increase the quantity of schooling and change the returns to human capital. Col. (3) examines the impact of reforms that increase the quantity of schooling and the returns to school only. Col. (4) examines the impact of reforms that increase the return to experience only. The last 3 columns report pcGDP in the developing economy after reforms to the returns to experience, relative to pcGDP in the developing economy after reforms that change the distribution of schooling and the returns to schooling to levels in the developed economy. Panel B: The columns replicate the same exercises for the low-income economy and the middle-income economy compared to the developed (i.e., high-income) economy.

Table A.23: Results of the Benchmark and Further Applications of the Accounting Model.

(4) / (3) ratio after y years:	$y = 25$	$y = 50$	$y = 100$
A. Benchmark	1.18	1.06	0.98
B. Raising the retirement age	1.17	1.08	0.98
C. Lowering the retirement age	1.20	1.02	0.98
D. Raising population growth	1.18	1.04	0.98
E. Lowering population growth	1.18	1.08	0.98
F. High U 1	1.14	1.00	0.92
G. High U 2	1.11	0.95	0.88
H. Low participation	1.11	0.97	0.90

Notes: The three columns report per capita GDP in the developing economy after reforms to the returns to experience, relative to per capita GDP in the developing economy after reforms that change the distribution of schooling and the returns to schooling to levels in the developed economy.