Economic Growth in the Long Run*

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Abstract

We present new data on real output per worker, schooling per worker, human capital per worker, real physical capital per worker for 168 countries. The output data represent all available data from Maddison. The physical capital data represent all available data from Mitchell. One major contribution is a new set of human capital per worker, the foundation of which comes mostly from Mitchell. We provide original estimates of schooling per worker & per young worker. We find strong support for intergenerational accumulation of human capital with spillovers. With our preferred measure of human capital, over 90 percent of the variation in long run growth can be explained by variation in the growth of inputs per worker, and less than 10 percent from variation in TFP growth. Furthermore between 55% and 70% of the variation in log of output per worker can be explained by variation in the log input levels, and less than half of the log level output per worker variation is explained by variation in log TFP levels. These results are robust to different time periods, and different parameter values on the human capital accumulation technology. We find positive correlation with micro based cross country estimates of human capital, particularly those provided by Hendricks (2002) and Schoellman (2012).

1 Introduction

Since 1820, during the Industrial Revolution, the disparity in income per capita has increased dramatically. In 1820, the Netherlands, with highest output per worker ($5945), was 6.5 times richer than North Korea, the country with the lowest output per worker ($911).[1] In 2010, the top to bottom distance is between the United States ($76,500) and Zaire ($834), or a factor of 90.[2] The standard deviation of the log of output per worker has increased from .42 in 1820 to 1.12 in 2010. The primary objectives of this paper are to account for the factors that have resulted in the growth of output per worker, and to

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[1]All values are expressed in 2000 PPP dollars. We acknowledge that some have expressed concern about the underlying quality of Maddison data, see Barro and Ursúa (2008). However we are not concerned with crises, nor short run cyclical deviations, but rather, long run growth, so we believe that Maddison is the appropriate long run source. We believe this result is robust as the ratio of the second highest output per worker country, United States ($5079), with the second lowest output per worker country, Nepal ($986), is 5.2

[2]Luxembourg is the most productive country with output per worker of more than $137,000 in 2010, but we chose to go with the second most productive country instead.

explain the increase in dispersion of output per worker. To this end, we use data from Maddison (Bolt and van Zanden (2013)), Mitchell (2003a,b,c), and Lindert (2004) to produce a data set that has per worker measures of output, physical capital, and human capital, and covers 168 countries from the onset of the Industrial Revolution for every region of the world.[3] Over this long horizon, the growth in factors of production account for between three fifths and 85 percent of output per worker growth. More striking, the variation in the growth rates of inputs can account for at least one half, and as much as 95 percent of the variation in the growth rates of output per worker. This is in marked contrast to previous work over shorter time horizons that find that TFP growth variation is much more important than input growth variation in explaining output per worker growth variation. For example Klenow & Rodriguez-Clare (1997) find less than 20% of output growth variation is explained by input growth variation. Baier, Dwyer and Tamura (2006), hereafter BDT, have a longer time series, but still find that barely 20% of output per worker growth variation is explained by input per worker growth variation.

In this paper we develop a new data set, which dramatically expands the data available in BDT. The number of countries is expanded from 145 to 168, but more importantly, the length of coverage for all countries is increased. Further we have the growth of formal schooling in every region from illiteracy to universal primary schooling, near universal secondary schooling and rising attendance in higher education.[4] Using a Bils-Klenow definition of human capital, we find that 46% of the variation in growth rates of output per worker is captured by variations in growth rates of inputs. If one uses an intergenerational human capital accumulation technology, over 90 percent of growth in output per worker can be explained by the growth in real physical capital per worker and human capital per worker. Of log level differences, development accounting, 44% are explained using the Bils-Klenow human capital definition, however with intergenerational human capital accumulation anywhere from 55% to 70% of the variation are explained by log level differences in inputs.

One important caveat to bear in mind. We take the time path of input accumulation, physical capital and human capital as given. We think that high quality institutions matter a great deal in providing both a higher return on existing inputs, more output per worker, as well as greater incentives to accumulate. If inputs explain output per worker differences at a point in time, and differential growth rates of inputs explain differential output per worker growth rates, then institutions can be primary. The list of contributors to this line of research is large, but certainly includes: Acemoglu, Johnson and Robinson (2001,2002, 2005a,b), Canaday and Tamura (2009), Engerman and Sokolof (2012), Gwartney and Lawson (2008), Keefer and Knack (1997a,b), Kormendi and Meguire (1985), North (1981, 1990), Parente and Prescott (1994, 1999, 2002) and Tamura, Simon and Murphy (2016).

The paper is organized as follows. In the next section we give a brief overview of the data used in the paper. The interested reader can read our companion Data Appendix (2016) for more details on methods and sources. Section 3 contains the growth accounting. Section 4 contains our variance decomposition of growth. We use three different measures of input importance for capturing disparate economic performance. We present intergenerational human capital in Section 5, with and without spillovers. Section 6 examines

[3]See our Data Appendix (2016) for more detail on other primary data sources, as well as methodology.

[4]After the penultimate version of this paper was written, we became aware of Lee & Lee (2016). Their paper produces original estimates of years of schooling for 15-64 men and women, separately, from 1870-2010. They use many of the same sources as we do, but do not convert enrollment rates for some countries in 1820 into years of schooling as we do here. We also make use of Morrisson and Murtin (2009). They use many similar sources, but for 74 instead of 168 countries. Their series covers 1870-2010, whereas ours covers about half a century earlier. However we are able to benchmark primary, secondary and occasionally tertiary schooling enrollment rates prior to 1870 as their work provides estimates of the exposure share of these three categories starting in 1870. For more details see our Data Appendix.

the robustness of our conclusions. Evidence from micro data is presented in Section 7. Section 8 concludes.

2 Data

We use Maddison for data on real PPP per capita output.[5] All values are in real 2000 dollars. We use Mitchell (2003a,b,c) for historical data on labor force.[6] From these base data we produce measures of PPP real output per worker. For investment rates in physical capital we used both Mitchell (2003a,b,c) for historical values as well as Summers, Heston and Aten (2009).[7] To produce physical capital stock values, we use a variety of methods. When other researchers have computed capital output ratios, we use their estimates, for example Picketty and Zucman (2014) estimate capital output ratios for nine countries, three of them back to 1700. We used their results for all of the observations on these countries. If we do not have country specific estimates of investment rates, we were able to create sectoral output shares for all but 22 observations. From these measures of sectoral output shares, agriculture, industry and services, we applied the US capital output ratio for agriculture, industry and services for the decade of country observation. These sector specific ratios for the US cover every census year 1850 - 2000. We used the 1850 values for years 1800-1840. Finally if we had investment rates, we used them with perpetual inventory methods, using the aforementioned capital estimates as initial conditions for the first missing year. For example all values for 2010 come using perpetual inventory calculations, with the exception of the nine countries provided by Piketty and Zucman (2014). We use the standard perpetual inventory method to produce real physical capital per worker.[8]

For human capital, we first produce original estimates of schooling for each country by age cohort as well as the average schooling in the labor force.[9] This is an original contribution to the literature as prior to this the earliest measures of years of schooling are contained in Baier, Dwyer and Tamura (2006).[10]

[5]Data are from Bolt and van Zanden (2013) at: `http://www.ggdc.net/maddison/madison-project/home.htm`. For some countries missing 2010 values, we used the growth rate of PPP output per capita from 2008 to 2010 from *World Development Report 2011 and 2012* to produce our 2010 value.

[6]See our Data Appendix (2016) for greater detail. For 2010 labor force we used the *World Development Indicators*. For historical labor force earlier than what Mitchell provides, we found additional secondary sources. However for many countries we used a procedure in which we use the urban-rural population shares. We have information on all but 3 countries back to their initial year of observation. We are able to find 15-64 labor force to population ratios in the urban population and the rural population to fit the labor force data that we observe. We then use these to apply in the earlier years, either the average values or the closest set of early observations.

[7]We used overlapping year observations to produce PPP real investment rates for years not covered in Summers, Heston and Aten (2009). See our Data Appendix (2016) for greater detail.

[8]One major change between this data and Baier, Dwyer and Tamura (2006) is in the treatment of physical capital depreciation. The earlier paper used a 7% annual depreciation rate. This produced implausibly small capital-output ratios, significantly less than 2 in 2000. Picketty and Zucman (2014) estimate capital output ratios of 3 or more in 2010 for the top eight developed economies, and above 3 in the eighteenth and nineteenth century for France, Germany and the UK. In this paper we used a depreciation rate of 3.33%. For a commonly assumed capital output ratio of 3, a 3.33% depreciation rate produces a depreciation charge against output of 10% of output, which is at the high end of rates used in public finance. With the lower depreciation rates, this paper produces much more plausible capital-output ratios. For 1810 Piketty and Zucman (2014) find reproducible wealth to income ratios of 3.5 (France), 1.8 (US) and 4.2 (UK), these are net of agricultural land. Using perpetual inventory calculations for many countries produced values quite similar to these using our depreciation rate.

[9]We use enrollments in schooling for all years that are available in Mitchell's three volume set, as well as modern day sources like *Human Development Reports* and *World Development Reports*. In addition we use literacy information contained in Morris and Adelman (1988), Steckel and Floud (1997) and Benavot and Riddle (1988). We follow the rule that it takes three years to become literate, see Harman (1970) and Resnick and Resnick (1977), so if 20 percent of the adult population is literate, we assume that 20 percent of the population attended school for 3 years, producing a measured schooling level of .6 years in the population. For more on the details of the computation of schooling in the labor force see our companion data appendix, *Data Appendix for Economic Growth in the Long Run* (2016).

[10]After the main draft of this paper was written, we became aware of Lee & Lee (2016). In their paper, they construct original estimates of years of schooling using similar and often identical sources as we used. They provide original estimates of

To compute our initial human capital, we use the same method as in Baier, Dwyer and Tamura (2006), Hall & Jones (1999) and Klenow & Rodriguez-Clare (1997).[11] We use cross sectional evidence from labor economists to compute human capital as a function of schooling and experience.[12]

$$h_t = exp(f(\text{schooling}) + g(\text{experience})) \tag{1}$$

$$f(E) = .10E \tag{2}$$

$$g(\text{experience}) = .0495\text{experience} - \frac{.0495}{67}\text{experience}^2 \tag{3}$$

Notice that if all countries have reached the same schooling level, as well as the same average experience, then all countries will have the same human capital.[13] This implies that human capital is bounded by the level of schooling and experience. While schooling would be expected to rise with rising life expectation, and or falling fertility, schooling cannot grow without bound. Thus human capital would be bounded. Furthermore this convergence result predicts very rapid convergence in levels of income across countries as their schooling levels become more similar. Both of these assumptions will be relaxed in later sections in order to better explain the distribution of income across the countries of the world.

If, however, countries have permanent differences in the level of schooling, then there would be permanent differences in human capital input. Consider two countries, one with 13.75 years of schooling and the other with 2.15 years of schooling.[14] Ignoring the experience term, the relative amount of human capital in these countries would be given by:

$$\frac{h(13.75)}{h(2.15)} = exp(.1[13.75 - 2.15]) = exp(1.16) \tag{4}$$

With perfect physical capital mobility, and no difference in technology levels, the model would predict that the more schooled country would be 3.2 times as productive per worker than the less schooled country.

schooling from 1820-2010. Even more fascinating, they provide breakdown by sex, computing separate estimates of schooling for men and women. We consider our estimates and their estimates to be complementary.

[11]Recent work by Manuelli and Seshadri (2014), Erosa, Koreshkova and Restuccia (2010) use different human capital accumulation technologies, In the former a Ben-Porath (1967) model of human capital accumulation is calibrated to the US. Differing prices of human capital investment goods, and different levels of market TFP can produce large differences in steady state human capital levels across countries. Their development accounting focuses on the ability to explain the incomes relative to the US by decile. The model fits extremely well both the schooling distribution, an expenditure shares on education. Most impressive is the ability to explain the relative income without much variation in TFP. The bottom decile has relative income of 2%, but their TFP is 63% of the US, thus the overwhelming bulk of differences arise from steady state differences in human capital. Erosa (2010) et al use a slightly different approach, but with similar results. A 20 fold difference in output per worker only requires a 5 fold difference in TFP in the tradable sector because of human capital differences, whereas if human capital were identical, it would require an 18 fold difference in TFP. In both models higher quality education induces greater human capital differences, which is consistent with the evidence in Hanushek (2013).

[12]One difference is that unlike Hall & Jones and Klenow & Rodriguez-Clare, we do not assume decreasing returns to additional years of schooling. In Turner, Tamura, Mulholland and Baier (2007) there was no evidence of decreasing returns to schooling over the 160 years of US state data. Banerjee and Duflo (2005) present estimates of Mincer returns to schooling, Table 1. The average of these estimates is .0995, and if we exclude poor quality data the average is .0958. Thus the human capital input in high schooling countries will be higher and TFP correspondingly lower than their counterparts computed in Hall & Jones and Klenow & Rodriguez-Clare.

[13]We parameterize experience returns as in Klenow & Rodriguez-Clare (1997), and Hall & Jones (1999). The choice of parameters on experience returns reflects two points, (1) that the returns per year of experience starts at .0495, and (2) peak earnings occurs at 33.5 years of experience. While this is consistent with the macro literature, it is at odds to cross country micro evidence of rich and poor countries, see Lagakos, Moll, Porzio and Qian (2013). The authors find that over the life cycle human capital accumulates more rapidly in rich countries than in poor countries. Typically these cross country differences in experience returns are ignored in this paper. The one major exception to this are the countries of the *Central & Eastern Europe* region. During communism we reduced the market return to years of experience, and after the end of the communist regime in the Soviet Union, we eliminated all years of experience and reset the counter to 0 in 1990.

[14]These are the 2010 values of the most educated country, United States, and the least educated country, Eritrea.

The gap between the US and Eritrea in 2010 is about 45, $76,500 vs. $1707. Human capital measured in this way explains only about one-sixth of the gap in output per worker.

We summarize the data by regional averages in Figures 1-7.[15] We present real output per worker, real physical capital per worker, schooling per worker, schooling per young worker, human capital and TFP.[16] These regional averages are labor force weighted values for each region.[17] Regions that have almost complete coverage in 1820 include: *Western Countries*, *Southern Europe*, *NIC*, *Asia* and *North Africa*. In the case of the *Western Countries*, we observe France, Germany, Netherlands, Sweden, UK and the United States by 1800, and these six countries constitute 83 percent of the *Western Countries* 2010 labor force.[18] We observe Greece, Italy, Portugal, Spain and Turkey of the *Southern Europe* region in 1820; together they contain ninety-five percent of the 2010 *Southern Europe* labor force. All of the *NIC* countries are observed in 1820, and Japan in 1800, which by itself is 60% of the 2010 labor force of *NIC*. In the *Asia* region, we observe eight countries in 1820, including China, India, Indonesia, and Thailand; these countries constitute 91 percent of the 2010 *Asia* labor force. In 1800 we observe eight countries in the *Latin America* region, including Argentina, Brazil, Chile, Colombia, Cuba, Mexico, Uruguay and Venezuela, which represent over three-fifths of the 2010 *Latin America* labor force. For the *Middle East* region, we observe five countries, Iran, Iraq, Jordan, Lebanon and Syria in 1820. These five countries represent three-fifths of the 2010 labor force of the *Middle East* region. Of the five countries in *North Africa*, four are observed in 1820. These constitute 96 percent of the 2010 *North Africa* labor force.

Figure 1 contains the regional average real output per worker. The *Western Countries* region has been home to the world's highest output per worker countries for over two centuries. The vertical axis is in log scale, so that constant vertical gaps are constant proportionate differences. In 1820 there are clearly three equivalence classes. The *Western Countries* form the highest group, the middle income group contains the *Southern Europe* and *Middle East*, and the rest of the countries are in the lowest income group. In 2010 there are still three classes: (1) the highest group consisting of *Western Countries*, *NIC* and *Southern Europe* (average real output per worker of $60,000), (2) the middle group including *Middle East*, *Central & Eastern Europe*, *North Africa* and *Asia* (average real output per worker of $15,000), (3) the lowest group, *Sub-Saharan Africa* (average real output per worker of $5000). In order to see more clearly the evolution of these regions, we produce the ratio of the average real output per worker in the *Western Countries* relative to the average real output per worker in the other eight regions. This is presented in Figure 2. Only one region, *NIC* has converged relative to *Western Countries* between 1820 and 2010.

Figure 3 contains the regional average real physical capital per worker. Physical capital mirrors real output per worker.[19] There are three equivalence classes of real physical capital per worker in 2010. The

[15]We follow the convention of Lucas (1988) in region composition, with the only exceptions being the placement of Israel and Turkey in the *Southern Europe* region. See Appendix Table A1 for a list of countries by region, as well as their first and last observation information.

[16]To compute TFP we used a Cobb-Douglas formulation with capital share of .33 and human capital share of .67.

[17]For 1800 we observe *Western Countries*, *Southern Europe*, *N.I.C.*, *Sub-Saharan Africa* and *Latin America*. All other regions we observe in 1820. Our first observation in each region consists of countries whose labor force in 2010 constitutes at least half of the region's 2010 total labor force. The only exceptions to this rule are *Southern Europe* where we observe Portugal and Spain in 1800, which represent one third of the 2010 labor force for *Southern Europe*, *Sub-Saharan Africa*, where we observe only South Africa, which represents slightly more than five percent of the 2010 labor force in *Sub-Saharan Africa*, and *Central & Eastern Europe* where we observe the Czech Republic, and Russia, which represents 42 percent of the 2010 labor force of *Central & Eastern Europe*.

[18]We observe the UK in 1801.

[19]By construction we imposed an additional higher depreciation rates on *Central & Eastern Europe* countries between 1990 and 2000. For all countries in the *Central & Eastern Europe* region, we depreciated 1990 physical capital by 50% to take into account the market pricing of capital, see our Data Appendix for more details. In addition for some of these countries

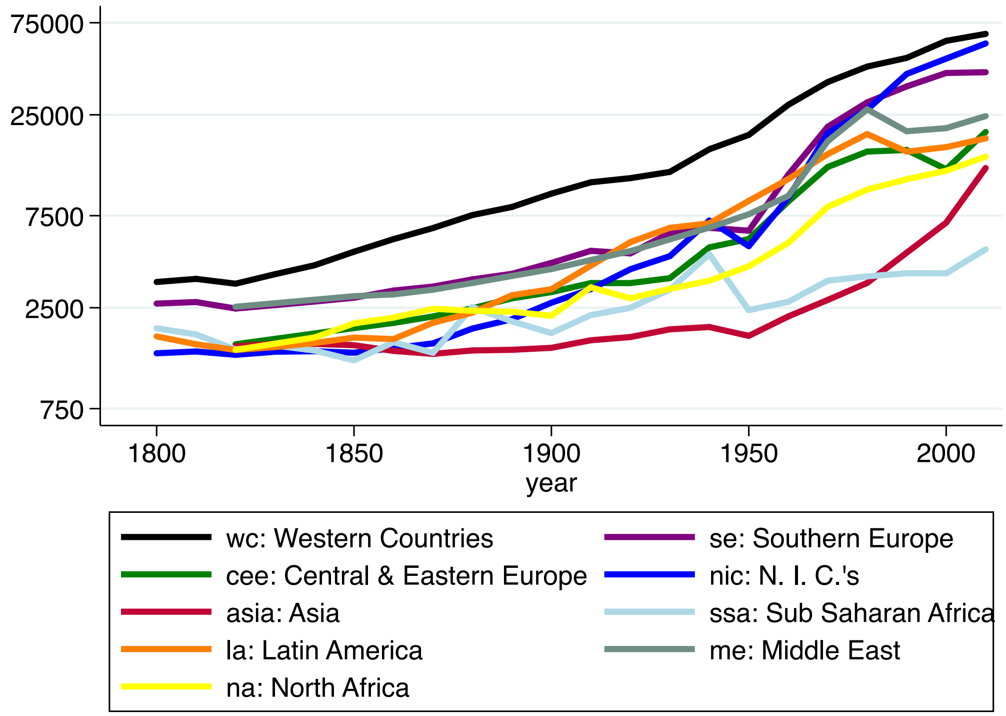

Figure 1: Real Output Per Worker: by Region

top group contains *N.I.C.*, *Western Countries* and *Southern Europe*. The middle group contains *Middle East*, *Central & Eastern Europe*, *North Africa* and *Asia*. The lowest group contains *Sub-Saharan Africa*. In 2010, the typical worker in the top group uses \$270,000 of real physical capital. In comparison workers in the middle group and the bottom group only have real physical capital of \$42,000 and \$11,500, respectively.

Figure 4 contains the regional average schooling per worker. If it takes 3 years of schooling to provide basic literacy, then the typical worker of *Western Countries* was literate in 1850.[20] Literacy of the typical worker outside of this region happened much later: 1920 *Southern Europe*, 1930 *Central & Eastern Europe*, 1910 *NIC*, 1965 *Asia*, 1980 *Sub-Saharan Africa*, 1950 *Latin America*, 1975 *Middle East*, and 1970 *North Africa*. Thus the regions that behaved most like *Western Countries*, *Southern Europe* and *NIC*, attained literate work forces no later than 70 years after *Western Countries*' attainment.[21] As with output per worker and physical capital per worker, there are three equivalence classes of worker education: the top tier includes Western Countries, N.I.C., *Southern Europe* and *Central & Eastern Europe*. The middle tier contains *Latin America*, *North Africa*, *Middle East* and *Asia*. The bottom group is made up of *Sub-Saharan Africa*.

we depreciated capital between 2000 and 2010 at an additional rate, typically 14%. Again see our Data Appendix for more details.

[20] Mitch, (1984, 2004), uses three years of schooling as a sufficient level of schooling for basic literacy. UNESCO uses four years as minimum required level of schooling for literacy, see also Harman (1970) and Resnick and Resnick (1977).

[21] While the *Central & Eastern Europe* region attained literate workforce by 1930, their failure to join *Southern Europe* and *NIC* in the first output per worker equivalence class group shows the lower institutional productivity of centrally planned vs. market based economies.

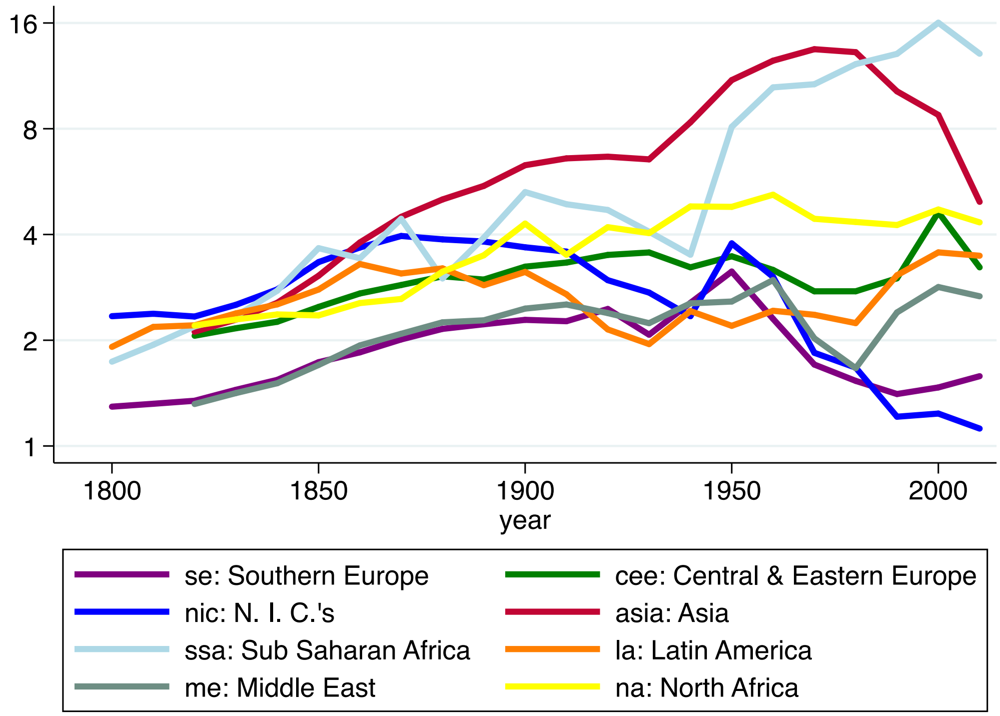

Figure 2: Relative Real Output Per Worker: by Region

Outside of the top tier, the lagging regions took at least a century or more to make the typical worker literate. This can be seen in Figure 5, where we graph the regional average years of schooling of the youngest worker cohort. Young workers were literate in *Western Countries* by 1830, followed by 1880 young *Southern Europe* workers. The young workers of *N.I.C.* became literate by 1890.[22] Young workers of *Central & Eastern Europe* did not attain literacy until 1910. Young workers in *Asia* became literate by 1950. Youngsters of *Latin America* were literate by 1930, but their *North Africa* brethren did not become literate until around 1955. Young workers of *Middle East* and *Sub-Saharan Africa* were literate by 1965.

We see in both Figures 4 and 5 that there are three equivalence classes in education. With the exception of *Central & Eastern Europe*, which is in the top education class compared with their middle output and physical capital classifications, all the other group memberships remain the same. Focusing on young workers, the average years of schooling for the youngest worker cohort in the top group is 13.7 years. The middle and bottom education group for young workers have average schooling of 10.1 years and 7.7 years, respectively. Thus the best educated young workers have something like 2 years of schooling beyond high school, whereas their counterparts have 2 years of high school in the middle group, and primary schooling in the bottom group.[23]

Using the Klenow & Rodriguez-Clare (1997), Hall and Jones (1999) method for computing human capital based on schooling and average experience we construct human capital by region. These are presented in Figure 6. As with education per worker and per young worker, there exists three equivalence

[22]However the *N.I.C.* begin catching up faster than all other regions, starting in 1870.

[23]We are explicitly using the US schooling measures, 8 years of primary schooling and 4 years of high school.

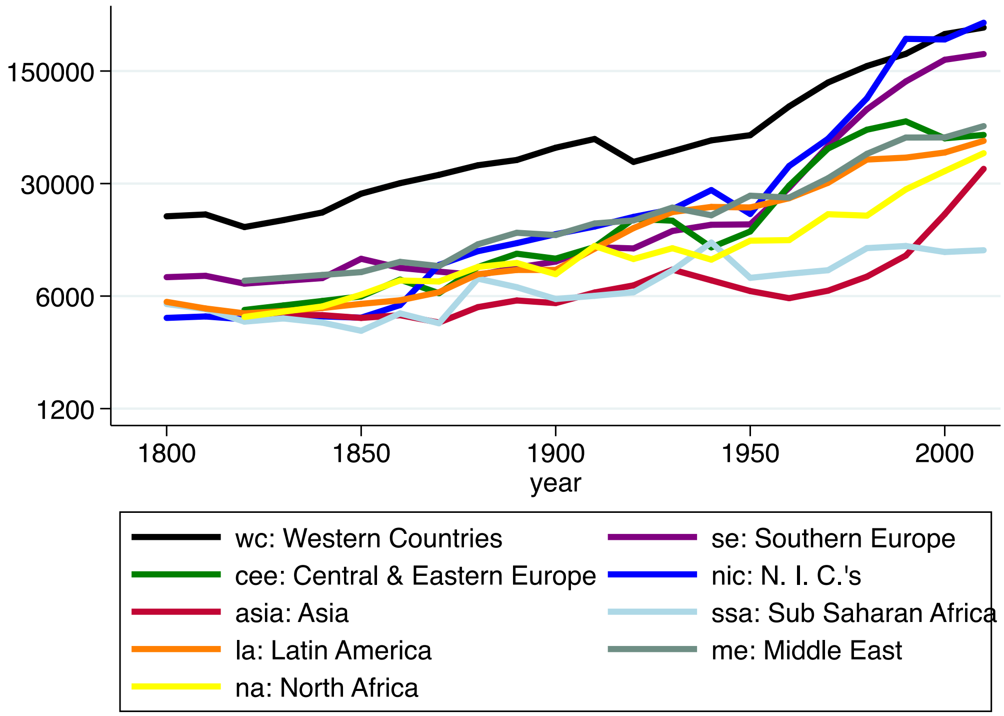

Figure 3: Real Physical Capital Per Worker: by Region

classes of countries in human capital per worker. For any country i, we assume a standard Cobb-Douglas production technology, using total factor productivity, Z_{it}, in combination with physical capital per worker, K_{it}, and human capital per worker, H_{it}, to produce output per worker, Y_{it}:

$$Y_{it} = Z_{it} K_{it}^{\alpha} H_{it}^{1-\alpha}, \tag{5}$$

where $\alpha = .33$, similar to that found in Gollin (2002), and used by Caselli (2005) and Turner, Tamura and Mulholland (2013). Figure 7 contains the regional average TFP. The *Western Countries* have been the world leader in TFP, although since 1950 the *N.I.C.* and *Southern Europe*, *Middle East* and surprisingly *Central & Eastern Europe* have converged. There are two more equivalence classes; the middle group consisting of *Latin America*, *North Africa* and *Asia*, and the bottom group of *Sub-Saharan Africa*. Interestingly membership in the bottom group usually included *Asia*, and in fact from 1900-1980, *Asia* was below even the *Sub-Saharan Africa* region. This reverses in 2000, and by 2010, *Asia* is clearly in the middle group. This obviously reflects the market reforms in China since 1979 and India from 1990 onward. There has been a clear TFP slowdown since 1970 throughout the world, excluding *Asia*.[24]

One consistent theme emerges from the Figures. There exists three different development groups: rich, middle and poor. The poor group in all measures of output, inputs and TFP is the *Sub-Saharan Africa*

[24]We conjecture that a fair amount of this is mismeasured output. There has been a dramatic increase in life expectancy, a sharp reduction in air and water pollution in the developed world, and a dramatic increase in worker safety. None of these are priced in GDP. Murphy and Topel (2006) estimate that the US gains in life expectancy over 1970-2000 added about 3.2 trillion \$ *per year* to national wealth in the US!

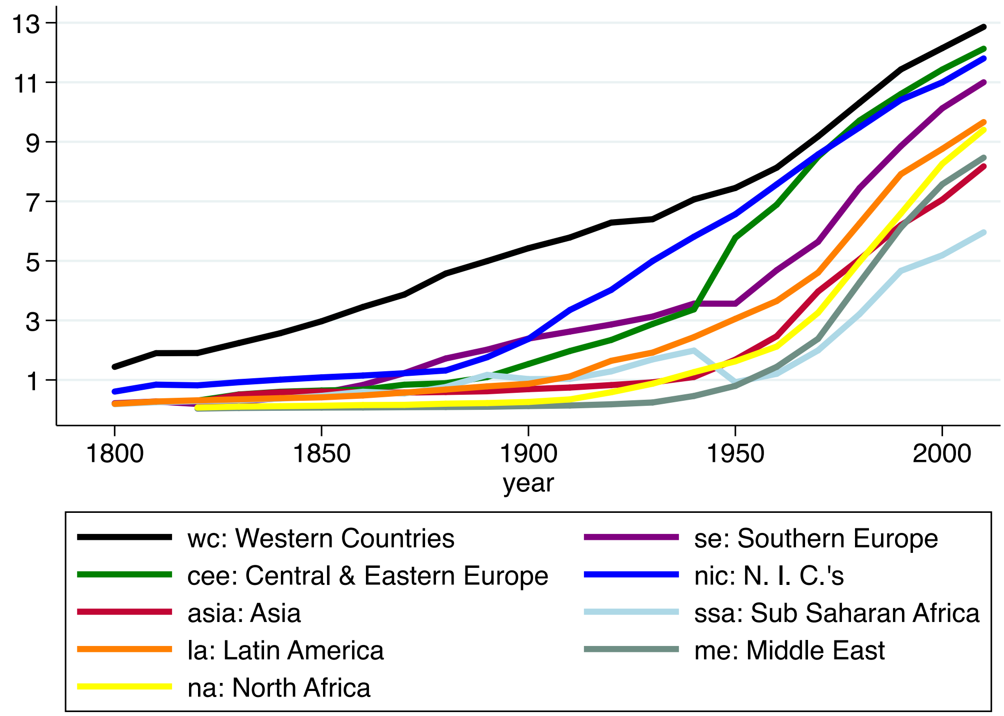

Figure 4: Education Per Worker: by Region

group. The top group in output, inputs and TFP always includes *Western Countries*, *Southern Europe* and *N.I.C.* The middle group in output, inputs and TFP always includes *Latin America*, *North Africa*, *Asia*. The middle group also includes *Middle East* in every category, except for TFP, where the *Middle East* is more closely related to the top group. Finally the *Central & Eastern Europe* region is a middle group in output per worker, and physical capital per worker, but a top group region for schooling, human capital and TFP.

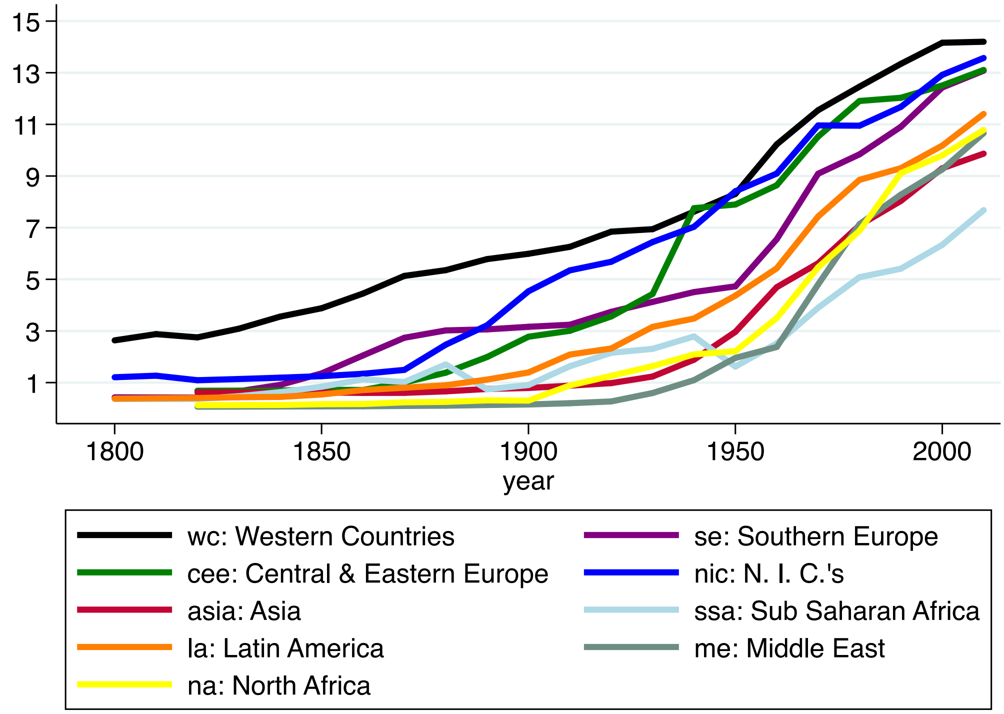

Figure 5: Education Per Young Worker: by Region

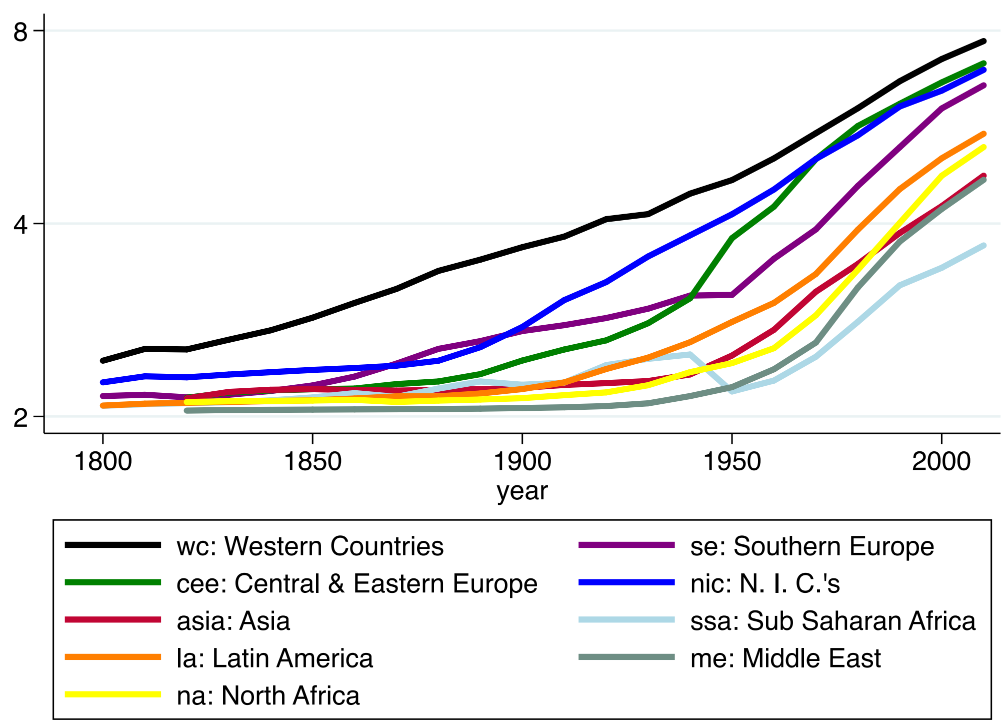

Figure 6: Human Capital Per Worker, Base: by Region

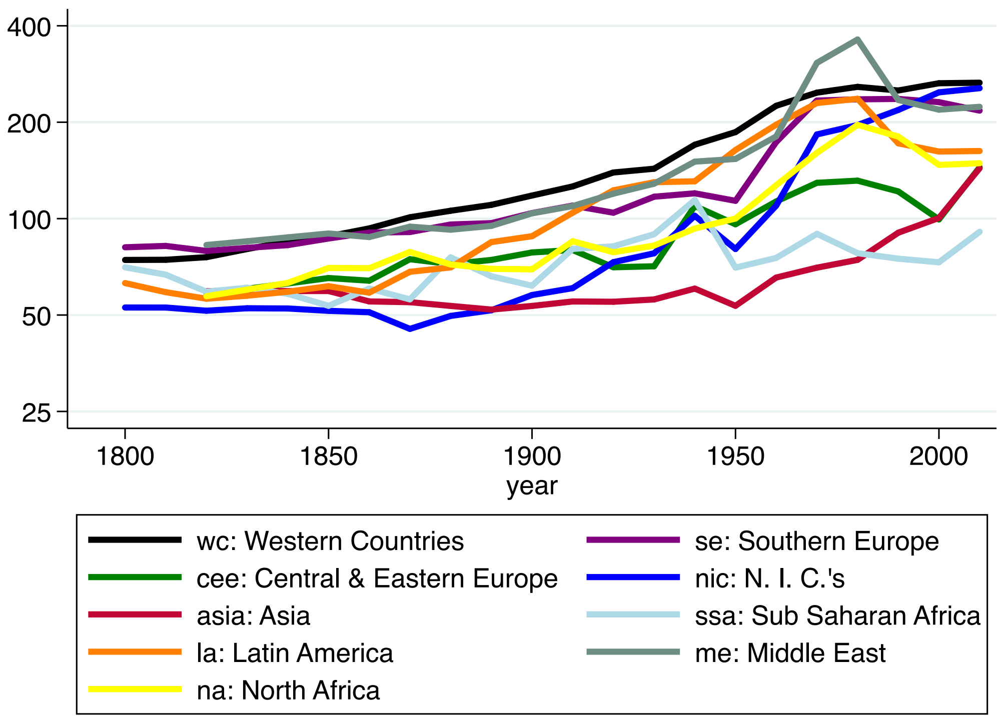

Figure 7: Total Factor Productivity, Base: by Region

3 Growth Accounting

In this section we report growth accounting results. We summarize the data in three ways: (1) we weight the data by the 2010 labor force multiplied by the number of years of observation; we call this the *labor force-duration* estimates, (2) we weight each country by their 2010 labor force, (3) all countries are treated equally. In earlier works, like Klenow & Rodriguez-Clare (1997), each country's growth rates are equally weighted. In data sets where all countries are observed over the same time period this makes some sense. However it does have the disadvantage of equally weighting economic performance achieved in a country like China, with a labor force of three-quarters of a billion, the same as a country with fewer than 100,000 workers, like Seychelles. In addition if the number of years a country is observed differs greatly, then a country that achieves annualized growth rate of 1.4% for 220 years (US) is treated the same as a country which manages annualized 2.3% growth for 20 years (Slovak Republic). In the former living standards are 22 times their initial value, whereas in the latter case living standards are only 60% higher than the initial observation.

Growth accounting produces the relationship in growth rates:

$$g_i = \frac{lny_{iT} - lny_{it_{i0}}}{T - t_{i0}} = \frac{lnZ_{iT} - lnZ_{it_{i0}} + \alpha(lnK_{iT} - lnK_{it_{i0}}) + (1-\alpha)(lnH_{iT} - lnH_{it_{i0}})}{T - t_{i0}} \tag{6}$$

In the first third of Table 1 we present the *labor force-duration* weighted results. The middle third of the table weights each country's observation by their 2010 labor force, and the final third of the table is unweighted. There is little difference between the two weighted results. In both weighted cases real output per worker growth is 1.23% per year, with real input per worker growth of .72% per year. Over the two weighted cases, input growth explains almost 60 percent of output per worker growth, with a range of 55% for *Asia* to 98% for *Central & Eastern Europe*. In both weighted cases, all regions have positive TFP growth. In the unweighted case, the worker in the typical country had annualized growth rates of 1.32% for output, .90% for inputs, and .42% for TFP. Input growth accounts for almost 70% of measured output per worker growth. In contrast, in BDT, the worker in the typical country had annualized growth rates of .74% for output, 1.55% for inputs, and −.81% for TFP. A comparison of the different regions shows that all regions now have positive economic growth. They range from a high of 2.54% per year real output growth in *Southern Europe* to a low of .89% per year in *Central & Eastern Europe*. Only the *Central & Eastern Europe* region has negative TFP growth.

Table 1: Growth Accounting

Region	N	% Annualized Growth Rates					input	TFP
		y	k	hc	inputs	TFP	share	share
		g_y	g_k	g_h	g_x	g_z		
Labor Force-Duration Weights								
World	168	1.23	1.19	0.49	0.72	0.51	0.585	0.415
(wc) Western Countries	18	1.42	1.43	0.52	0.82	0.60	0.579	0.421
(se) Southern Europe	8	1.46	1.64	0.57	0.92	0.54	0.630	0.370
(see) Central and Eastern Europe	24	1.29	1.33	0.77	0.96	0.33	0.741	0.259
(nic) Newly Industrialized Countries	5	1.83	2.07	0.57	1.06	0.77	0.580	0.420
(asia) Asia	20	1.15	1.10	0.43	0.65	0.50	0.569	0.431
(ssa) Sub-Saharan Africa	48	1.16	0.54	0.73	0.67	0.49	0.579	0.421
(la) Latin America	28	1.20	1.15	0.50	0.71	0.49	0.592	0.408
(me) Middle East	12	1.16	1.10	0.57	0.68	0.48	0.585	0.415
(na) North Africa	5	1.21	1.18	0.49	0.72	0.49	0.596	0.404
Labor Force Weights								
World	168	1.23	1.11	0.54	0.73	0.51	0.590	0.410
wc	18	1.42	1.44	0.52	0.82	0.60	0.579	0.421
se	8	1.53	1.69	0.58	0.94	0.58	0.618	0.382
cee	24	1.02	1.07	0.96	1.00	0.03	0.975	0.025
nic	5	1.84	2.07	0.57	1.06	0.78	0.578	0.422
asia	20	1.19	1.10	0.44	0.66	0.53	0.554	0.446
ssa	48	1.17	0.43	0.78	0.66	0.51	0.566	0.434
la	28	1.20	1.14	0.53	0.73	0.47	0.608	0.392
me	12	1.22	1.15	0.72	0.70	0.52	0.576	0.424
na	5	1.22	1.17	0.52	0.74	0.48	0.603	0.397
Unweighted								
World	168	1.32	1.15	0.82	0.90	0.42	0.685	0.315
wc	18	1.69	1.79	0.55	0.96	0.73	0.567	0.433
se	8	2.54	2.51	0.73	1.32	1.22	0.519	0.481
cee	24	0.89	0.84	1.36	1.19	-0.29	1.330	-0.330
nic	5	1.92	2.01	0.55	1.03	0.88	0.540	0.460
asia	20	1.38	1.16	0.63	0.81	0.57	0.585	0.415
ssa	48	1.22	0.73	0.85	0.81	0.41	0.661	0.339
la	28	1.28	1.26	0.73	0.91	0.37	0.709	0.291
me	12	0.93	0.89	0.83	0.47	0.46	0.507	0.493
na	5	1.34	1.24	0.68	0.86	0.48	0.645	0.355

4 Variance Decomposition

There is a wide range of growth rates in the data, and it is useful to ask how much of the variation in output growth rates can be directly tied to variation in input growth rates. The previous literature have found that most of the variation in growth rates are accounted for by variation in TFP growth rates. In this section we present the results of the variance decomposition of growth rates. We construct plausible upper bounds on the share of real output per worker growth variance explained by variations in real input growth rates and variations in TFP growth rates. We proceed as in Turner, Tamura, and Mulholland (2013). We aggregate inputs, physical capital per worker and human capital per worker, into the single measure X_t. Thus output per worker is given as:

$$X_t = K_t^{\alpha} H_t^{1-\alpha} \tag{7}$$

$$Y_t = Z_t X_t \tag{8}$$

Taking logs and using g_s represent growth rate of s produces:

$$g_y = g_z + g_x \tag{9}$$

Although our countries all are observed in 2010, we first observe the US in 1790, while for others we first observe as late as 1990.[25] For each country we construct the annualized growth rates of output per worker, input per worker and TFP over the entire observation length of the country. The variance of the annual growth rate of output per worker across these countries is given by:

$$\sigma_{g_y}^2 = \sigma_{g_z}^2 + 2\sigma_{g_x,g_z} + \sigma_{g_x}^2 \tag{10}$$

In much of the empirical growth and development literature it is standard to allocate one-half of the covariance terms to the inputs and one-half of the covariance terms to the residual, TFP, term, see Klenow & Rodriguez-Clare (1997), Caselli (2005), Weil (2009). This "egalitarian" assignment is then used to discuss the proportion of the variance of annual growth rates in output per worker "explained" or "accounted" for by inputs and the remainder allocated to TFP. This assignment can also be written as:

$$\sigma_{g_y}^2 = \sigma_{g_x,g_y} + \sigma_{g_z,g_y} \tag{11}$$

$$1 = \frac{\sigma_{g_x,g_y}}{\sigma_{g_y}^2} + \frac{\sigma_{g_z,g_y}}{\sigma_{g_y}^2} \tag{12}$$

Klenow & Rodriguez-Clare (1997) also argue that a better way to think about the contributions of input growth and TFP growth is to only credit variations in the growth rate of capital intensity to inputs. We modify this slightly by assuming human capital growth rates are not induced by TFP growth rates, but acknowledge that growth rates of physical capital could be induced by TFP growth rates. Thus rewrite

[25] East Germany is only observed from 1950-1990.

the output equation as:

$$Y_t = (\frac{K_t}{Y_t})^{\frac{\alpha}{1-\alpha}} Z_t^{\frac{\alpha}{1-\alpha}} H_t \tag{13}$$

$$Y_t = \hat{Z}_t \hat{X}_t \tag{14}$$

$$\hat{X}_t = (\frac{K_t}{Y_t})^{\frac{\alpha}{1-\alpha}} H_t \tag{15}$$

$$\hat{Z}_t = Z_t^{\frac{\alpha}{1-\alpha}} \tag{16}$$

Proceeding as before we can compute the growth rates of output per worker, and the new inputs per worker and TFP and produce:

$$\sigma^2_{g_y} = \sigma_{g_{\hat{x}},g_y} + \sigma_{g_{\hat{z}},g_y} \tag{17}$$

$$1 = \frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}} + \frac{\sigma_{g_{\hat{z}},g_y}}{\sigma^2_{g_y}} \tag{18}$$

These two variance decomposition methods proposed by Klenow & Rodriguez-Clare (1997) arise from priors as to the causal link of the correlation of growth rates of inputs and TFP. Under (18) the proportion of growth rate variations that co-vary with input (TFP) growth variations is assigned to inputs (TFP). Under (18) a priori TFP growth variations induce physical capital growth rate variations, and only physical capital intensity growth rate variations are ascribed to inputs. Further it is assumed in (18) that human capital growth rate variations are not induced by TFP growth rate variations.[26]

Returning to the original variance decomposition and dividing by the variance of growth rate of output per worker also produces:

$$1 = \frac{\sigma^2_{g_z}}{\sigma^2_{g_y}} + \frac{\sigma^2_{g_x}}{\sigma^2_{g_y}} + 2\rho_{x,z}\frac{\sigma_{g_x}\sigma_{g_z}}{\sigma^2_{g_y}} \tag{19}$$

However as noted above the correlation of growth rates of inputs and total factor productivity growth is not zero. However, a priori it is not clear that the appropriate decomposition implies equal split of the covariance term between inputs and TFP, nor to favor TFP as in the Klenow & Rodriguez-Clare capital intensity approach. Even if endogenous technological progress was the best model of TFP growth, it does not automatically follow that input accumulation is not logically prior to TFP growth. Not all societies purposely spend to invent new products, and processes. The societies that do accumulate new goods and processes are also the highest human capital economies and with the most physical capital. Thus we use another method of variance decomposition in order to allow the data inform us which economic theories of growth are more likely. This is not a Bayesian approach strictly, but one that produces what we term plausible shares or plausible explanations.

We proceed as in Turner, Tamura and Mulholland (2013). There are two sets of theories that explain the correlation between input growth and TFP growth. The exogenous technological growth neoclassical growth model implies that factor accumulation is induced by the growth in TFP. The same induced input accumulation result arises from endogenous technological progress models, e.g. Romer (1990). At the opposing end of the assignment, Romer (1986), Lucas (1988), and Tamura (2002,2006) construct theories

[26] Klenow & Rodriguez-Clare (1997) assume that human capital growth rates may be induced by TFP growth rates, and hence only capital intensity, inclusive of both physical capital intensity and human capital intensity are varying "independently" from TFP growth rate variations.

in which physical capital accumulation or human capital accumulation induces endogenous TFP growth. These theories imply that the correlation between TFP growth and input growth are due to input growth and hence the correlated or predictable component should be assigned to input growth.

If TFP growth induces factor accumulation, then the predictable or correlated portion of input growth should be assigned to TFP growth, the share of growth of output per worker variation can be written as:

$$1 = \frac{(\sigma_{g_z} + \sigma_{g_x}\rho_{g_x,g_z})^2}{\sigma^2_{g_y}} + \frac{(1-\rho^2_{g_x,g_z})\sigma^2_{g_x}}{\sigma^2_{g_y}} \tag{20}$$

where the first term is now a plausible upper bound on the proportion of the variation in growth rates of output per worker caused by variation in growth rates of TFP.[27] If the predictable or correlated component of TFP growth arises from endogenous factor accumulation, then assigning this predictable component to factor accumulation produces the following variance decomposition:

$$1 = \frac{(\sigma_{g_x} + \sigma_{g_z}\rho_{g_x,g_z})^2}{\sigma^2_{g_y}} + \frac{(1-\rho^2_{g_x,g_z})\sigma^2_{g_z}}{\sigma^2_{g_y}} \tag{21}$$

The first term is now the proportion of the variation of growth rates of output per worker that is explained by variation in input growth.[28] Since it is not obvious which of the theories is true, we propose to let the data guide us. As in Turner, Tamura and Mulholland (2013), we construct the average of the contributions for inputs and TFP and compare them with the other decompositions. Thus we produce the average BDT decompositions as:

$$\overline{S}_{g_x} = \frac{\sigma^2_{g_x}}{\sigma^2_{g_y}} + \frac{1}{2}\frac{\rho^2_{g_x,g_z}\left(\sigma^2_{g_z} - \sigma^2_{g_x}\right)}{\sigma^2_{g_y}} + \frac{\sigma_{g_x}\sigma_{g_z}\rho_{g_x,g_z}}{\sigma^2_{g_y}} \tag{22}$$

$$\overline{S}_{g_z} = \frac{\sigma^2_{g_z}}{\sigma^2_{g_y}} + \frac{1}{2}\frac{\rho^2_{g_x,g_z}\left(\sigma^2_{g_x} - \sigma^2_{g_z}\right)}{\sigma^2_{g_y}} + \frac{\sigma_{g_x}\sigma_{g_z}\rho_{g_x,g_z}}{\sigma^2_{g_y}} \tag{23}$$

The results of these three bounds, (12), (18), (22)-(23), are contained in Table 2.[29] Columns (1) and (2)

[27] One way of seeing that the least squares decomposition holds for this representation is to note that the variance decomposition is $\sigma^2_{g_y} + \sigma^2_{e_{g_y|g_z}} + \beta^2_{g_y,g_z}\sigma^2_{g_z}$ where β_{g_y,g_z} is the regression coefficient from a regression of g_y on g_z and $e_{g_y|g_z}$ is the regression residual.

[28] One way of seeing that the least squares decomposition holds for this representation is to note that the variance decomposition is $\sigma^2_{g_y} = \beta^2_{g_y,g_x}\sigma^2_{g_x} + \sigma^2_{e_{g_y|g_x}}$, where β_{g_y,g_x} is the regression coefficient from a regression of g_y on g_x and $e_{g_y|g_x}$ is the regression residual.

[29] All of these calculations assumes that the correlation between growth of inputs and growth of TFP is positive. A negative correlation has several possible explanations. One possibility is measurement error. If we systematically overestimate growth of inputs, we downwardly bias the growth rate of TFP. Some of this could arise from investment that is driven by the government, see below. However for private investment, we would assume that over the very long run, investments have a positive return, and produce measurable results. Anything that reduces allocative efficiency such as institutional change that reduces property rights, that fosters corruption, etc. can produce large negative TFP growth. One that does not make economic sense is forgetting. While it is possible to forget technology, and it has happened to some peoples in Europe after the fall of the Roman Empire, as well in China after the fall of the Qin Empire and the rise of the Han Empire, over the 1800-2010 period there is a reduced sense of forgetting. It is possible that the conversion of economies toward central planning after World War II in Central and Eastern Europe and the switch back from central planning to market based economies after the fall of the Soviet Union can be captured as forgetting. Communist collectivization and rising capital accumulation would more likely than not produce falling TFP, e.g. Maoist China. Centrally planned accumulation of inputs that have extremely low returns, building zero value public roads, investing in "critical" private sector industries that no profit making investor would ever authorize, spending on "education," but failing to provide the basics such as textbooks, blackboard an chalk, qualified teachers, etc. All of these would be measured as productive factor accumulations, that have 0 or possibly negative returns.

present the relative importance based on covariance shares of input growth rates and TFP growth rates. Columns (3) and (4) contain the covariance shares of relative input intensity growth rates and TFP growth rates. Columns (5) and (6) contain the shares from the average BDT decomposition. In columns (7) and (8) we also report the average BDT decomposition, but using the BDT data. Comparing the results for all countries, there is a big increase in explanatory power contained in input growth variation compared with BDT and Klenow & Rodriguez-Clare (1997). The increase in years of coverage as well the increase in number of countries observed, results in a substantial rise in the input share of growth rate variation. Whereas only 22% of growth rate variation is explained using the BDT average decomposition before, column (7), now 46% of output growth rate variation is explained by input growth variation. Using the standard covariance share, produces a similar 46% explanatory share for input growth rate variations. Only the more restrictive Klendow & Rodriguez-Clare covariance share of physical capital intensity variations lowers the explanatory power of input growth rate variations, 24%. Still this is an increase from the 3% share found by Klenow & Rodriguez-Clare. Comparing column (5) with (7) is informative. While the overall increase

Table 2: Growth Variance Decomposition: Plausible Shares

Region	N	egalitarian covariance share $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}}$ (1)	$\frac{\sigma_{g_z,g_y}}{\sigma^2_{g_y}}$ (2)	capital intensity covariance share $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}}$ (3)	$\frac{\sigma_{g_{\hat{z}},g_y}}{\sigma^2_{g_y}}$ (4)	plausible shares new data $\overline{S}_{g_x}$ (5)	$\overline{S}_{g_z}$ (6)	plausible shares BDT data $\overline{S}_{g_x}$ (7)	$\overline{S}_{g_z}$ (8)
World	168	0.455	0.545	0.238	0.762	0.458	0.542	.22	.78
wc	18	0.344	0.656	0.022	0.978	0.408	0.592	.46	.54
se	8	0.368	0.632	0.057	0.943	0.496	0.504	.50	.50
cee	24	0.554	0.446	0.334	0.666	0.551	0.449	.28	.72
nic	5	0.097	0.903	-0.348	1.348	0.171	0.829	.64	.36
asia	20	0.475	0.525	0.217	0.783	0.478	0.522	.40	.60
ssa	48	0.417	0.583	0.130	0.870	0.447	0.553	.37	.63
la	28	0.408	0.592	0.117	0.883	0.439	0.561	.22	.78
me	12	0.719	0.281	0.833	0.167	0.666	0.334	.44	.56
na	5	1.145	-0.145	1.217	-0.217	0.761	0.239	.84	.16
larger regions									
(1): wc & nic	23	0.341	0.659	0.017	0.983	0.403	0.597		
(2): (1) & se	31	0.373	0.627	0.065	0.935	0.482	0.518		
(3): (2) & na	36	0.376	0.624	0.069	0.931	0.476	0.524		
(4); (3) & asia	56	0.408	0.592	0.117	0.883	0.453	0.547		
(5): (4) & la	84	0.393	0.607	0.095	0.905	0.439	0.561		
(6); (5) & ssa	132	0.406	0.594	0.113	0.887	0.443	0.557		
(7): (6) & me (no opec)	135	0.406	0.594	0.114	0.886	0.443	0.557		
(8): (7) & cee	159	0.399	0.601	0.104	0.896	0.405	0.595		

in explanatory power in input growth variations is large, 46% vs. 22%, the change in explanatory power of input growth variations by region is heterogeneous. Five out of nine regions increase in explanatory power of input growth variations, while three decrease in explanatory power, and one is constant. In contrast to previous work, e.g. Klenow and Rodriguez-Clare (1997), there is increased explanatory power in variations in input growth rates, however there is still much left unexplained. Looking at larger groups of regions, the bottom half of Table 2 shows that the variance decomposition results are robust. Using either the standard covariance accounting, or the average BDT decomposition, we see that the variation explained by input variation stabilizes around 40%. The more restrictive Klenow and Rodriguez-Clare capital intensity covariance accounting converges to 10%. Clearly there is more work to do, and to this we now turn.

5 Intergenerational Human Capital Calculation

One conclusion from above is that despite adding many additional years of observations, and a non-trivial number of new countries, output per worker growth rate variation still is better explained by TFP growth rate variation (average BDT decomposition or covariance decomposition), or almost completely captured by TFP growth rate variation (Klenow & Rodriguez-Clare capital intensity input). To see how robust TFP growth differences are for explaining differential growth, we return to some theories of endogenous growth. In particular we examine the role of human capital accumulation in promoting growth of output per worker. The original Lucas (1988), Becker, Murphy and Tamura (1990), Tamura (1994), Galor and Weil (2000), Galor and Moav (2004), Galor (2005) papers introduce the idea that time spent away from production can be used to accumulate human capital.[30] In Lucas infinite lived agents perpetually accumulate human capital, whereas in all of the other papers, parents spend time away from production and educate their children. In both of these models human capital builds off of the existing human capital, hence accumulation has the property of standing on the shoulders of others. Allowing for human capital spillovers across borders as in Tamura (1991, 1996, 2002, 2006) produces the following specification for country i between generations t and $t+1$:

$$h_{it+1} = \mathrm{A}\overline{h}_t^{\rho} h_{it}^{\beta - \frac{\rho}{10}} \exp(f(\text{schooling}) + g(\text{experience})) \tag{24}$$

where h_{it} represents the human capital of the parent, $\overline{h}_t$ represents the frontier human capital in the world, ρ is the degree to which the frontier human capital can be diffused through teaching, and the two functions, f and g in the exponential are defined as in (2) and (3), $0 < \rho, \beta < 1, \rho + .9\beta \leq 1$.[31] The key innovation here is that we allow for intergenerational accumulation in human capital.[32] We initialized 15-24 year old human

[30]Rosen (1976) actually originally produces perpetual endogenous growth in a human capital model, but discards it in favor of one with standard life cycle properties.

[31]If $\rho + .9\beta = 1$, then perpetual endogenous growth is possible; this formulation is used in Tamura, Simon and Murphy (2016) examining human capital convergence across states and races in the US from 1840 to 2000. If $\rho + .9\beta < 1$, then a steady state human capital level exists, once schooling becomes constant. Either technological progress in output production, or rising A would be required for perpetual growth. One possibility for rising A would be if A grew as a function of those enrolled in higher education. These would be consistent with Jones (1995a,1995b, 2001).

[32]This is similar to the specification in Bils and Klenow (2000), although in their model they do not allow for spillovers across countries.

capital in a country using information on the output per worker relative to the US.[33] The virtues of this method are twofold: (1) it allows for human capital across generations to accumulate, while allowing for the possibility of late developers to converge to the human capital level of early developers via the spillover effect, (2) it keeps a demographic age structure of human capital in the population that incorporates the Mincer age earnings quadratic profile. That is to say, if we compare individuals in a country of the same age, but different schooling levels, their earnings would differ by $exp(f(schooling) + g(experience))$ and be consistent with Mincerian wage regressions on returns to schooling. Second if we compare individuals in a country over their life cycle, their human capital has the standard inverted U-shape age earnings profile consistent with Mincerian wage regressions. Now consider the ability of this specification to capture differences in long run human capital levels. First assume that there is no spillover, i.e. $\rho = 0$. Consider two economies, one where each generation attains 14.6 years of schooling, and one where each generation attains only 2.2 years of schooling, this is equal to the 2010 young worker schooling gap between the least schooled country, Eritrea, and the most schooled country, the United States. Ignoring experience returns, the stationary human capital values of these respective countries are given by:

$$h(14.6) = A^{\frac{1}{1-\beta}} exp(\frac{1.46}{1-\beta}) \tag{25}$$

$$h(2.2) = A^{\frac{1}{1-\beta}} exp(\frac{.22}{1-\beta}) \tag{26}$$

$$\frac{h(14.6)}{h(2.2)} = exp(\frac{1.24}{1-\beta}) \tag{27}$$

Compared to the human capital accumulation technology without intergenerational human capital accumulation, this specification accentuates permanent differences in schooling. For a value of $\beta = .375$, the model delivers a 7.25 relative human capital gap between these two countries, about one-sixth of the 2010 income difference between the US ($76,500) and Eritrea ($1707).[34] Without intergenerational human capital the human capital gap between these two countries would be 3.5 or one-thirteenth of the income difference between the US and Eritrea.[35]

We constructed the human capital in a country as the population weighted average of human capital of

[33] We did not follow an explicit rule in creating our initial human capital values. A brief description of our assignment methodology is as follows. We construct initial output per worker relative to the US output per worker in the comparable decade. Let E_{it}^{15-24} be the 15 to 24 year old cohort's education in initial year t in country i. Let E_{USt}^{15-24} be the 15 to 24 year old US cohort's education in year t. Schoellman (2012) finds that a very good approximation to human capital adjusting for school quality differences is simply given by exp(.2*years of schooling). Thus using Schoellman (2012) we construct initial relative young human capital as $exp(.2 * [E_{it}^{15-24} - E_{USt}^{15-24}])$. Our initial young human capital for country i in year t relative to the US is well described by a log linear regression on log relative output per worker, log relative human capital from Schoellman (given above), region dummies and a few other region or country variables. Table A1 in the Appendix lists the initial human capital for workers age 15-24 and the initial average human capital for each country, as well as the 2010 values. See section 1.5 of our data appendix for full details.

[34] For a larger value, $\beta = \frac{2}{3}$, the income gap would be almost exactly explained.

[35] Of course in transition the US could have a much larger relative human capital advantage.

5 age groups, 15-24, 25-34, 35-44, 45-54, 55-64. Human capital in country i in year t is:

$$H_{it} = s_{it}^{1524}h_{it}^{1524} + s_{it}^{2534}h_{it}^{2534} + s_{it}^{3544}h_{it}^{3544} + s_{it}^{4554}h_{it}^{4554} + s_{it}^{5564}h_{it}^{5564} \tag{28}$$

where s_{it} is the share of the population in age category i in year t, and human capital accumulates via the age earnings profile from above, for example:

$$h_{it+1}^{3544} = h_{it}^{2534} \exp(g(\text{experience}_i^{2534} + 10) - g(\text{experience}_i^{2534})) \tag{29}$$

where each generation is assumed to have an average schooling and hence their first set of expected experience in the age group 15-24 is given by:

$$\text{experience}^{1524} = \max(0, \text{avg age}^{1524} - 6 - \text{avg schooling}^{1524}) \tag{30}$$

and from then on, every observation they age 10 years.[36] For the new generation, represented by h^{1524} we assume that the parents are between the ages of 35-54 today. That is to say we use the arithmetic average human capital of adults 25-34 and 35-44 in the prior observation to produce human capital for current 15-24 children. This assumes parents had their children between the ages of 20-39. Our intergenerational human capital accumulation equation is:

$$h_{it}^{1524} = \mathrm{A}\overline{h}_{t-1}^{\rho} \left(\frac{h_{it-1}^{2534} + h_{it-1}^{3544}}{2}\right)^{\beta - \frac{\rho}{10}} \exp(f(\text{schooling}) + g(\text{experience})) \tag{31}$$

where, $\beta = .375$, $A = .38028169$, f(schooling) and g(experience) are given by (2) and (3), where initial experience is max(0,average age - 6 - expected schooling of cohort born in period t-1).[37] In our human capital calculations the time subscripts refer to birth cohort, and typically are spaced 10 years apart. The human capital of 15-24 year olds in 1860 use the school enrollment rates in 1850 to produce an estimate of expected years of schooling. Our choice of $\beta = .375$, $A = .38028169$ come from micro evidence of the intergenerational elasticity of earnings, and from a grid search of values from .25 to .65 for A.[38] Table 3 lists estimates of intergenerational elasticity of earnings, β. This summarizes previous research with 299

[36]The human capital arising from experience returns are different for *Central and Eastern Europe* during communism. Over the period of post World War II communist central planning, the typical return is .0625*.0495 per year of experience, see our Data Appendix for details. Before the post World War II communist period, the returns to labor market experience are identical with all other countries. However the way we compute market return we remove all experience return that was gained prior to 1950, and evaluate all experience at the new lower rate, .0625*.0495. This causes human capital between the pre war period to fall in the post war period. Additionally after 2000 we eliminated all human capital accumulation from experience, and restarted their experience measure at 0 in year 2000. We do this to capture the shock of a completely new system of production, mixed or market based, and the complete depreciation of experience arising from life under the communist system.

[37]In our robustness checks we varied β and ρ. With one exception, we kept constant, $\beta + \rho = .725$. The exception was when we examined $\beta = .375, \rho = 0$. In addition to keeping the sum of $\beta + \rho = .725$, we kept the share of world mean growth explained by inputs, in the weighted duration-labor force case constant. We did this by varying A.

[38]We also did robustness check on our results by varying $\beta = .025$ to $\beta = .7$. These are reported later.

estimates of β. Our functional form allows for a maximum own parental effect, at 0 years of child schooling, $\beta = .375$. For a value $\rho = .35$, then the own parental effect declines to $\beta = .340$. The high value is nearly identical to the average of estimates, and the low value is nearly identical to the median of the estimates.

Table 3: Estimates of Intergenerational Elasticity of Earnings: β

Country	links	estimate range	median estimate	source estimate
USA	father & sons	[.146, .495]	.327	Table 4 Olivetti & Paserman
USA	father & sons in law	[.180, .493]	.340	Table 4 Olivetti & Paserman
USA	father & sons	[.005, .275]	.261	Table 4.2 Grawe
USA	father & sons	[.355, .535]	.535	Table 4.2 Grawe
Canada	father & sons	[.110, .256]	.211	Table 4.3 Grawe
Germany	father & sons	[-.280, .313]	.065	Table 4.4 Grawe
UK	father & sons	[.344, .814]	.579	Table 4.5 Grawe
Malaysia	father & sons	[.283, .791]	.537	Table 4.6 Grawe
Nepal	father & sons	[.333, .539]	.436	Table 4.8 Grawe
Pakistan	father & sons	[.153, .773]	.463	Table 4.8 Grawe
USA	parents & sons	[.302, .521]	.343	Table 5.5 Mayer & Lopoo
USA	parents & daughters	[.289, .469]	.363	Table 5.5 Mayer & Lopoo
USA	father & sons	[.106, .416]	.368	Table 3 Lefgren, Lindquist & Sims
multiple	father & children	[.110, .600]	.400	Table 7.5 Mulligan
multiple	father & sons	[.130, .570]	.240	Table 1 Solon
multiple	father & sons	[-.044, .707]	.356	Table 4 & appendix Bjorklund & Jantti
	[avg low, avg high]	[.158, .535]	median=.344 average = .367	

We first assumed no spillover in the human capital accumulation function, i.e. $\rho = 0$.[39] Figures 8 and 9 present the regional graphs of human capital per worker and TFP. In both figures we computed the average human capital and TFP weighting by the labor force. There is more rapid growth in human capital and thus slower growth in TFP. Figures 8 and 9 are both on log scale, so vertical gaps represent proportionate differences. For human capital, in Figure 8, the vertical distance between the top region and the bottom region appears quite stable, and hence the world relative distributions of human capital appear to be stable.[40] As before there is a cluster of three equivalence classes: high human capital (including *Western Countries*, *N.I.C.* and *Southern Europe*), a middle human capital group (including *Asia*, *Central & Eastern Europe*, *Latin America*, *North Africa* and the *Middle East*), and a low human capital group, *Sub-Saharan Africa*. For TFP, in Figure 9, the final distribution contains really only two groups: a low TFP group containing *Sub-Saharan Africa* and *Asia*, and a high TFP group consisting of all other regions.

The growth accounting results and the results from the variance decomposition of growth rates are contained in Tables 4 and 5, respectively. There is a large increase in the share of overall growth explained

[39]For this case we assumed $A = .5696268$.

[40]This is similar in flavor to a point made previously by Parente and Prescott (1993) about relative output.

by input growth in all cases. Whereas previously inputs explained between 60% and 70% of growth, they now explain between 80% and 85% of growth. Table 5 shows the value of introducing intergenerational human capital accumulation for explaining cross sectional variation in long run growth rates.

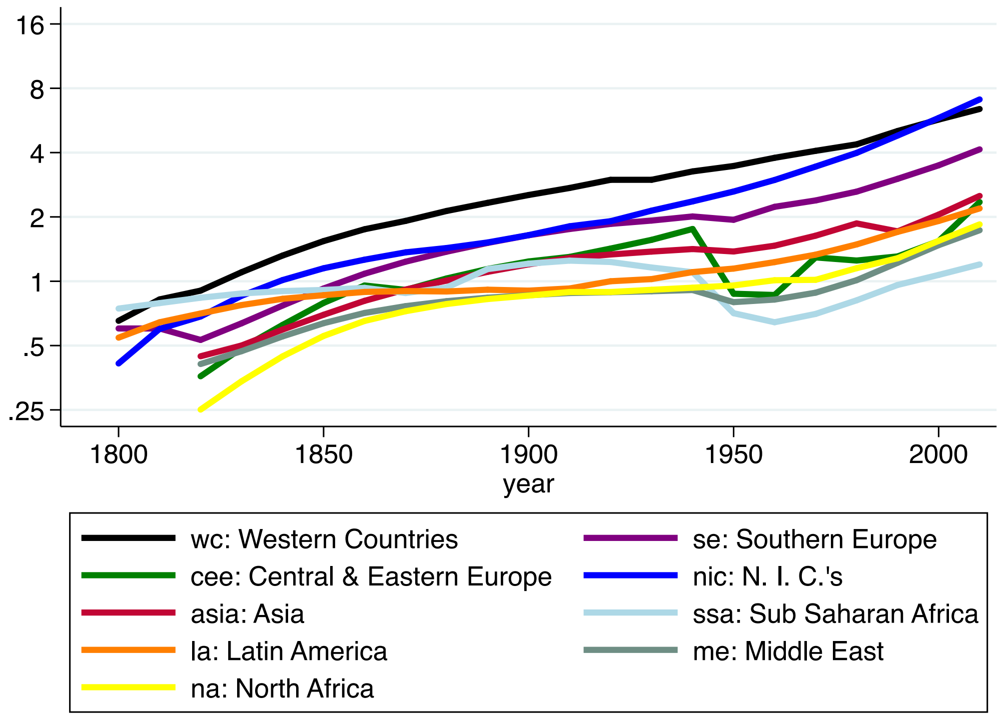

Figure 8: Human Capital Per Worker, $\beta = .375, \rho = 0$: by Region

Whereas Table 2 shows that variation in input growth explains 46% of the variation in output per worker growth, the introduction intergenerational accumulation raises the share of input growth rate variation to 96%. The increase is broad based; all regions outside of *North Africa*, have higher or equal shares of growth rate variation captured by input growth rate variation, when comparing any of the three variance decompositions, cols (1), (3) and (5), in Table 5 with their counterparts in Table 2. When we look at larger regions, the improved ability of input growth variations to explain output per worker growth variations continues. At least 90% of growth rate variations are captured by input growth rate variations for all combinations of regions in the lower panel of Table 5. This is true whether we use the standard covariance accounting, the plausible shares (average BDT decomposition) or the more conservative Klenow & Rodriguez-Clare capital intensity covariance accounting. It is problematic that two covariance accounting results produce greater than 100% explanatory power, for *Southern Europe* and *N.I.C*, as well as *Middle East* using Klenow & Rodriguez-Clare capital intensity decomposition, and in the larger aggregates up through the inclusion of *Latin America*. The great disparity in input shares across regions, the excessive input share for the *N.i.C* region and the greater than 100% share for large regions up to an including *Latin*

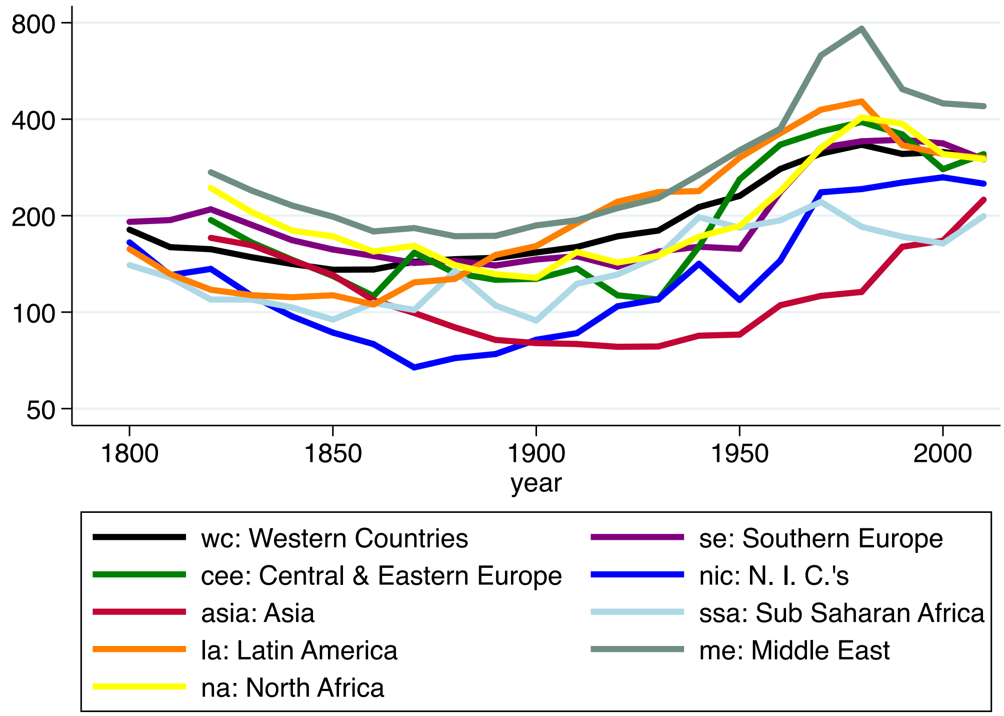

Figure 9: Total Factor Productivity, $\beta = .375, \rho = 0$: by Region

America indicate that the intergenerational model needs some modification.

Table 4: Growth Accounting: New Human Capital $\beta = .375$, $\rho = 0$

Region	N	% Annualized Growth Rates g_y	g_k	g_h	g_x	g_z	input share	TFP share
Labor Force-Duration Weights								
World	168	1.23	1.19	0.97	1.04	0.19	0.844	0.156
(wc) Western Countries	18	1.42	1.43	1.04	1.17	0.25	0.826	0.174
(se) Southern Europe	8	1.46	1.64	1.13	1.29	0.17	0.885	0.115
(see) Central & Eastern Europe	24	1.29	1.33	0.91	1.05	0.25	0.809	0.191
(nic) Newly Industrialized Countries	5	1.83	2.07	1.56	1.73	0.11	0.942	0.058
(asia) Asia	20	1.15	1.10	0.95	1.00	0.15	0.870	0.130
(ssa) Sub-Saharan Africa	48	1.16	0.54	1.01	0.85	0.30	0.739	0.261
(la) Latin America	28	1.20	1.15	0.69	0.84	0.36	0.699	0.301
(me) Middle East	12	1.16	1.10	0.97	0.94	0.22	0.806	0.194
(na) North Africa	5	1.21	1.18	1.05	1.09	0.11	0.907	0.093
Labor Force Weights								
World	168	1.23	1.11	0.99	1.03	0.20	0.834	0.166
wc	18	1.42	1.44	1.05	1.18	0.25	0.827	0.173
se	8	1.53	1.68	1.17	1.34	0.19	0.876	0.124
cee	24	1.02	1.07	0.52	0.70	0.32	0.684	0.316
nic	5	1.84	2.07	1.57	1.74	0.10	0.946	0.054
asia	20	1.19	1.10	1.01	1.04	0.15	0.874	0.126
ssa	48	1.17	0.43	1.10	0.88	0.29	0.750	0.250
la	28	1.20	1.14	0.70	0.85	0.36	0.703	0.297
me	12	1.22	1.15	1.18	0.99	0.22	0.815	0.185
na	5	1.22	1.17	1.07	1.10	0.12	0.904	0.096
Unweighted								
World	168	1.32	1.15	1.04	1.05	0.26	0.800	0.200
wc	18	1.69	1.79	1.23	1.41	0.27	0.837	0.163
se	8	2.54	2.51	2.37	2.42	0.13	0.951	0.049
cee	24	0.90	0.84	0.32	0.49	0.40	0.554	0.446
nic	5	1.92	2.01	1.87	1.92	-0.00	1.002	-0.002
asia	20	1.38	1.16	1.29	1.25	0.13	0.904	0.096
ssa	48	1.22	0.73	1.03	0.93	0.29	0.763	0.237
la	28	1.28	1.26	0.82	0.97	0.31	0.757	0.243
me	12	0.93	0.89	1.04	0.67	0.26	0.722	0.278
na	5	1.34	1.24	1.21	1.22	0.12	0.909	0.091

Table 5: Growth Variance Decomposition: Plausible Shares, New Human Capital $\beta = .375$, $\rho = 0$

Region	N	egalitarian covariance share $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}}$ (1)	$\frac{\sigma_{g_z,g_y}}{\sigma^2_{g_y}}$ (2)	capital intensity covariance share $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}}$ (3)	$\frac{\sigma_{g_{\hat{z}},g_y}}{\sigma^2_{g_y}}$ (4)	plausible shares new data $\overline{S}_{g_x}$ (5)	$\overline{S}_{g_z}$ (6)	plausible shares BDT data $\overline{S}_{g_x}$ (7)	$\overline{S}_{g_z}$ (8)
World	168	0.963	0.037	1.026	-0.026	0.960	0.040	.22	.78
wc	18	0.896	0.104	0.845	0.155	0.871	0.029	.46	.54
se	8	1.135	-0.135	1.201	-0.201	0.883	0.117	.50	.50
cee	24	0.974	0.026	0.961	0.039	0.974	0.026	.28	.72
nic	5	2.028	-1.028	2.535	-1.535	0.556	0.444	.64	.36
asia	20	0.964	0.036	0.946	0.054	0.964	0.036	.40	.60
ssa	48	0.868	0.132	0.802	0.198	0.838	0.162	.37	.63
la	28	0.865	0.135	0.799	0.201	0.834	0.166	.22	.78
me	12	0.962	0.038	1.378	-0.378	0.927	0.073	.44	.56
na	5	0.700	0.300	0.553	0.447	0.676	0.324	.84	.16
larger regions									
(1): wc & nic	23	0.983	0.017	0.974	0.026	0.933	0.067		
(2): (1) & se	31	1.111	-0.111	1.166	-0.166	0.905	0.095		
(3): (2) & na	36	1.096	-0.096	1.144	-0.144	0.918	0.082		
(4): (3) & asia	56	1.049	-0.049	1.072	-0.072	0.953	0.047		
(5): (4) & la	84	1.022	-0.022	1.033	-0.033	0.963	0.037		
(6); (5) & ssa	132	0.946	0.054	0.919	0.081	0.944	0.056		
(7): (6) & me no opec	135	0.946	0.054	0.919	0.081	0.944	0.056		
(8): (7) & cee	159	0.963	0.037	0.944	0.056	0.958	0.042		

5.1 Spillovers

The previous sub-section showed that intergenerational links between parents and children improve our understanding of growth differences, but at the cost of often times producing greater than 100% explanatory shares. In this section we examine the role international spillovers can play in explaining cross country growth differences. We find reasonable values for ρ, which determines how much use a generation gets from the spillover $\overline{h}$. We assume that human capital spillover arises from the maximum human capital country, which is the US.[41] Tamura (1996) showed that conditional convergence from 1960-1985 was captured by the share of eligible population enrolled in secondary school.[42] Benhabib and Spiegel (2005) derive a general model of diffusion with human capital, that includes both exponential and logistic models as special cases, and provide empirical evidence of the importance of human capital for diffusion of technology. Similar to

[41] The US certainly led the world in universal secondary schooling, c.f. Goldin (2001) and Goldin and Katz (2008), and tertiary schooling. A few countries have measured primary school enrollment rates higher than the US in the first third of the nineteenth century, e.g. Netherlands, however literacy was quite high in the US from the initial settlement.

[42] If a country had 15% of its eligible population enrolled in secondary school in 1960, the country converged toward the US living standard over the next 25 years. Tamura (1996) used a step function approach, beyond a critical exposure rate to secondary school, children could fully access the spillover human capital. We modify that approach by making the access a continuous function of schooling exposure, similar to Tamura and Simon (2016), and Tamura, Simon and Murphy (2016).

Behabib and Spiegel (2005), we allow the rate of diffusion to depend directly on the level of schooling. As a country becomes more educated, it can better draw on the body of knowledge in the world:.

$$\rho = \min\left\{.35, \frac{S}{30}\right\},$$

where S is the schooling of the children. In this specification the lower bound for ρ is 0 (when children have no schooling) and the upper bound is .35 (when children have 10.5 years of schooling). Thus at the lower extreme there is no convergence in human capital, unless schooling was identical to 0 across countries, and all countries converge to the same steady state human capital. At the upper extreme, human capital converges at a rate of 1.75 (.875) % per year, depending on a generation of 20 (or 40) years. In the upper bound case, it would take a country 39 (78) years to close the gap by 50 percent. With the data at hand, this more rapid convergence can be seen by the NIC's, as well as China and India recently. For low levels of schooling, the slow convergence, would just as likely appear to be non convergence.

Again, suppose we compare the US with a country like Eritrea. As an approximation, let's assume that $\rho = 0$ for Eritrea (but schooling is constant at 2.2 years), but is given by the above for the US. These would produce a stationary human capital for the US and Eritrea of:

$$h(14.6) = A^{\frac{1}{1-\beta-.9\rho}} exp(\frac{1.46}{1-\beta-.9\rho}) \tag{32}$$

$$h(2.2) = A^{\frac{1}{1-\beta}} exp(\frac{.22}{1-\beta}) \tag{33}$$

$$\frac{h(14.6)}{h(2.2)} = A^{\frac{.9\rho}{(1-\beta-.9\rho)(1-\beta)}} exp(\frac{1.46}{1-\beta-.9\rho} - \frac{.22}{1-\beta}) \tag{34}$$

For a value of young schooling in the US of 14.6, $\rho = .35$. For $\beta = .375$, and an $A = .38028169$, the stationary relative income gap between the US and Eritrea would be 16.2, which is almost 40% of the observed gap of about 45. Recall that without spillovers, the stationary relative human capital gap would be 7.25, so the introduction of conditional spillovers more than doubles the gap between high education economies and low education economies. Thus while allowing for convergence for those countries with well educated young workers, the model also allows for an even greater relative income gap between the richest countries and the lowest schooling countries.

The results of this new calculation for human capital are presented in Figure 10. We plot the weighted average human capital by region. As before there is a surprising amount of stationarity in the relative gap between the *Western Countries* and the other regions. With spillovers there appears to be more separation of the regions. As before there are three distinct human capital regimes, high human capital, middle human capital and low human capital. The membership in these regimes is the same as the model without spillovers. While the high human capital group is more diffusely spread, the middle human capital group appears to be clustered the same as before. In Figure 11 we plot the new TFP levels for regions. In

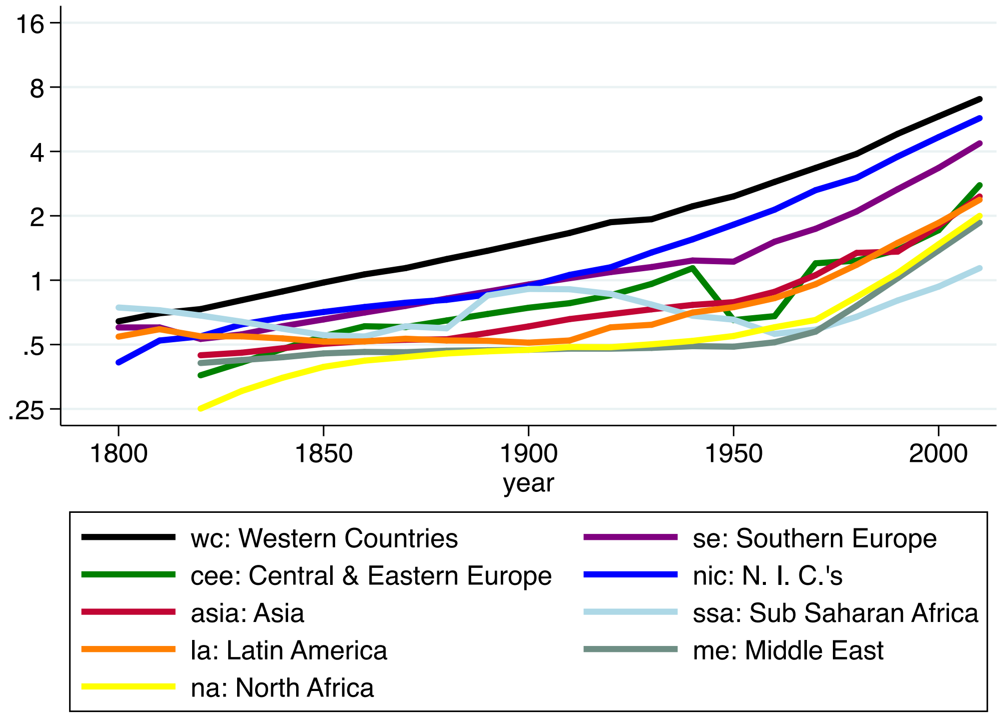

Figure 10: Human Capital Per Worker, $\beta = .35, \rho > 0$: by Region

contrast to the previous TFP graph, there is slower long term trend growth in TFP across regions, and a more prominent post 1970 TFP decline in every region except *Asia*.

Table 6 presents the results for growth accounting using the new measure of human capital with spillovers. Whether weighted or unweighted, between 80% to 85% of real output growth per worker is captured by input growth. This result is similar across regions. From a low of 7.5 percent of growth explained by TFP growth, *North Africa*, to a high of one third of growth explained by TFP growth, *Sub-Saharan Africa*, we find that the new measure of human capital better captures the growth of output per worker, than the Mincer model of human capital and equally well as the intergenerational human capital model without spillovers.

Table 7 contains the variance decomposition of growth rates. Introducing conditional human capital spillovers has little overall effect on the variance decomposition of growth rates at the world level. While the base intergenerational human capital model explains 96% of growth variation, the conditional spillover model explains 95% of the variation of growth rates. This hides the improvement for each region. Table 5 shows that the model without spillovers the range of input shares for covariance share is 70%, *North Africa*, and 200%, *N.I.C.*. The range of input shares for covariance share in Table 7 is much tighter, 92% *Sub-Saharan Africa* and 105% *North Africa*. With the more restrictive Klenow and Rodriguez-Clare capital intensity covariance share, input shares in three regions are substantially in excess of 100%, 120% for

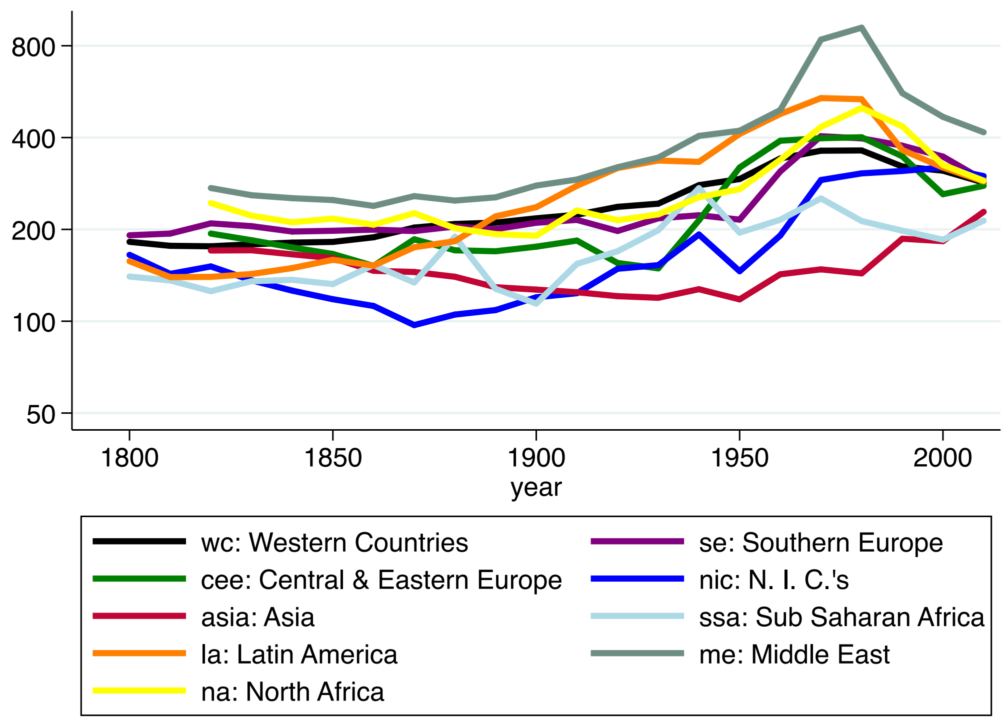

Figure 11: Total Factor Productivity, $\beta = .35, \rho > 0$: by Region

Southern Europe, 250% for *N.I.C.* and 138% for *Middle East*, and one region has input share of only 55%, *North Africa*. Of the remaining five regions, two have input shares greater than 90% and the remaining three have input shares less than 85%. The Klenow and Rodriguez-Clare capital intensity covariance share results for the spillover model show improvement. The number of regions with input share in excess of 100% remains at three, they are much closer to 100%, 104% for *N.I.C.*, 108% for *North Africa* and 133% for *Middle East*. The remaining six regions have a tighter range for input shares of 88% to 95%. Without spillovers, the plausible input share has two of nine regions have input shares less than 70%. The range of the remaining seven regions is 84% to 97%. Table 7 reveals that using the spillover model produces a very tight plausible input share range of 90% to 96%.

Examining larger groupings is informative. For the Mincer human capital model over multiple regions, the plausible input share of growth variations ranged from 40% to 48%. With Intergenerational human capital accumulation the plausible input share of growth variations ranges from 91% to 96%. Finally with conditional spillovers, using the plausible input share metric, the model explains between 95% and 97% of the cross sectional variation in growth rates, no matter the sample. In all large regions in the model with spillovers produces 92% to 98% input share whether the egalitarian input covariance share or the capital intensity covariance share metric is used. In contrast the intergenerational human capital accumulation model without spillovers has egalitarian covariance shares in excess of 100% for all large regions until

Sub-Saharan Africa is used. This is also true for the capital intensity covariance share. Thus conditional spillovers help to restrain the intergenerational human capital accumulation model from explaining more than 100% of the variation in growth rates across regions.

Table 6: Growth Accounting: New Human Capital $\beta = .375$ & $.35 \geq \rho > 0$

Region	N	% Annualized Growth Rates g_y	g_{hc}	g_x	g_z	input share	TFP share
Labor Force-Duration Weights							
World	168	1.23	0.97	1.04	0.19	0.843	0.157
wc	18	1.42	1.09	1.20	0.22	0.847	0.153
se	8	1.46	1.15	1.31	0.15	0.897	0.103
cee	24	1.29	1.04	1.14	0.16	0.879	0.121
nic	5	1.83	1.45	1.66	0.18	0.903	0.097
asia	20	1.15	0.94	0.99	0.16	0.861	0.139
ssa	48	1.16	0.88	0.77	0.39	0.663	0.337
la	28	1.20	0.73	0.87	0.33	0.722	0.278
me	12	1.16	1.02	0.96	0.20	0.829	0.171
na	5	1.21	1.08	1.12	0.09	0.926	0.074
Labor Force Weights							
World	168	1.23	0.98	1.02	0.21	0.827	0.173
wc	18	1.42	1.09	1.21	0.22	0.848	0.152
se	8	1.53	1.19	1.35	0.17	0.887	0.113
cee	24	1.02	0.72	0.84	0.18	0.820	0.180
nic	5	1.84	1.46	1.66	0.18	0.904	0.096
asia	20	1.19	0.98	1.02	0.17	0.856	0.144
ssa	48	1.17	0.94	0.77	0.40	0.658	0.342
la	28	1.20	0.75	0.88	0.33	0.728	0.272
me	12	1.22	1.26	1.03	0.19	0.845	0.155
na	5	1.22	1.11	1.13	0.09	0.927	0.073
Unweighted							
World	168	1.32	1.06	1.06	0.25	0.807	0.193
wc	18	1.69	1.30	1.46	0.23	0.864	0.136
se	8	2.54	2.16	2.28	0.27	0.896	0.104
cee	24	0.89	0.61	0.69	0.20	0.773	0.227
nic	5	1.92	1.60	1.74	0.18	0.907	0.093
asia	20	1.38	1.23	1.21	0.17	0.877	0.123
ssa	48	1.22	0.92	0.86	0.37	0.700	0.300
la	28	1.28	0.92	1.04	0.24	0.810	0.190
me	12	0.93	1.17	0.72	0.21	0.777	0.223
na	5	1.34	1.29	1.27	0.07	0.948	0.052

Table 7: Growth Variance Decomposition: Plausible Bounds, New Human Capital $\beta = .375$, $.35 \geq \rho > 0$

Region	N	egalitarian covariance share $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}}$ (1)	$\frac{\sigma_{g_z,g_y}}{\sigma^2_{g_y}}$ (2)	capital intensity covariance share $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}}$ (3)	$\frac{\sigma_{g_{\hat{z}},g_y}}{\sigma^2_{g_y}}$ (4)	plausible shares new data $\overline{S}_{g_x}$ (5)	$\overline{S}_{g_z}$ (6)	plausible shares BDT data $\overline{S}_{g_x}$ (7)	$\overline{S}_{g_z}$ (8)
World	168	0.950	0.050	0.996	0.004	0.947	0.053	.22	.78
wc	18	0.966	0.034	0.949	0.051	0.963	0.037	.46	.54
se	8	0.959	0.041	0.939	0.061	0.959	0.041	.50	.50
cee	24	0.962	0.038	0.944	0.056	0.929	0.071	.28	.72
nic	5	1.024	-0.024	1.035	-0.035	0.959	0.041	.64	.36
asia	20	0.945	0.055	0.918	0.082	0.936	0.064	.40	.60
ssa	48	0.918	0.082	0.878	0.122	0.901	0.099	.37	.63
la	28	0.935	0.065	0.903	0.097	0.935	0.065	.22	.78
me	12	0.968	0.032	1.333	-0.333	0.952	0.048	.44	.56
na	5	1.054	-0.054	1.080	-0.080	0.920	0.080	.84	.16
larger regions									
(1): wc & nic	23	0.981	0.019	0.972	0.028	0.972	0.028		
(2): (1) & se	31	0.960	0.040	0.940	0.060	0.960	0.040		
(3): (2) & na	36	0.948	0.052	0.923	0.077	0.946	0.054		
(4): (3) & asia	56	0.945	0.055	0.918	0.082	0.940	0.060		
(5): (4) & la	84	0.952	0.048	0.928	0.072	0.951	0.049		
(6); (5) & ssa	132	0.947	0.053	0.921	0.079	0.947	0.053		
(7): (6) & me no opec	135	0.947	0.053	0.921	0.079	0.946	0.054		
(8): (7) & cee	159	0.947	0.053	0.921	0.079	0.945	0.055		

6 Robustness

In this section we present evidence on the robustness of the results. First we examine a range of other parameter specifications. Also we use development accounting to assess the ability of variations in log inputs per worker at explaining measured differences in log output per worker. Second we split the data into two equal time periods. For each country we found the closest midpoint observation year and then produced samples with that midyear observation as the terminal and initial value. This evidence is consistent with the conclusion that the model with intergenerational human capital accumulation with spillovers fits the data well.

6.1 Development Accounting

We have shown that variations in growth rates are captured mostly by the variations in input growth rates when inputs include intergenerational human capital accumulation. Does this also hold for variations in levels of output per worker? Similar to variance decomposition analysis of growth rates, we conduct a variance decomposition on log levels of output per worker. Our analysis differs from recent work on development account such as Caselli (2005), and the recent work with human capital accumulation such as Manuelli and Seshadri (2014) and Erosa, Koreshkova and Restuccia (2010). The major point of departure is that in these previous works the authors focus on explaining the difference in output per worker or per capita at a single point in time. Here we have 22 different cross sections on living standards around the world. With observations in every decade from 1800-2010, it allows us to conduct multiple development accounting exercises. We follow two strategies that complement each other. For each development accounting variance decomposition we use the same three metrics as in variance decomposition of growth rates: (1) covariance accounting, (2) covariance accounting with only physical capital intensity, (3) plausible shares. In the first strategy we construct the shares of the variance of log per worker income explained by inputs for each decade, and average them over the 22 observations. The second strategy is to pool all of the observations together in a single sample and perform the development accounting exercises on this universe of data. These two different strategies produce very similar results. Variations in log per worker inputs explain between 55% and 70% of the observed log variations in output per worker.

Once again we can combine the factors of production per worker into the variable x. Assuming a Cobb-Douglas production function produces the following result:

$$\ln y_{it} = \ln z_{it} + \ln x_{it}, \tag{35}$$

$$\ln x_{it} = \alpha \ln k_{it} + (1-\alpha) \ln h_{it} \tag{36}$$

As with our variance decomposition of growth rates, we use the two covariance decompositions suggested by Klenow and Rodriguez-Clare (1997). These are versions of Caselli (2005) *success 3*.[43] In the first, we assume that output variations arise from both input variations and TFP variations:

$$\sigma^2_{\ln y_t} = \sigma_{\ln x_t, \ln y_t} + \sigma_{\ln z_t, \ln y_t} \tag{37}$$

In the second, we assume that higher TFP induces input accumulation of physical capital, and hence only the variations in physical capital intensity and variations in human capital are variations in inputs that account for variations in output per worker. Thus we have:

$$\sigma^2_{\ln y_t} = \sigma_{\ln \hat{x}_t, \ln y_t} + \sigma_{\ln \hat{z}_t, \ln y_t} \tag{38}$$

$$\ln \hat{x}_t = \frac{\alpha}{1-\alpha}\left[\ln k_t - \ln y_t\right] + \ln h_t \tag{39}$$

$$\ln \hat{z}_t = \frac{\alpha}{1-\alpha}\ln z_t \tag{40}$$

Finally we can use the two different theories of the correlation between factor accumulation and TFP growth to help assign the correlated component of log levels of inputs and TFP. First under the view that TFP induces factor accumulation, and that the predictable or correlated portion of inputs should be assigned to TFP, the share of output per worker can be written as:

$$1 = \frac{(\sigma_{\ln z} + \sigma_{\ln x}\rho_{\ln x, \ln z})^2}{\sigma^2_{\ln y}} + \frac{(1-\rho^2_{\ln x, \ln z})\sigma^2_{\ln x}}{\sigma^2_{\ln y}} \tag{41}$$

where the first term is now a plausible upper bound on the proportion of the variation in log output per worker explained by variation in log TFP. At the other end of the theoretical spectrum, the predictable or correlated component of TFP arises from endogenous factor accumulation. Assigning this predictable component to factors produces the following variance decomposition:

$$1 = \frac{(\sigma_{\ln x} + \sigma_{\ln z}\rho_{\ln x, \ln z})^2}{\sigma^2_{\ln y}} + \frac{(1-\rho^2_{\ln x, \ln z})\sigma^2_{\ln z}}{\sigma^2_{\ln y}} \tag{42}$$

The first term is now the proportion of the variation of output per worker that explained by variation in inputs. We examine these for the initial conditions as well as the terminal observation.[44] Thus the shares

[43] Caselli's first two measures of *success* are the ratio of the variance of log inputs to the variance of log output, and the ratio of two 90-10 ratios, $\frac{x_{90}/x_{10}}{y_{90}/y_{10}}. We focus on version of his success\ 3 as these are most similar to the variance decomposition of growth rates.$

[44] All terminal years are 2010, except for East Germany, which has a terminal observation in 1990.

of the variance of log output per worker are given by:

$$\overline{S}_{\ln x} = \frac{\sigma^2_{\ln x}}{\sigma^2_{\ln y}} + \frac{1}{2}\frac{\rho^2_{\ln x,\ln z}\left(\sigma^2_{\ln z} - \sigma^2_{\ln x}\right)}{\sigma^2_{\ln y}} + \frac{\sigma_{\ln x}\sigma_{\ln z}\rho_{\ln x,\ln z}}{\sigma^2_{\ln y}} \tag{43}$$

$$\overline{S}_{\ln z} = \frac{\sigma^2_{\ln z}}{\sigma^2_{\ln y}} + \frac{1}{2}\frac{\rho^2_{\ln x,\ln z}\left(\sigma^2_{\ln x} - \sigma^2_{\ln z}\right)}{\sigma^2_{\ln y}} + \frac{\sigma_{\ln x}\sigma_{\ln z}\rho_{\ln x,\ln z}}{\sigma^2_{\ln y}} \tag{44}$$

Figures 12 - 14 contain the time series of the share of variations in log output per worker explained by variations in log inputs per worker. In each graph we present three different cases, the base case with no intergenerational human capital accumulation (only Mincer human capital), and intergenerational human capital accumulation, $\beta = .375$ with no spillover, $\rho = 0$, and with spillover $.35 \geq \rho \geq 0$. The thick curves in each of the three human capital specifications are the results from using all of the 2044 observations in a single estimation. The thinner curves, in each of the three human capital specifications, are the results from each decade cross section. We start with the most restrictive assumption that only physical capital intensity, $\frac{k}{y}$, variations contribute to input explanations of log level output per worker variations. This is contained in Figure 12.

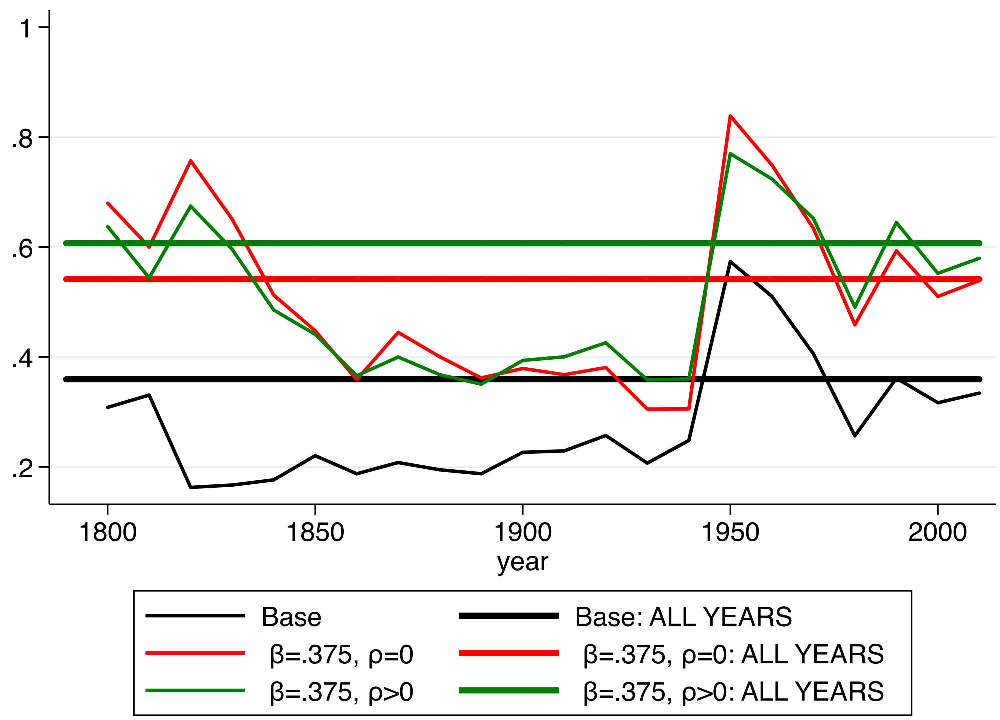

Figure 12: Covariance Development Accounting (Klenow & Rodriguez-Clare): Base, $\beta = .375, \rho = 0$, $\beta = .375, \rho > 0$

Both intergenerational human capital models significantly improve on the base Mincer human capital cross section model. In every cross section they outperform the base Mincer human capital model in explaining cross sectional output per worker differences. The spillover model has an average capital intensity covariance share of 49.4%, and the no spillover model has an average capital intensity covariance share of 49.7%.[45] However when we use all data for a single covariance share, the spillover model clearly outperforms the no spillover model, 61.1% to 54.6%.[46] For the model with spillovers, its lowest decade value is typically equal to the base Mincer model value for all data, that is 36%.[47]

Figure 13 contains the results for the covariance share decomposition without the limiting the contribution of physical capital only to physical capital intensity. The time series of all three human capital models are identical to the previous case, except for level. Under the assumption that inputs per worker include only physical capital intensity and human capital, all three human capital models explained less than 50 percent of output per worker variations. When inputs include physical capital and human capital, all three models explain better than 50 percent of output per worker differences. Using the 22 repeated cross sections and averaging, the base Mincer human capital model explains only 52.1% of log output per worker differences. Using the 22 repeated cross sections and averaging, the models with and without spillovers explain 67.7% and 67.4%of log output per worker differences, respectively.[48]

Allowing the data to determine how much of the correlation or predictable component of log input and log TFP to allocate to each other produces the final metric on the importance of input variations. Figure 14 contains the results for the three human capital specifications, and there are almost no differences compared with the covariance share results above. Averaging over the 22 cross sections, log input variations explain 52.1%, 64.4% and 64.2% of the difference in log output per worker for the Mincer model, the no spillover model and the conditional spillover model, respectively. Using all 2044 observations in a single sample, log input differences explain 59.1%, 70.5% and 73.9% of log output per worker differences. With intergenerational human capital accumulation, we find that input variations are capable of explaining at least half of the observed variation in output per worker. With the standard Mincer human capital model, the typical share of log level differences in living standards arising from log inputs is less than 50%. By introducing intergenerational human capital accumulation, both models with and without human capital spillovers are able to explain over half of the log level differences in living standards. Once one allows the data to help inform about the importance of the association, we find that log input variation explains between half and as much as three-fourths of the variation in log output per worker.

[45]The Mincer model has and average capital intensity covariance share 27.0%.

[46]The Mincer model has capital intensity covariance share of only 36.1% when all 2044 observations are used.

[47]The model without spillovers is similar, except for two decades, 1930 and 1940 in which the input share falls below the base Mincer model with all data.

[48]When using all 2044 observations are used in a single sample, the base Mincer model explains 59.3%, the model without spillovers explains 72.4% and the full spillover model explains 76.3%.

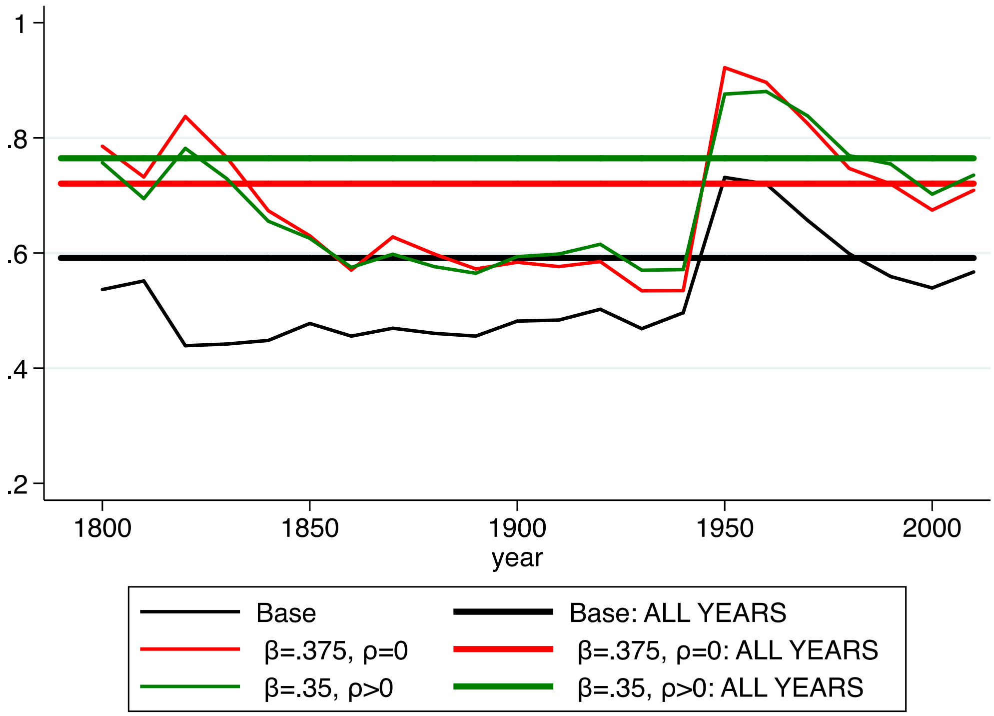

Figure 13: Covariance Development Accounting: Base, $\beta = .375, \rho = 0$, $\beta = .375, \rho > 0$

6.2 Alternative Parameter Specifications

In this section we show that the results of the previous sections are robust to different parameter values. Our conclusion that intergenerational human capital accumulation models with spillovers dramatically help to explain variation in long run growth rates, as well as variations in living standards is robust. We examine a range of values on the triple (A, β, ρ) with the restriction that the labor force and duration weighted average growth rate of output per worker is explained by input growth is 84%, the value in Table 6. For various combinations of (A, β, ρ) we show that between 80% to 94% of the variation in growth rates of output per worker is captured by input growth variations. In our preferred specification, $(\beta = .375, .35 \geq \rho \geq 0)$, 94.1% is reached, second only to the 94.5% from $(\beta = .35, .375 \geq \rho \geq 0)$ specification. We also conduct development accounting exercises, and show that between 55% and 70% of the variation in log levels of output per worker are explained by variations in inputs per worker, with stronger belief towards the higher range.

We searched over a wide range of values of β and ρ. For β we examined values from $[.025, .70]$, and for ρ we examined maximum values from $[0, .70]$ with the constraint $\beta + \rho = .725$.[49] We combine both the variance decomposition of growth results and the development accounting results in Table 8.[50] The top

[49]With one exception, the $\beta = .375$, $\rho = 0$ case.
[50]We think of this exercise as one of quantitative identification. That is the parameters chosen in order to best fit both

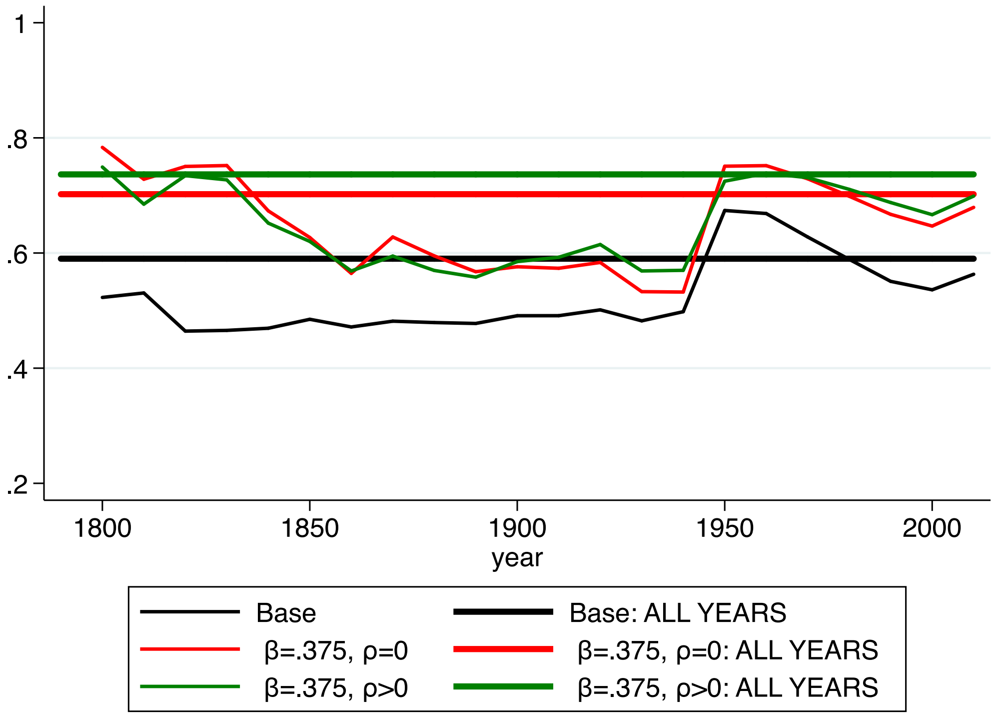

Figure 14: Plausible Shares, Development Accounting: Base, $\beta = .375, \rho = 0$, $\beta = .375, \rho > 0$

half of Table 8 contains the variance decomposition analyses of growth rates, and the bottom half contains the variance decomposition analyses of log levels. The results are presented as pairs, columns (1) and (2) form the first pair, and the remainders are (3) & (4), (5) & (6), (7) & (8). The odd columns contain results when all countries are in a single group. Thus each contains the variance decompositions of 168 growth rate histories using the egalitarian covariance assignment (1), the capital intensity covariance assignment (3), the plausible share from capital intensity (5), and plausible share with both physical and human capital treated symmetrically (7).[51] The even columns present the average results from treating the 9 regions as separate samples. For example in column (2), we compute the egalitarian covariance share of inputs for

the growth accounting and the variance decomposition of growth rates. This exercise is conducted similar to Tamura and Simon (2016), Tamura, Simon and Murphy (2016), Murphy, Simon and Tamura (2008) and Tamura (2006). Their models are forced to fit actual time series, and the forcing variables, such as price of space, or efficiency of schooling time, are allowed to be whatever they need to be to fit the series. That is given a specific model, what must parameters be in order to fit the data. In theory we could use a search algorithm for the best fitting parameters that minimizes a loss function. We leave that to future research. We experimented with other combinations of (A, β, ρ) but the overwhelming majority of those specifications performed worse than those presented in Table 8 either in the variance decomposition of growth rates or the variance decomposition of log levels.

[51] In both the egalitarian covariance share, column (1), $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}}$, and the capital intensity covariance share, column (3), $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}}$, it is possible that $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}} > 1$, or $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}} > 1$ or $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}} < 0$ or $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}} < 0$. It never is the case $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}} < 0$, nor ever the case that $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}} < 0$. It is never the case $\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}} > 1$, but often the case that $\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}} > 1$. In those cases we replaced the result to $\frac{\sigma^2_{g_y}}{\sigma_{g_{\hat{x}},g_y}}$.

each of the 9 regions separately and then average the results.[52]. Finally column (9) reports the average of the first eight columns for each parameter specification. Overall measures, (9) shows that input growth rate variations explain anywhere from 80% to 94% of growth rate variations across countries. Our preferred specification, ($\beta = .375, .35 \geq \rho \geq 0$) produces an average explanatory power of 94%, which is the second highest of the range presented.

In the development accounting portion of Table 8, column (1) presents the covariance share when using all years of data. Column (2) presents the average covariance share, where we average the decadal cross sections from 1800 to 2010.[53] Columns (3)-(4) repeat the analysis, but restrict the physical capital input to be variations in physical capital intensity. Column (3) is the covariance share when using all years. Column (4) presents the average covariance share over the 22 decadal cross sections. The plausible share from physical capital intensity variations are presented in columns (5)-(6). Column (5) comes from all years, and column (6) is the average of the 22 cross sections. Columns (7)-(8) present the plausible share allowing physical capital and human capital to vary. Finally column (9) presents the average across all eight measures for each parameter specification. Overall measures, (9) shows that log level input differences explain somewhere between 56% to as much as70% of the log level variation across countries. Our preferred specification, ($\beta = .375, .35 \geq \rho \geq 0$) averages 63% over all development accounting measures, the median of the distribution of development shares.

The final column, (10), of Table 8 is an arithmetic average of a parameter specification's growth decomposition and level decomposition input share. In the 17 cases, the average input share ranges from a low of 74%, ($\beta = .025, .70 \geq \rho \geq 0$), to a high of 79%, ($\beta = .375, .35 \geq \rho \geq 0$). Thus we see that intergenerational human capital accumulation with conditional human capital spillovers can help to explain the observed variation in growth rates and the observed log level differences in living standards.

6.3 First Half & Second Half

In this section we examine how well the model works for early years and later years. For each country we found the midpoint year observation, hereafter referred to as midyear, and split the country's time series into two parts. We examine how the three models fit the data when comparing the period from the first year of observation until the midyear, and then from the midyear to 2010. If the human capital calculations are robust, then they should fit each of these periods as well as the overall period, absent innovations to the underlying structure of the economy. There are certainly many alternative ways to decompose the time

[52]In both the egalitarian covariance share, $\frac{\sigma_{g_x, g_y}}{\sigma^2_{g_y}}$, and the capital intensity covariance share cases, $\frac{\sigma_{g_{\hat{x}}, g_y}}{\sigma^2_{g_y}}$, it is possible that $\frac{\sigma_{g_x, g_y}}{\sigma^2_{g_y}} > 1$, or $\frac{\sigma_{g_{\hat{x}}, g_y}}{\sigma^2_{g_y}} > 1$ or $\frac{\sigma_{g_x, g_y}}{\sigma^2_{g_y}} < 0$ or $\frac{\sigma_{g_{\hat{x}}, g_y}}{\sigma^2_{g_y}} < 0$. It never is the case $\frac{\sigma_{g_x, g_y}}{\sigma^2_{g_y}} < 0$, nor ever the case that $\frac{\sigma_{g_{\hat{x}}, g_y}}{\sigma^2_{g_y}} < 0$. However in the event $\frac{\sigma_{g_x, g_y}}{\sigma^2_{g_y}} > 1$, or the event that $\frac{\sigma_{g_{\hat{x}}, g_y}}{\sigma^2_{g_y}} > 1$, we replaced those values with the reciprocal value, i.e. In those cases we replaced the result to $\frac{\sigma^2_{g_y}}{\sigma_{g_{\hat{x}}, g_y}}$, or $\frac{\sigma^2_{g_y}}{\sigma_{g_{\hat{x}}, g_y}}$

[53]We defined a country observation in year t is in decade X if $X + 4 \geq t \geq X - 5$.

periods of each country's observation. For example for those countries that we have data from 1820, one could imagine looking at the 19th century and then the remaining years. Or breaking up the 20th century into pre World War I, Interwar years, and then post World War II. However many countries do not have data spanning most of the 19th century. Instead of having composition changes across periods, we chose to keep the samples balanced.

Tables 9 - 12 contain the results of both the growth accounting and the variance decompositions for the Mincer human capital model (hereafter referred to as base model), and the intergenerational human capital model both with and without spillovers. Tables 9 and 10 present growth accounting for each period, and Tables 11 and 12 present the variance decomposition results for the original model. We concentrate on the results contained in the top third of Tables 9 and 10, those arising from *labor force-duration* weights. There is a noticeable acceleration in growth rates between the first half and the second half, tripling from .62% per year to 1.91% per year. Growth rates accelerate in every region except for *Sub-Saharan Africa* and the *Middle East*. It is all the more remarkable since for all of these regions, except for *Sub-Saharan Africa*, the second half of the data include both World Wars, and the Great Depression. The base model explains two-thirds of growth in the first half and 57% of growth in the second half. The intergenerational model of human capital accumulation without spillovers explains more than 100% of the growth in the first half, and 57% of growth in the second half. With spillovers the intergenerational human capital model captures 109% of growth in the first half and almost 80% of growth in the second half.

Recall that in the variance decomposition of growth rates, the base model explained 46% of the variance of growth, see Table 2. When the data is split, the base model explains 34% of growth rate variations in the first half of the data, and 38% in the second half, (based on using the covariance share and plausible share). The intergenerational human capital model improves the ability to explain the cross sectional variation in growth rates. Without spillovers the model explains 55% of the variation in growth rates in the first half, and 49% in the second half. The model with conditional human capital spillovers explains 53% of the variation in growth rates in the first half, and 51% in the second half. All of the results, from all models, are robust to larger regions. While the ability to fit the time series, split into two equal halves, is not as good as the entire time series for each country, the intergenerational human capital models both outperform the Mincer model. In general at least 50% of the variation in growth rates is captured by variation in growth rates of inputs.

Table 8: Robustness Analysis: Average Input Share

Model	Growth Variance Decomposition									Growth & Development
	egalitarian covariance share		capital intensity covariance share		capital intensity plausible share		plausible share			
(β, ρ)	$\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}}$	$\overline{\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}}}$	$\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}}$	$\overline{\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}}}$	$\overline{S}_{g_x}$	Avg $\overline{S}_{g_x}$	$\overline{S}_{g_x}$	Avg $\overline{S}_{g_x}$	Avg.	Average
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(.025, .700)	.9803	.9109	.9702	.8468	.9142	.8127	.9696	.8541	.9073	.7318
(.075, .650)	.9787	.9180	.9711	.8554	.9191	.8218	.9715	.8625	.9123	.7386
(.125, .600)	.9763	.9259	.9731	.8652	.9233	.8345	.9723	.8745	.9181	.7460
(.175, .550)	.9728	.9344	.9764	.8765	.9266	.8539	.9713	.8932	.9256	.7544
(.225, .500)	.9684	.9428	.9811	.8894	.9288	.8794	.9682	.9177	.9345	.7635
(.275, .450)	.9628	.9525	.9876	.9050	.9295	.8970	.9626	.9341	.9414	.7718
(.325, .400)	.9555	.9570	.9971	.9129	.9288	.9059	.9537	.9417	.9441	.7784
(.350, .375)	.9522	.9579	.9987	.9147	.9280	.9108	.9495	.9456	.9447	.7813
(.375, .350)	.9499	.9533	.9964	.9081	.9271	.9050	.9466	.9394	.9407	.7820
(.400, .325)	.9469	.9470	.9936	.8988	.9254	.8838	.9428	.9186	.9321	.7804
(.450, .275)	.9397	.9309	.9866	.8774	.9200	.8387	.9341	.8720	.9124	.7761
(.500, .225)	.9301	.9038	.9761	.8415	.9116	.8063	.9230	.8370	.8912	.7716
(.550, .175)	.9182	.8714	.9627	.7986	.8993	.7712	.9107	.8012	.8667	.7652
(.600, .125)	.9078	.8334	.9516	.7485	.8837	.7388	.9032	.7694	.8420	.7586
(.650, .075)	.8994	.7890	.9441	.6913	.8635	.7027	.8987	.7385	.8159	.7509
(.700, .025)	.8958	.7400	.9444	.6291	.8386	.6585	.8940	.7083	.7886	.7430
(.375, .000)	.9628	.8448	.9753	.7621	.9092	.7847	.9602	.8357	.8794	.7400

Model	Development Variance Decomposition								
	egalitarian covariance share		capital intensity covariance share		capital intensity plausible share		plausible share		
(β, ρ)	$\frac{\sigma_{\ln x,\ln y}}{\sigma^2_{\ln y}}$	$\overline{\frac{\sigma_{\ln x,\ln y}}{\sigma^2_{\ln y}}}$	$\frac{\sigma_{\ln \hat{x},\ln y}}{\sigma^2_{\ln y}}$	$\overline{\frac{\sigma_{\ln \hat{x},\ln y}}{\sigma^2_{\ln y}}}$	$\overline{S}_{ln_x}$	Avg $\overline{S}_{ln_x}$	$\overline{S}_{ln_x}$	Avg $\overline{S}_{ln_x}$	Avg.
(.025, .700)	.6203	.7026	.4139	.5155	.4015	.5125	.5949	.6889	.5563
(.075, .650)	.6273	.7111	.4241	.5278	.4107	.5224	.6007	.6959	.5650
(.125, .600)	.6343	.7199	.4345	.5406	.4201	.5326	.6066	.7031	.5740
(.175, .550)	.6414	.7290	.4450	.5539	.4297	.5430	.6127	.7103	.5831
(.225, .500)	.6487	.7384	.4558	.5676	.4393	.5536	.6190	.7175	.5925
(.275, .450)	.6563	.7482	.4670	.5819	.4494	.5645	.6256	.7248	.6022
(.325, .400)	.6649	.7583	.4797	.5968	.4608	.5756	.6331	.7321	.6127
(.350, .375)	.6694	.7630	.4865	.6038	.4669	.5807	.6372	.7354	.6179
(.375, .350)	.6743	.7676	.4938	.6105	.4735	.5856	.6417	.7386	.6232
(.400, .325)	.6797	.7719	.5018	.6169	.4807	.5902	.6467	.7416	.6287
(.450, .275)	.6916	.7796	.5194	.6283	.4965	.5981	.6577	.7466	.6397
(.500, .225)	.7057	.7874	.5404	.6396	.5148	.6059	.6708	.7516	.6520
(.550, .175)	.7199	.7944	.5615	.6499	.5323	.6127	.6836	.7559	.6638
(.600, .125)	.7338	.8017	.5823	.6604	.5483	.6193	.6952	.7599	.6751
(.650, .075)	.7479	.8091	.6031	.6710	.5628	.6252	.7056	.7633	.6860
(.700, .025)	.7635	.8179	.6262	.6836	.5766	.6311	.7151	.7662	.6975
(.375, .000)	.6766	.7244	.4973	.5462	.4753	.5365	.6442	.7052	.6007

Table 9: Growth Accounting First Half: Base & New Human Capital $\beta = .375$ & $.35 \geq \rho \geq 0$

Region	N	g_y	g_k	g_{hc}^{base}	$g_{hc}^{\rho=0}$	$g_{hc}^{\rho\geq 0}$	share^{base}	share$^{\rho=0}$	share$^{\rho\geq 0}$
		% Annualized Growth Rates							
Labor Force-Duration Weights									
World	168	0.58	0.79	0.21	1.22	0.59	0.688	1.853	1.130
wc	18	1.11	1.22	0.37	1.33	0.82	0.583	1.164	0.854
se	8	0.75	0.58	0.27	1.34	0.77	0.496	1.450	0.937
cee	24	0.86	1.57	0.29	1.25	0.79	0.830	1.574	1.214
nic	5	0.56	1.12	0.19	1.49	0.93	0.878	2.420	1.756
asia	20	0.15	0.35	0.07	1.22	0.48	1.097	6.320	2.995
ssa	48	1.36	1.14	0.67	1.03	0.39	0.605	0.781	0.468
la	28	0.86	0.65	0.16	0.53	-0.02	0.377	0.666	0.232
me	12	1.63	1.02	0.18	1.24	0.58	0.211	0.639	0.372
na	5	1.03	1.19	0.09	1.39	0.74	0.443	1.285	0.864
Labor Force Weights									
World	168	0.74	0.88	0.30	1.12	0.53	0.656	1.397	0.870
wc	18	1.12	1.23	0.37	1.34	0.82	0.579	1.159	0.850
se	8	0.89	0.71	0.30	1.42	0.84	0.487	1.328	0.897
cee	24	0.88	1.96	0.45	0.49	0.26	1.043	1.071	0.896
nic	5	0.56	1.11	0.19	1.50	0.94	0.873	2.439	1.769
asia	20	0.26	0.25	0.09	1.33	0.60	0.548	3.706	1.844
ssa	48	1.43	1.20	0.70	1.06	0.40	0.604	0.770	0.465
la	28	1.07	0.70	0.28	0.53	-0.00	0.389	0.549	0.213
me	12	2.50	1.11	0.32	1.50	0.85	0.150	0.457	0.289
na	5	1.45	1.38	0.19	1.39	0.77	0.403	0.957	0.674
Unweighted									
World	168	1.49	1.20	0.55	0.89	0.42	0.491	0.651	0.442
wc	18	1.58	1.59	0.37	1.61	1.15	0.492	1.019	0.820
se	8	2.43	2.16	0.61	2.95	2.20	0.462	1.106	0.898
cee	24	0.72	1.87	0.80	-0.17	-0.11	1.603	0.699	0.754
nic	5	0.59	0.76	0.08	2.00	1.35	0.513	2.688	1.957
asia	20	1.18	1.07	0.34	1.36	0.71	0.489	1.064	0.697
ssa	48	1.72	0.78	0.70	0.62	0.04	0.421	0.390	0.164
la	28	1.65	1.15	0.52	0.67	0.24	0.440	0.500	0.327
me	12	1.71	0.66	0.40	0.69	0.16	0.021	0.221	0.027
na	5	1.90	1.57	0.31	1.47	0.90	0.383	0.791	0.590

Table 10: Growth Accounting Second Half: Base & New Human Capital $\beta = .375$ & $.35 \geq \rho \geq 0$

Region	N	% Annualized Growth Rates g_y	g_k	g_{hc}^{base}	$g_{hc}^{\rho=0}$	$g_{hc}^{\rho\geq 0}$	share^{base}	share$^{\rho=0}$	share$^{\rho\geq 0}$
Labor Force-Duration Weights									
World	168	1.96	1.70	0.82	0.81	1.43	0.565	0.561	0.773
wc	18	1.63	1.58	0.64	0.74	1.30	0.584	0.623	0.852
se	8	2.18	2.65	0.87	0.89	1.48	0.669	0.675	0.856
cee	24	1.74	1.06	1.21	0.54	1.28	0.668	0.411	0.695
nic	5	3.06	3.13	0.96	1.47	1.82	0.547	0.658	0.735
asia	20	2.11	1.78	0.79	0.76	1.41	0.529	0.519	0.727
ssa	48	1.11	0.15	0.88	1.13	1.46	0.580	0.728	0.932
la	28	1.72	1.68	0.91	0.88	1.55	0.678	0.665	0.926
me	12	1.19	1.28	1.00	0.94	1.64	0.866	0.815	1.194
na	5	1.53	1.26	0.89	0.74	1.41	0.661	0.596	0.889
Labor Force Weights									
World	168	1.84	1.52	0.86	0.87	1.46	0.582	0.587	0.800
wc	18	1.63	1.59	0.64	0.74	1.30	0.585	0.625	0.855
se	8	2.19	2.63	0.87	0.91	1.49	0.662	0.674	0.852
cee	24	1.20	0.23	1.40	0.56	1.19	0.849	0.377	0.729
nic	5	3.07	3.14	0.97	1.48	1.83	0.548	0.660	0.735
asia	20	2.14	1.84	0.79	0.81	1.44	0.533	0.538	0.736
ssa	48	0.96	-0.23	0.89	1.24	1.56	0.544	0.788	1.013
la	28	1.62	1.65	0.93	0.90	1.56	0.722	0.709	0.986
me	12	0.65	1.38	1.17	1.22	1.98	1.690	1.675	2.378
na	5	1.40	1.17	0.91	0.78	1.45	0.712	0.649	0.970
Unweighted									
World	168	1.14	1.09	1.08	1.19	1.68	0.936	0.998	1.280
wc	18	1.80	1.98	0.71	0.88	1.44	0.627	0.689	0.897
se	8	2.52	2.74	0.83	1.74	2.07	0.580	0.822	0.910
cee	24	1.05	-0.21	1.91	0.82	1.34	1.159	0.460	0.796
nic	5	3.16	3.20	1.00	1.76	1.84	0.545	0.705	0.723
asia	20	1.65	1.35	0.89	1.22	1.71	0.632	0.767	0.964
ssa	48	0.72	0.68	0.99	1.44	1.79	1.236	1.655	1.979
la	28	0.88	1.33	0.93	0.96	1.58	1.214	1.232	1.708
me	12	0.12	1.12	1.24	1.38	2.16	6.557	7.018	10.09
na	5	0.76	0.90	1.02	0.97	1.65	1.290	1.241	1.844

Table 11: Growth Variance Decomposition: First Half, Base, New Human Capital $\beta = .375, \rho = 0$, $\beta = .375, .35 \geq \rho \geq 0$

Region	N	$\frac{\sigma_{g_x, g_y}}{\sigma^2_{g_y}}$	$\frac{\sigma_{g_{\hat{x}}, g_y}}{\sigma^2_{g_y}}$ k/y	$\overline{S}^{base}_x$	$\frac{\sigma_{g_x^{\rho=0}, g_y}}{\sigma^2_{g_y}}$	$\frac{\sigma_{g_{\hat{x}}^{\rho=0}, g_y}}{\sigma^2_{g_y}}$ k/y	$\overline{S}^{\rho=0}_x$	$\frac{\sigma_{g_x^{\rho\geq0}, g_y}}{\sigma^2_{g_y}}$	$\frac{\sigma_{g_{\hat{x}}^{\rho\geq0}, g_y}}{\sigma^2_{g_y}}$ k/y	$\overline{S}^{\rho\geq0}_x$
World	168	.3376	.2462	.3380	.5574	.5850	.5505	.5373	.5561	.5341
wc	18	.3946	.0964	.4569	.6114	.4199	.6109	.7060	.5612	.6977
se	8	.4450	.1716	.4965	.9693	.9542	.9250	.8837	.8264	.8828
cee	24	.0231	-.4580	.1635	.4047	.1115	.4293	.2872	-.0639	.3154
nic	5	.5072	.2645	.5063	.7583	.6393	.6718	.7688	.6550	.7063
asia	20	.4081	.1166	.4433	.4901	.2389	.4905	.4607	.1950	.4665
ssa	48	.3253	-.0071	.3253	.4491	.1777	.4604	.5112	.2704	.5089
la	28	.4895	.2381	.4926	.5887	.3861	.5864	.6945	.5441	.6806
me	12	.5008	1.9894	.5008	.7220	2.4003	.7074	.6636	2.3221	.6616
na	5	.3028	-.0407	.4991	.1420	-.2806	.4532	.1960	-.2001	.4711
larger regions										
(1): wc & nic	23	.4188	.1325	.4673	.4540	.1850	.4541	.5546	.3353	.5540
(2): (1) & se	31	.4371	.1598	.4911	.8657	.7995	.8504	.8120	.7194	.8118
(3): (2) & na	36	.3990	.1029	.4815	.6643	.4989	.6628	.6397	.4622	.6387
(4): (3) & asia	56	.4023	.1079	.4647	.6176	.4293	.6176	.5943	.3944	.5922
(5): (4) & la	84	.4231	.1389	.4627	.5970	.3985	.5941	.6072	.4138	.6062
(6); (5) & ssa	132	.3936	.0949	.4122	.5387	.3115	.5339	.5634	.3483	.5570
(7): (6) & me no opec	137	.3938	.0952	.4129	.5371	.3092	.5327	.5625	.3471	.5565
(8); (7) & cee	161	.3176	-.0186	.3200	.5328	.3027	.5289	.5215	.2858	.5196

Table 12: Growth Variance Decomposition: Second Half, Base, New Human Capital $\beta = .375, \rho = 0$, $\beta = .375, .35 \geq \rho \geq 0$

Region	N	$\frac{\sigma_{g_x,g_y}}{\sigma^2_{g_y}}$	$\frac{\sigma_{g_{\hat{x}},g_y}}{\sigma^2_{g_y}}$ k/y	$\overline{S}_x^{base}$	$\frac{\sigma_{g_x^{\rho=0},g_y}}{\sigma^2_{g_y}}$	$\frac{\sigma_{g_{\hat{x}}^{\rho=0},g_y}}{\sigma^2_{g_y}}$ k/y	$\overline{S}_x^{\rho=0}$	$\frac{\sigma_{g_x^{\rho\geq 0},g_y}}{\sigma^2_{g_y}}$	$\frac{\sigma_{g_{\hat{x}}^{\rho\geq 0},g_y}}{\sigma^2_{g_y}}$ k/y	$\overline{S}_x^{\rho\geq 0}$
World	168	.3803	-.1773	.3804	.4857	-.0184	.4857	.5008	-.0109	.5008
wc	18	.2030	-.1896	.2134	.3891	.0881	.3956	.3994	.1035	.4080
se	8	.1368	-.2883	.2434	1.0265	1.0395	.8455	.8140	.7225	.8081
cee	24	.6089	.4163	.5933	.6129	.4223	.6115	.6663	.5020	.6654
nic	5	.7618	.6445	.6885	1.0362	1.0540	.8936	.6041	.4091	.5865
asia	20	.3187	-.0168	.3395	.4595	.1933	.4611	.4920	.2418	.4922
ssa	48	.3651	.0525	.3741	.5166	.2785	.5161	.5328	.3026	.5325
la	28	.0989	-.3450	.0997	.1753	-.2309	.1774	.1895	-.2097	.1906
me	12	.5025	-1.434	.5025	.5280	-1.366	.5277	.5997	-1.371	.5956
na	5	.1247	-.3064	.4288	.0555	-.4097	.2494	.0311	-.4461	.0911
larger regions										
(1): wc & nic	23	.3373	.0109	.3833	.5791	.3718	.5664	.4524	.1826	.4689
(2): (1) & se	31	.2807	-.0736	.3380	.7630	.6463	.7541	.6059	.4119	.6017
(3): (2) & na	36	.2154	-.1711	.3189	.4558	.1878	.4559	.3524	.0335	.3602
(4): (3) & asia	56	.2509	-.1181	.3126	.4634	.1991	.4634	.3945	.0963	.3956
(5): (4) & la	84	.1922	-.2056	.2389	.3744	.0662	.3753	.3199	-.0151	.3243
(6); (5) & ssa	132	.3011	-.0431	.3204	.4428	.1684	.4441	.4424	.1678	.4435
(7): (6) & me no opec	135	.3008	-.0436	.3201	.4414	.1663	.4427	.4415	.1663	.4426
(7); (6) & cee	159	.3720	.0627	.3720	.4892	.2377	.4893	.5016	.2561	.5016

7 Evidence from Micro Literature

Our work produces human capital across countries. How would one get an independent measure of human capital, separate from the macro approach here? This is answered in the work of Hendricks (2002) and Schoellman (2012). Both of these works estimate education quality differences between the US and many countries. We use their estimates of differential education quality to compute Mincer adjusted human capital for their sample of countries, and in the case of Schoellman, our entire database of countries in 2000 and 2010.

Hendricks typically reports higher 1990 quality schooling in many countries compared with the US. In order to compare results, we construct an alternative human capital measure using Hendricks quality measures. Thus we assume that the relative 1990 human capital implied by differential school quality can be constructed as:

$$r_{i1990}^{Hendricks} = exp(.1 * Q_i * education_i^{1524} - .1 * education_{US}^{1524}) \tag{45}$$

where Q_i is the Hendricks (2002) measure of relative school quality of country i compared to the US, and $education_i^{1524}$ is the years of schooling of the youngest worker cohort in country i.

A pre publication version of Schoellman (2012) contained estimates of relative human capital by country, adjusted for differences in education quality. These were removed from the published version. In personal correspondence, Schoellman states that useful estimates of human capital can be constructed using the simple formula $lnh_{it} = .2 * Educ_{it}$. Thus our estimates of year t=2000 and t=2010 country i's Schoellman human capital relative to the US is given by:

$$r_{it}^{Schoellman} = exp(.2 * [education_{it}^{1524} - education_{USt}^{1524}]) \tag{46}$$

Using our model with intergenerational human capital accumulation and international human capital spillovers, we find no country with human capital in excess of the US, nor any country with young worker human capital in excess of young US worker human capital. For our full sample of 167 countries in 1990, the labor force weighted average relative young human capital is .38. For the 73 countries that Hendricks reports education quality, our constructed relative human capital has a weighted average of .62. For these 73 countries our model relative young human capital has weighted average of .39. We report the values of 1990 relative output per worker, 1990 relative human capital by cohort for all countries, as well as our constructed 1990 Hendricks relative human capital in Table **??**.

In 2000 for all countries exclusive of the US, our constructed Schoellman relative young human capital has a labor force weighted average of .43. Our model relative human capital for the youngest worker cohort has a labor force weighted average of .39. We report the values of 2000 relative output per worker, 2000 relative human capital by cohort for all countries, as well as our constructed 2000 Schoellman relative human capital in Table ??.

Finally we constructed the predicted Schoellman relative human capital for 2010. Using the same method as for 2000, this measure has a labor force weighted average of .48. Our model relative human capital for the youngest worker cohort has a corresponding labor force weighted average of .43.

Table 13 presents regression results comparing our model relative human capital and those from Hendricks (2002) and Schoellman (2012). The Table is broken into four panels. In the northwest panel, labeled Hendricks, we present results of the regression of young relative human capital from our Hendricks inspired computation against the model relative human capital.[54] The first two columns contain the log-log specification, and the second two columns report the levels regressions. For each specification we run with and without regional dummies. The northeast panel repeats the exercise, but for our 2000 Schoellman relative young human capital specification. The southwest panel reports the results from our 2010 Schoellman specification. Finally the southeast panel pools all three years together. In all the years, 1990, 2000, 2010 and pooled, our model relative human capital is strongly positively correlated with the Hendricks and Schoellman relative human capital. This is true whether we control for regions or not, or in levels or logs.

8 Conclusion

The paper presents a simple model of human capital accumulation and physical capital accumulation within the framework of a standard Cobb-Douglas aggregate production function. We use the new data created here to estimate new values of country specific human capital. Using a method standard in the labor literature we allow for Mincerian age-earnings relationships to hold within each country, but allow for human capital to accumulate across generations. This accumulation technology is similar to Bils and Klenow (2000), Lucas (1988), Tamura (1991,2002,2006), and Galor (2005). We allow human capital to build on the shoulders of the previous generation. We find that an intergenerational human capital accumulation model with conditional spillovers can explain about 85 percent of the long term growth of output per worker, and 95 percent of the cross sectional variation in output per worker growth. The results of the development accounting show that this human capital model is capable of explaining about 63% of the differences in log output per worker. These results are robust to different parameter specifications and different time periods.

The plausibility of the estimates can be determined by examining other predictions that can be made with the data. Our construction produces a distribution of human capital for every country. Theories that consider the inequality of human capital (usually without an age distribution) and their effects on growth can be tested with our measures of the distribution of human capital, for example Banerjee and Newman

[54] We do this with and without population weights. The results do not vary much with population weights, so we only report the unweighted regressions.

(1993), Barro (2000), Chen (2003), Benabou (1996a,b), Benhabib and Spiegal (1994), Galor and Tsiddon (1997), Persson and Tabelllini (1994), etc. Additionally we can combine our data with that contained in Tamura (2006), to examine the connection between mortality risk and human capital accumulation. Finally the data augmented with fertility provides an ability to test long run growth theories of Galor (2005) and his coauthors, Galor and Weil (2000), Galor and Moav (2004), Galor, Moav and Vollrath (2009).

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Table 13: Regressions with Model Relative Human Capital: $\beta = .375, .35 \geq \rho > 0$

	Hendricks				Schoellman			
Variable	ln(H)	ln(H)	H	H	ln(H)	ln(H)	H	H
ln(rel. hc)	0.6589***	0.4872***			0.8144***	0.6837***		
	(.0431)	(.0490)			(.0274)	(.0355)		
rel. hc			1.2687***	0.9297***			0.9549***	0.7739***
			(.0757)	(.1275)			(.0344)	(.0542)
constant	.1804***	.1750	.1354***	.3826***	-.0472	-.1468	.0709***	.1537***
	(.0449)	(.1417)	(.0377)	(.1087)	(.0362)	(.0935)	(.0149)	(.0378)
N	73	73	73	73	166	166	166	166
R^2	.7672	.9048	.7983	.8947	.8439	.8999	.8248	.8934
region dummies	no	yes	no	yes	no	yes	no	yes

	Predicted 2010 Schoellman				Pooled Regression			
	ln(H)	ln(H)	H	H	ln(H)	ln(H)	H	H
ln(rel. hc)	0.7648***	0.5903***			0.8039***	0.6268***		
	(.0290)	(.0385)			(.0209)	(.0292)		
rel. hc			1.0318***	0.9225***			1.0799***	0.8180***
			(.0382)	(.0673)			(.0301)	(.0546)
constant	-.0092	-.0489	.0790***	.2003***	.0450*	-.0705	.0738***	.2093***
	(.0354)	(.0959)	(.0179)	(.0481)	(.0258)	(.0767)	(.0139)	(.0402)
N	166	166	166	166	405	405	405	405
R^2	.8097	.8749	.8165	.8702	.7864	.8385	.7611	.8075
region dummies	no	yes	no	yes	no	yes	no	yes

9 Appendix

Appendix Table A1 shows that the data has greatly expanded in depth of coverage relative to BDT. We list each country by geographic region, as in BDT. We also list the first year of observation for each country and the final year of information in this data set.[55] For all countries, our average initial year of observation is 1900. Thus we observe the average country for 110 years. We observe 18 countries starting no later than 1801. We observe an additional 40 countries starting in year 1820. Therefore we observe 58 countries for at least 190 years. These 58 countries represent a 2010 population of 5.2 billion out of a world population of 6.8 billion, and 2.5 billion workers out of 3.1 billion total workers.[56]

For region 1, *Western Countries*, the average initial year of observation is 1827, and thus we observe these 18 countries for over 180 years. In region 2, *Southern Europe*, the initial year of observation is 1865, and we now have data for these 8 countries for over 140 years.[57] We observe an initial year of 1934 for region 3, *Central and Eastern Europe*. *Central and Eastern Europe* is predominated by former Soviet republics, now independent. In BDT the initial year of observation was 1990. Now for all of these countries we observe them starting in 1970. Furthermore for the countries that were never Soviet republics, we have an average initial observation year of 1872.[58] Four of 5 countries among the *Newly Industrialized Countries*, region 4, have an initial year of observation of 1820. Japan is observed in 1800. Our new initial year of observation in *Asia*, region 5, is 1880. Some of this extension arises from the additional countries added to the sample, Afghanistan, Bhutan, Mongolia, North Korea. However the bulk of the extension arises from the additional years found for previously observed countries. We were able to start observations in 1820 for China, India, Indonesia, Malaysia, Myanmar, Nepal, North Korea, Philippines, Sri Lanka, Thailand and Vietnam. Thus for the overwhelming bulk of Asian population, we have complete data for 190 years. For region 6, *Sub-Saharan Africa*, our average initial year of observation is 1946. Hence even for the continent with the youngest independent countries, we now observe the typical Sub-Saharan African country for more than 6 decades. The new initial year of observation in *Latin America* is 1888. Here we added 5 additional countries, Bahamas (1950), Barbados (1950), Belize (1950), Cuba (1800), and Suriname (1950). We now observe the largest Latin American countries in 1800: Argentina, Brazil, Chile, Colombia, Cuba, Mexico, Uruguay and Venezuela. The *Middle East* has an average starting year of 1896.[59] Five of the dozen *Middle*

[55] For all countries, except for the defunct East Germany, we now observe them in 2010, instead of 20. Thus each country has at least 10 years of additional coverage.

[56] Three of the countries not observed early, Bangladesh, Nigeria and Pakistan constitute almost 500 million population and 175 million workers in 2010. We observe 67 countries before 1900. These 67 countries represent a 2010 population and labor force of 5.3 billion and 2.5 billion, respectively.

[57] We moved Israel into the *Southern Europe* region as it is most similar to these countries than their *Middle East* region neighbors. Without Israel, the average initial year of observation is 1853, and hence we observe the average country for over 150 years.

[58] We excluded the Slovak Republic since it is not observed separately from the Czech Republic until 1990.

[59] Of all the regions, the *Middle East* is potentially most problematic. This has to do with using modern PPP international dollars to value past output. Most of the oil producing countries of this region in fact were oil producers as early as 1950, as can be seen in Tsui (2011). However the real price of oil in 1950 was very different from today. We often times separate out the oil producers in the Middle East from the rest of the Middle East in the empirical work.

East countries have initial observation year of 1820: Iran, Iraq, Jordan, Lebanon and Syria. Finally we observe four of five *North Africa* countries starting in 1820.[60] The average initial observation year is 1846.

Table A1: First and Last Observations: By Region

Country	1^{st} yr	$h_{15-24}^{\text{1st yr}}$	$h^{\text{1st yr}}$	$\text{k}^{\text{1st yr}}$	$\text{y}^{\text{1st yr}}$	$h_{15-24}^{\text{last yr}}$	$h^{\text{last yr}}$	$\text{k}^{\text{last yr}}$	$\text{y}^{\text{last yr}}$
Western Countries									
Australia	1820	0.32	0.27	4456	1354	5.37	5.88	261,002	59,214
Austria	1820	0.57	0.56	7189	2591	5.14	5.06	234,118	58,057
Belgium	1820	0.70	0.68	9538	3300	5.35	5.91	259,690	65,567
Canada	1820	0.80	0.79	9535	3464	5.86	6.66	226,350	56,696
Denmark	1820	0.99	0.97	6568	2420	6.00	6.45	235,164	55,350
Finland	1820	0.75	0.73	3640	1297	5.52	5.94	226,972	57,579
France	1800	0.48	0.46	18,555	2651	4.99	5.17	288,657	57,572
Germany	1800	0.80	0.78	9020	3236	5.40	5.62	203,625	49,552
Iceland	1950	2.70	2.64	50,119	14,604	5.65	6.56	214,001	48,692
Ireland	1820	0.50	0.49	6505	2418	5.19	5.95	198,530	57,771
Luxembourg	1950	1.25	0.77	73,639	21,221	4.44	4.66	413,880	136,997
Netherlands	1800	0.60	0.85	18,672	6142	5.54	6.55	204,859	56,667
New Zealand	1820	0.32	0.31	2956	1027	6.00	6.35	152,859	44,864
Norway	1820	0.45	0.44	6505	2288	5.55	6.00	248,808	63,871
Sweden	1800	0.50	0.49	6979	2368	5.40	5.90	181,230	59,645
Switzerland	1820	0.65	0.63	8532	2720	5.15	5.45	237,632	55,655
United Kingdom	1801	0.80	0.79	30,978	4589	5.70	6.12	262,708	58,637
United States	1790	1.00	0.77	15,287	3474	6.56	8.38	325,533	76,578
Southern Europe									
Cyprus	1950	0.12	0.10	5679	1735	2.92	2.54	110,274	43,425
Greece	1820	0.44	0.43	5474	1953	5.10	5.09	147,022	39,066
Israel	1948	2.50	1.33	32,909	8695	4.00	3.72	171,860	59,695
Italy	1820	0.62	0.60	6974	2521	5.24	5.12	336,118	55,294
Malta	1960	0.60	0.38	14,831	4144	4.09	3.76	138,778	45,757
Portugal	1800	0.62	0.60	8499	3059	4.59	4.20	166,120	35,137
Spain	1800	0.62	0.60	7728	2531	5.04	4.93	180,819	41,018

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[60]The lone exception is Libya, which we observe starting in 1950.

Country	1^{st} yr	$h_{15-24}^{\text{1st yr}}$	$h^{\text{1st yr}}$	$k^{\text{1st yr}}$	$y^{\text{1st yr}}$	$h_{15-24}^{\text{last yr}}$	$h^{\text{last yr}}$	$k^{\text{last yr}}$	$y^{\text{last yr}}$
Turkey	1820	0.28	0.27	6266	2044	3.42	3.15	80,772	28,569
Central & Eastern Europe									
Albania	1870	0.24	0.24	2899	1115	2.33	1.55	42,546	14,592
Armenia	1970	1.10	1.10	55,176	18,569	2.63	1.72	65,403	30,033
Azerbaijan	1970	0.75	0.96	48,484	12,286	3.27	2.05	37,549	21,144
Belarus	1970	0.75	0.98	33,618	13,398	3.71	2.29	76,933	35,344
Bulgaria	1870	0.29	0.29	7055	2280	3.53	2.47	63,883	24,017
Czech Republic	1820	0.44	0.44	6222	2175	3.40	2.46	125,712	32,216
East Germany	1950	1.11	1.24	18,333	8892	1.33	0.77	87,446	12,113
Estonia	1970	2.05	1.89	74,078	21,831	4.07	3.32	170,259	46,639
Georgia	1970	2.50	3.21	61,494	16,487	3.75	2.83	61,925	16,466
Hungary	1869	0.70	0.69	2367	2887	3.37	2.56	81,270	23,962
Kazakhstan	1970	1.75	2.23	75,474	19,585	3.77	2.69	92,659	26,608
Kyrgyzstan	1970	2.50	3.13	31,179	10,636	3.22	2.76	16,578	8002
Latvia	1970	2.05	2.70	56,132	19,552	4.02	3.29	95,369	28,900
Lithuania	1970	2.05	2.67	53,883	19,309	4.05	3.40	76,722	27,638
Moldova	1970	3.00	3.84	34,977	14,885	1.37	2.09	43,049	11,139
Poland	1870	0.35	0.35	5420	2030	3.38	2.66	72,234	27,991
Romania	1870	0.47	0.47	6158	2181	3.17	2.14	48,895	12,072
Russia	1820	0.35	0.35	4762	1549	3.84	3.32	58,391	20,021
Slovak Republic	1990	1.98	1.19	60,795	19,389	3.08	1.90	91,107	30,654
Tajikistan	1970	3.00	3.59	41,653	13,829	1.41	2.25	6801	5508
Turkmenistan	1970	2.75	3.44	63,235	15,897	3.51	2.74	50,812	13,932
Ukraine	1970	2.75	3.57	39,152	13,280	4.05	2.66	40,359	11,821
Uzbekistan	1970	1.75	2.12	50,932	16,704	3.28	2.14	35,637	17,795
Yugoslavia	1910	0.20	0.20	10,168	2553	1.83	1.00	100,183	21,280
Newly Industrialized Countries									
Hong Kong	1820	0.20	0.19	5291	1646	4.39	4.57	286,154	72,705
Japan	1800	0.60	0.41	4392	1452	5.38	6.55	359,333	57,393
Singapore	1820	0.20	0.19	5730	1656	4.31	4.54	214,515	66,264
South Korea	1820	0.20	0.17	3841	1279	4.82	4.56	221,489	57,910

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Country	1^{st} yr	$h_{15-24}^{\text{1st yr}}$	$h^{\text{1st yr}}$	$\text{k}^{\text{1st yr}}$	$\text{y}^{\text{1st yr}}$	$h_{15-24}^{\text{last yr}}$	$h^{\text{last yr}}$	$\text{k}^{\text{last yr}}$	$\text{y}^{\text{last yr}}$
Taiwan	1820	0.20	0.20	4930	1654	4.46	4.34	159,576	59,732
Asia									
Afghanistan	1950	0.51	0.51	6878	2124	0.99	0.87	11,563	3856
Bangladesh	1950	0.35	0.37	4060	1140	1.11	1.09	7604	3320
Bhutan	1980	0.20	0.20	6928	1640	0.77	0.55	23,411	5186
Cambodia	1950	0.20	0.19	4032	1173	1.47	1.36	8073	5588
China	1820	0.44	0.44	5106	1723	2.73	2.54	50,824	16,897
Fiji	1950	2.00	2.00	31,370	10,224	2.64	2.65	56,967	16,891
India	1820	0.44	0.44	3353	1367	2.56	2.45	26,803	10,725
Indonesia	1820	0.46	0.56	5549	1832	3.14	2.87	27,348	12,197
Laos	1950	0.50	0.47	5764	1622	1.34	1.27	12,905	4586
Malaysia	1820	0.35	0.35	5996	1944	3.44	3.31	99,643	30,283
Mongolia	1950	1.00	1.96	4407	1104	3.39	3.19	18,113	2981
Myanmar	1820	0.20	0.20	4643	1381	2.05	1.94	7458	10,003
Nepal	1820	0.44	0.61	2841	986	1.81	1.70	7344	2680
North Korea	1820	0.30	0.55	2616	911	2.83	3.35	2585	2461
Pakistan	1950	0.35	0.36	9670	2796	0.85	0.85	18,012	8488
Papua New Guinea	1960	0.80	0.80	9050	2910	0.90	1.12	14,297	4874
Philippines	1820	0.82	1.27	5816	1863	4.17	4.53	26,405	9298
Sri Lanka	1820	0.44	0.61	6581	2075	3.86	4.04	43,970	16,390
Thailand	1820	0.44	0.44	3671	1205	3.46	3.30	67,927	19,497
Vietnam	1820	0.44	0.44	3276	1014	2.69	2.32	15,490	6821
Sub-Saharan Africa									
Angola	1950	0.33	0.33	8907	2500	0.70	0.74	7989	5407
Benin	1950	0.71	0.71	9739	2740	1.33	1.13	9712	4568
Botswana	1950	0.24	0.24	2797	815	2.26	1.93	55,073	11,533
Burkina Faso	1950	0.29	0.29	4519	1368	0.65	0.58	7520	3207
Burundi	1950	0.79	0.78	3247	966	0.91	0.85	2530	1224
Cameroon	1950	0.99	0.98	5777	1633	1.69	1.70	8615	3682
Cape Verde	1950	0.66	0.65	5946	1582	1.74	1.55	35,089	6816
Cent. Afr. Rep.	1950	0.63	1.09	5083	1588	0.85	0.91	2725	1541
Chad	1950	0.55	0.55	6041	1681	0.83	0.77	4295	2416

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Country	1^{st} yr	$h_{15-24}^{\text{1st yr}}$	$h^{\text{1st yr}}$	$\text{k}^{\text{1st yr}}$	$\text{y}^{\text{1st yr}}$	$h_{15-24}^{\text{last yr}}$	$h^{\text{last yr}}$	$\text{k}^{\text{last yr}}$	$\text{y}^{\text{last yr}}$
Comoros	1950	0.51	0.89	5792	1593	1.23	1.07	8169	2753
Congo	1950	0.72	1.19	10,681	2982	1.91	2.16	15,647	6923
Djibouti	1950	0.32	0.31	24,499	6458	0.64	0.63	8610	4979
Equatorial Guinea	1950	0.04	0.04	3202	1223	1.29	1.14	101,881	47,832
Eritrea	1990	0.32	0.42	4960	1649	0.52	0.50	3175	1707
Ethiopia	1950	0.28	0.28	2891	887	0.78	0.67	4778	2435
Gabon	1950	0.90	1.67	38,629	12,508	2.12	2.03	67,862	12,663
Gambia	1950	0.47	0.47	5365	1432	1.16	0.93	6925	3219
Ghana	1870	0.79	0.74	3174	1092	1.74	1.66	13,822	5772
Guinea	1950	0.53	0.53	3534	1054	0.96	0.80	5448	1957
Guinea-Bissau	1950	0.50	0.50	2593	802	1.00	0.87	6092	2033
Ivory Coast	1950	0.81	0.81	4216	2764	1.06	1.06	8216	4286
Kenya	1950	0.85	1.32	7631	1286	2.52	2.42	10,155	3844
Lesotho	1950	0.64	0.64	3261	978	1.91	1.96	27,907	5522
Liberia	1950	0.77	1.31	8813	2740	1.28	1.05	8292	3115
Madagascar	1950	0.90	1.31	8726	2419	1.17	1.27	4605	1713
Malawi	1950	0.76	0.76	2544	756	1.44	1.26	5795	1884
Mali	1950	0.37	0.37	5123	1551	0.80	0.66	9111	3782
Mauritania	1950	0.54	0.53	6280	1963	0.98	0.82	15,990	4472
Mauritius	1950	0.76	0.76	36,571	8898	2.67	2.60	136,162	40,366
Mozambique	1950	0.36	0.36	4491	2307	0.82	0.77	15,113	6871
Namibia	1950	0.98	1.62	22,898	7571	2.21	2.09	55,041	13,990
Niger	1950	0.32	0.51	4832	1425	0.57	0.55	4106	1950
Nigeria	1950	0.29	0.29	8137	2384	1.09	1.02	12,912	7686
Reunion	1950	0.80	1.47	18,157	4790	3.01	2.88	35,020	12,175
Rwanda	1950	0.75	0.74	4882	1405	1.78	1.56	5244	2749
Senegal	1950	0.50	0.87	6147	3165	0.97	0.89	12,912	4415
Seychelles	1950	0.69	1.57	21,869	5538	3.03	3.27	77,157	15,771
Sierra Leone	1950	0.65	1.11	5956	1833	1.52	1.18	3775	2284
Somalia	1950	0.52	0.83	14,046	4222	0.53	0.57	10,692	3912
South Africa	1800	0.75	0.74	5356	1956	2.65	2.35	55,315	17,235
Sudan	1950	0.15	0.15	7675	2309	0.81	0.72	18,406	12,126

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Country	1^{st} yr	$h_{15-24}^{\text{1st yr}}$	$h^{\text{1st yr}}$	$\text{k}^{\text{1st yr}}$	$\text{y}^{\text{1st yr}}$	$h_{15-24}^{\text{last yr}}$	$h^{\text{last yr}}$	$\text{k}^{\text{last yr}}$	$\text{y}^{\text{last yr}}$
Swaziland	1950	0.71	0.70	7427	2421	2.23	2.13	33,275	11,334
Tanzania	1950	0.65	0.65	3317	948	1.13	1.06	5650	2008
Togo	1950	0.95	1.54	4837	1472	1.65	1.63	5051	1642
Uganda	1950	0.54	0.54	5504	1687	1.30	1.13	5106	3506
Zaire	1950	0.90	1.42	4848	1504	0.20	0.68	1420	834
Zambia	1950	0.95	1.63	9449	1770	1.89	1.85	8598	2445
Zimbabwe	1950	0.87	1.38	8805	2009	1.65	1.61	3457	1859
Latin America									
Argentina	1800	0.45	0.44	6499	2085	3.69	3.17	83,773	28,772
Bahamas	1950	2.20	3.49	135,809	33,805	3.10	3.36	147,904	30,983
Barbados	1950	0.90	0.90	19,066	5473	3.62	3.11	94,966	27,281
Belize	1950	1.80	1.76	19,734	6356	2.79	2.79	49,441	13,311
Bolivia	1880	0.50	0.65	6289	1884	2.57	2.16	13,720	9011
Brazil	1800	0.60	0.65	4044	1287	2.65	2.35	47,718	16,534
Chile	1800	0.45	0.44	7002	2365	3.51	3.16	104,333	34,527
Colombia	1800	0.42	0.42	5578	1834	2.25	1.95	46,406	18,465
Costa Rica	1920	0.80	0.79	20,609	5789	2.52	2.38	57,094	20,839
Cuba	1800	0.42	0.43	3354	1002	2.94	2.54	4626	10,448
Dominican Republic	1950	0.60	0.59	11,334	3362	2.53	2.29	36,775	15,174
Ecuador	1870	0.31	0.30	3932	1287	2.70	2.45	47,638	13,774
El Salvador	1920	1.45	1.42	11,271	3129	2.69	2.48	25,534	8860
Guatemala	1921	0.70	0.72	16,087	4528	1.68	1.49	37,213	14,490
Guyana	1946	1.45	1.54	14,926	3905	2.80	2.77	51,936	10,655
Haiti	1940	0.95	1.76	5733	2191	1.25	1.23	5594	2077
Honduras	1920	1.00	1.74	14,220	4314	1.85	1.77	27,696	7725
Jamaica	1820	0.70	0.82	6455	2177	2.87	2.73	64,875	10,162
Mexico	1800	0.55	0.54	6611	2104	2.63	2.36	78,702	22,355
Nicaragua	1920	1.15	2.47	15,520	4257	2.03	1.98	23,398	5248
Panama	1940	1.35	1.32	22,415	7089	2.99	2.90	57,206	19,234
Paraguay	1939	1.70	1.67	20,435	7065	2.29	2.31	27,555	9450
Peru	1870	0.70	0.79	8266	2723	2.84	2.57	38,584	14,301
Puerto Rico	1950	0.86	0.84	31,078	8654	3.56	3.40	165,087	48,022

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Country	1^{st} yr	$h_{15-24}^{\text{1st yr}}$	$h^{\text{1st yr}}$	$\text{k}^{\text{1st yr}}$	$\text{y}^{\text{1st yr}}$	$h_{15-24}^{\text{last yr}}$	$h^{\text{last yr}}$	$\text{k}^{\text{last yr}}$	$\text{y}^{\text{last yr}}$
Suriname	1950	0.86	0.86	20,039	6943	2.59	2.41	97,352	19,880
Trinidad	1946	0.80	0.78	25,704	10,455	3.01	2.85	134,469	47,143
Uruguay	1800	0.45	0.44	8028	3224	3.38	2.71	81,832	29,139
Venezuela	1800	0.40	0.36	3629	1371	2.58	2.26	58,506	27,339
Middle East									
Bahrain	1950	0.80	2.18	27,714	8054	3.28	2.94	39,332	10,535
Iran	1820	0.34	0.28	7537	2439	2.15	1.85	59,439	24,091
Iraq	1820	0.70	1.09	6030	2509	1.96	1.89	23,437	8720
Jordan	1820	0.51	0.51	8659	3704	2.12	1.93	100,567	26,618
Kuwait	1950	0.67	0.66	212,210	65,168	2.06	2.02	94,132	39,995
Lebanon	1820	0.75	0.89	8074	2458	3.01	2.70	66,308	16,643
Oman	1950	0.32	0.21	5987	2140	1.63	1.35	122,983	29,311
Qatar	1950	1.25	1.59	228,433	79,530	0.91	0.64	50,503	20,234
Saudi Arabia	1950	0.80	0.58	28,237	9994	2.04	1.69	127,437	35,889
Syria	1820	0.35	0.34	7835	2688	2.48	2.26	96,074	37,453
UAE	1950	0.67	0.65	109,630	37,233	2.63	2.37	52,736	28,279
Yemen	1950	0.40	0.29	10,311	3263	1.65	1.38	37,668	14,118
North Africa									
Algeria	1820	0.32	0.28	3548	1225	2.55	2.09	69,369	13,914
Egypt	1820	0.32	0.18	5472	1796	2.65	2.22	29,754	15,449
Libya	1950	0.71	0.73	10,934	3683	2.78	2.45	18,707	10,303
Morocco	1820	0.32	0.18	3906	1406	1.34	1.24	58,047	14,362
Tunisia	1820	0.32	0.19	5243	1705	2.47	2.12	78,959	22,276

Table A2: Relative Output per Worker, Human Capital, and School Quality Measures

Country	r^{y}_{1990}	Hendricks	r^{15-24}_{1990}	r^{25-34}_{1990}	r^{35-44}_{1990}	r^{y}_{2000}	Schoellman	r^{15-24}_{2000}	r^{25-34}_{2000}	r^{35-44}_{2000}
Australia	73.1	123.9	76.7	71.1	62.4	75.5	82.0	77.4	72.3	67.9
Austria	80.7	121.4	67.4	56.5	46.5	78.8	86.3	73.9	65.3	53.8
Belgium	95.3	116.1	75.9	73.6	61.2	86.1	77.1	79.4	73.4	71.6
Canada	75.2	156.2	86.8	76.0	65.2	77.8	92.7	94.8	86.5	74.1
Denmark	72.3	136.0	82.4	76.5	65.5	76.2	98.8	84.1	81.5	75.0
Finland	70.6		76.1	69.8	60.5	70.3	89.2	81.1	74.4	67.9
France	87.6	117.4	69.6	61.7	50.4	81.1	73.0	73.0	64.9	58.9
Germany	72.6	116.1	73.2	65.5	49.3	69.2	87.7	79.2	72.1	63.8
Iceland*	77.2		81.6	84.2	72.8	65.7	82.9	81.1	79.2	82.2
Ireland	68.0	100.6	76.4	70.7	62.7	81.9	70.5	77.3	74.1	68.2
Luxembourg*	122.1		64.4	54.6	43.3	159.0	52.9	65.1	61.7	51.4
Netherlands	82.6	98.3	83.4	80.4	72.9	77.1	77.3	84.4	81.7	78.9
New Zealand	59.0	120.9	80.5	76.9	71.0	58.8	101.6	81.5	75.9	73.9
Norway	78.5	128.1	76.1	74.9	62.3	83.7	87.5	81.3	73.8	72.9
Sweden	72.7	113.4	75.1	74.5	61.4	73.6	79.7	77.8	72.8	72.9
Switzerland	86.4	122.1	70.1	65.5	56.3	73.4	77.8	76.5	67.0	62.5
United Kingdom	71.4	114.4	78.5	74.8	67.5	76.3	92.3	78.9	75.9	72.8
average	76.8	120.3	75.9	69.6	58.3	75.6	85.1	79.8	73.6	67.5
Cyprus	34.3		31.6	26.3	17.0	47.5	48.1	37.0	29.6	25.0
Greece	52.4	81.8	67.4	61.9	49.0	47.3	79.6	72.1	64.4	59.1
Israel	85.3	88.4	58.0	41.9	39.9	75.9	66.9	58.2	44.0	40.6
Italy	87.1	97.3	67.0	62.4	48.1	83.2	87.3	71.4	64.3	60.0
Malta*	47.3		50.0	38.8	27.0	55.1	56.4	58.2	47.5	36.7
Portugal	50.4	74.4	55.5	49.4	39.9	49.7	70.6	61.4	52.1	46.8
Spain	65.1	93.0	68.4	56.2	41.0	61.4	78.9	72.3	66.9	53.3
Turkey	33.7	62.2	40.8	35.4	25.8	35.5	37.3	47.3	37.2	32.8
average	62.5	83.7	58.9	52.0	39.5	59.4	68.6	63.5	55.6	48.9
Albania*	13.0		21.4	9.7	4.8	14.1	49.3	18.6	14.2	4.3
Armenia*	27.2		37.6	26.0	10.5	19.1	40.0	32.7	24.8	9.4
Azerbaijan	24.0		45.2	31.1	7.5	10.0	56.5	39.3	29.9	6.7
Belarus	30.8		37.6	28.0	7.3	25.1	78.7	32.7	24.8	6.5
Bulgaria	26.8		42.5	28.2	11.9	18.0	60.4	37.0	28.1	10.6
Czech Republic	39.3	76.1	40.4	23.3	14.0	31.8	59.4	35.2	26.7	12.5
East Germany	21.5		27.1	14.6	8.6					
Estonia*	46.1		54.8	33.7	19.9	49.9	78.2	47.7	36.2	17.7
Georgia	37.1		68.3	47.3	25.0	13.8	58.2	59.4	45.1	22.3
Hungary	32.7	69.8	40.8	25.7	14.4	29.3	54.7	43.1	27.0	12.8
Kazakhstan*	34.7		58.4	37.2	17.0	22.0	65.3	50.8	38.6	15.1
Kyrgyzstan*	19.6		61.5	39.9	24.0	8.8	44.1	53.5	40.6	21.4
Latvia	41.0		51.6	40.0	20.0	30.8	69.1	44.9	34.1	17.8

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Country	r^y_{1990}	Hendricks	r^{15-24}_{1990}	r^{25-34}_{1990}	r^{35-44}_{1990}	r^y_{2000}	Schoellman	r^{15-24}_{2000}	r^{25-34}_{2000}	r^{35-44}_{2000}
Lithuania	37.4		54.5	41.5	20.2	27.1	67.4	47.4	36.0	18.0
Moldova*	35.5		56.2	40.3	27.9	8.1	51.9	48.9	37.1	31.3
Poland	24.4	70.4	38.7	22.6	10.9	29.5	62.2	44.8	25.6	17.5
Romania	17.3	65.6	36.5	21.8	9.9	11.3	51.5	31.8	24.1	8.8
Russia	30.2	79.8	47.9	27.0	14.2	18.9	79.2	58.8	31.7	20.9
Slovak Republic	34.4		40.6	23.4	14.1	30.6	58.4	35.3	26.8	12.5
Tajikistan*	18.1		60.5	45.3	28.7	4.5	54.0	26.3	40.0	35.1
Turkmenistan*	23.2		67.5	42.0	26.0	11.2	54.8	58.7	44.6	23.2
Ukraine	27.3		59.8	45.1	27.0	10.7	70.5	52.0	39.5	24.0
Uzbekistan	27.3		50.2	37.2	17.0	16.5	50.9	43.7	33.2	15.1
Yugoslavia	34.3	62.1	21.7	11.4	5.1	17.5	29.8	18.9	14.3	4.6
average	29.6	77.1	44.9	25.5	13.3	18.9	67.3	48.8	31.3	18.0
Hong Kong	76.9	72.9	58.5	46.9	36.6	82.3	60.0	63.2	55.4	43.9
Japan	83.9	125.4	81.4	82.6	69.1	74.0	69.0	81.3	79.3	81.5
Singapore	55.1		55.8	47.6	38.5	77.9	57.1	60.6	52.6	45.0
South Korea	43.5	61.0	58.2	45.7	34.9	59.5	86.7	64.7	55.3	43.3
Taiwan	53.3	65.8	54.5	48.6	37.8	66.7	65.5	60.0	51.0	45.8
average	72.5	105.0	73.4	70.7	58.1	70.5	71.9	74.6	70.0	67.7
Afghanistan	3.7		10.4	11.6	9.5	2.9	13.4	10.8	10.3	9.9
Bangladesh	3.4	35.9	13.8	13.3	11.4	3.3	17.6	14.7	13.8	11.5
Bhutan*	5.8		5.8	4.6	2.9	6.6	17.0	7.6	5.6	3.8
Cambodia	4.1		18.0	12.0	9.0	4.4	25.6	20.8	16.7	10.3
China	8.2	48.6	31.8	20.6	12.6	10.6	45.6	32.1	24.5	23.8
Fiji	30.4	50.3	36.8	34.2	31.3	29.1	37.7	38.7	31.4	31.4
India	7.6	51.0	34.1	27.5	22.1	8.5	27.2	37.4	30.6	24.7
Indonesia	13.2	55.5	38.8	28.8	21.9	13.4	34.2	42.6	35.4	25.7
Laos	4.6		17.0	14.9	10.4	4.6	22.6	18.3	15.9	12.9
Malaysia	28.6	57.8	42.6	33.1	28.1	33.7	39.0	49.3	38.6	30.0
Mongolia*	8.6		44.5	36.8	30.0	4.8	54.2	49.7	35.3	35.3
Myanmar	3.8		26.5	22.1	18.0	4.9	20.9	29.6	23.6	19.5
Nepal	3.3		24.4	16.6	13.5	3.4	21.0	27.7	21.2	14.1
North Korea*	10.7		47.5	42.6	37.7	3.7	26.6	46.4	44.0	39.9
Pakistan	13.5	33.0	11.1	11.7	9.2	11.0	13.9	11.3	10.6	10.1
Papua New Guinea*	7.5		17.5	18.2	14.6	6.9	13.7	15.1	17.0	16.0
Philippines	12.8	55.0	61.1	48.6	39.4	10.7	46.5	62.6	58.1	46.0
Sri Lanka	14.3	63.6	54.0	49.0	39.0	16.0	40.0	55.9	48.9	45.2
Thailand	17.9	48.4	44.2	37.3	29.6	21.0	35.9	46.9	40.6	34.0
Vietnam	3.7		31.4	22.4	15.1	6.2	35.3	35.0	28.6	19.3
average	8.4	49.1	32.8	23.7	16.9	10.0	36.4	34.1	27.4	23.9
Angola*	4.9		12.1	10.5	7.2	2.6	11.2	10.7	10.6	9.1
Benin*	6.7		13.6	12.4	10.1	5.9	24.7	15.2	11.9	10.6

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Country	r^{y}_{1990}	Hendricks	r^{15-24}_{1990}	r^{25-34}_{1990}	r^{35-44}_{1990}	r^{y}_{2000}	Schoellman	r^{15-24}_{2000}	r^{25-34}_{2000}	r^{35-44}_{2000}
Botswana*	16.3		21.8	13.7	8.5	16.5	42.9	27.8	20.1	12.2
Burkina Faso*	4.0		8.3	7.0	6.0	4.3	11.5	8.8	6.9	5.9
Burundi*	3.1		11.5	10.6	10.0	1.9	15.3	13.0	9.7	9.0
Cameroon	7.1		23.1	20.9	16.0	4.9	26.2	25.1	21.0	18.8
Cape Verde	8.4		19.2	14.4	11.8	8.3	31.1	21.9	17.2	12.6
Central African Republic*	2.8		14.1	13.1	10.6	2.0	13.9	13.5	12.4	11.5
Chad*	2.3		10.7	9.5	8.4	2.1	15.5	11.8	9.0	8.1
Comoros*	5.4		16.0	11.9	8.3	3.5	19.0	14.9	14.4	10.1
Congo*	14.0		34.4	25.9	17.2	8.4	26.2	31.4	32.6	23.8
Djibouti*	12.1		9.8	8.7	7.3	6.8	10.3	9.3	8.4	7.4
Equatorial Guinea*	6.7		16.0	11.7	5.9	25.7	24.3	16.5	14.7	10.6
Eritrea	2.9		6.6	5.1	4.4	2.9	9.4	7.0	6.4	4.3
Ethiopia	2.8	29.8	8.8	7.6	6.0	2.2	13.1	9.3	7.5	6.4
Gabon*	37.4		25.8	24.0	21.7	19.8	34.5	30.4	23.5	21.9
Gambia*	4.4		11.9	9.8	7.8	4.2	22.4	14.4	10.3	8.3
Ghana	6.1	39.5	22.1	19.5	15.1	5.8	26.1	22.6	19.9	17.5
Guinea*	3.1		9.8	9.8	8.5	2.8	16.8	11.1	8.3	8.4
Guinea-Bissau*	4.5		11.6	10.8	8.5	3.2	17.0	12.2	10.1	9.3
Ivory Coast*	7.9		15.1	13.7	11.7	6.3	18.7	15.7	13.3	12.0
Kenya	6.9	58.2	30.9	26.6	17.5	4.9	37.0	33.2	28.8	24.4
Lesotho*	7.1		27.4	22.5	18.4	7.1	29.4	28.7	25.1	20.5
Liberia	7.9		12.6	11.7	10.4	6.0	25.9	14.5	11.0	9.9
Madagascar*	3.9		19.2	18.6	14.4	2.8	17.5	18.9	17.1	16.6
Malawi*	2.5		15.8	13.7	12.0	2.4	24.0	17.4	13.9	11.8
Mali*	4.9		8.4	8.1	6.8	4.7	14.1	9.3	7.1	6.9
Mauritania*	7.4		10.4	9.0	7.6	6.3	19.3	12.1	8.9	7.6
Mauritius*	39.9		33.9	27.8	24.8	45.7	39.0	36.6	31.5	25.6
Mozambique*	6.7		11.4	9.8	8.1	6.2	14.3	11.1	9.9	8.4
Namibia*	28.7		27.1	21.5	16.4	20.5	34.4	31.1	24.8	19.4
Niger*	3.9		8.5	7.4	6.2	2.5	9.7	8.3	7.2	6.2
Nigeria	7.7	34.9	13.6	11.3	7.8	6.1	18.7	14.3	12.1	10.0
Reunion*	25.2		40.2	32.6	25.1	19.3	45.0	45.3	37.8	30.4
Rwanda*	4.2		17.7	18.1	14.5	2.6	30.3	21.2	15.6	16.2
Senegal	7.2		12.0	11.0	9.3	6.1	16.6	13.1	10.3	9.5
Seychelles*	30.5		40.1	34.3	26.0	24.0	43.7	49.6	37.7	32.4
Sierra Leone	6.2		13.0	12.0	9.8	2.3	30.0	15.8	11.4	10.4
Somalia	8.9		9.4	8.8	7.6	4.8	9.0	8.7	8.0	7.3
South Africa	24.3	95.0	28.4	23.1	20.8	19.6	43.8	39.6	25.9	21.3
Sudan	5.5		9.8	7.9	5.7	12.8	15.2	10.6	8.5	6.8
Swaziland*	18.9		28.6	23.6	15.5	15.4	35.9	31.9	26.6	21.6
Tanzania	2.5		15.8	12.7	9.6	2.3	18.5	14.2	14.2	10.9
Togo*	4.4		24.0	18.8	13.7	2.6	25.5	23.1	22.0	16.6

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Country	r^{y}_{1990}	Hendricks	r^{15-24}_{1990}	r^{25-34}_{1990}	r^{35-44}_{1990}	r^{y}_{2000}	Schoellman	r^{15-24}_{2000}	r^{25-34}_{2000}	r^{35-44}_{2000}
Uganda	2.9		13.8	11.5	9.9	3.3	23.7	16.7	11.9	9.9
Zaire*	3.1		21.5	21.7	15.8	1.1	12.6	3.7	12.1	14.3
Zambia*	4.4		22.4	24.4	16.9	2.4	28.4	26.4	20.2	22.4
Zimbabwe	7.5		33.7	23.9	19.1	4.6	34.6	29.4	22.3	18.6
average	9.3	45.1	17.0	14.3	10.8	5.4	20.8	16.5	14.1	12.3
Argentina	35.2	60.6	49.1	37.1	29.8	37.0	62.8	53.3	37.9	35.2
Bahamas	70.3		54.2	42.4	37.7	57.3	41.1	53.0	41.9	39.5
Barbados	34.7	67.9	44.7	34.9	29.2	29.7	63.1	48.3	35.7	33.1
Belize	26.6	50.7	37.6	36.0	34.6	21.8	39.5	39.6	31.9	33.6
Bolivia	13.9	48.3	28.7	21.4	15.8	11.0	43.1	32.4	24.5	19.7
Brazil	26.0	59.1	33.5	25.8	18.4	20.4	41.1	36.5	27.7	23.9
Chile	37.6	67.7	45.7	35.4	29.4	46.6	58.4	51.1	36.2	33.8
Colombia	23.3	48.7	25.5	20.9	16.2	22.5	34.3	29.0	22.8	19.0
Costa Rica	27.4	52.3	34.2	27.5	22.8	26.5	35.8	34.6	28.7	25.6
Cuba	15.8		37.2	26.1	20.4	10.4	48.9	40.0	30.4	23.7
Dominican Republic	13.8	49.8	31.3	25.2	20.1	16.3	38.5	34.8	26.5	23.2
Ecuador	24.1	54.3	38.3	25.6	18.6	17.3	41.4	37.7	30.5	23.7
El Salvador	13.2	44.7	30.0	27.7	25.7	13.9	40.6	34.1	26.3	25.9
Guatemala	21.6	39.8	18.2	15.9	12.8	20.9	27.0	20.6	17.4	14.0
Guyana	9.1	48.2	37.5	37.1	35.1	13.2	38.6	35.7	31.4	34.8
Haiti	5.6	36.4	13.6	12.6	14.1	3.4	18.6	18.2	15.8	10.9
Honduras	13.4	42.4	24.7	19.9	16.5	9.3	27.8	25.3	22.2	18.0
Jamaica	18.1	57.7	40.2	32.6	25.7	15.2	41.8	40.8	32.6	30.6
Mexico	39.0	49.5	33.1	25.9	19.9	33.4	40.3	36.2	27.7	23.9
Nicaragua	10.2	42.0	28.5	23.0	17.6	7.9	30.4	28.6	24.5	20.7
Panama	26.0	59.8	44.0	33.5	30.0	22.6	43.9	44.3	35.4	31.4
Paraguay	17.7		33.2	28.5	28.2	13.6	30.6	31.1	28.7	26.3
Peru	17.6	53.9	36.4	26.1	20.9	15.6	45.4	41.4	30.3	24.3
Puerto Rico	71.6	63.7	53.0	39.3	34.4	74.2	55.6	53.4	40.1	38.1
Suriname*	15.2		31.4	26.1	25.6	11.8	41.9	36.8	27.8	23.8
Trinidad	53.1		42.6	33.9	27.2	47.6	44.6	44.8	34.4	31.9
Uruguay	32.2	72.4	40.6	29.1	23.2	31.9	60.1	47.7	33.0	27.4
Venezuela	51.4	52.6	30.2	24.2	19.5	34.2	40.9	33.5	25.7	22.4
average	28.9	54.8	33.9	26.2	20.1	24.6	42.1	37.0	28.1	24.3
Bahrain*	21.3		39.5	30.9	24.0	20.3	55.8	48.9	32.7	28.9
Iran	30.4	51.8	22.8	18.0	11.7	28.2	34.1	26.8	20.2	16.2
Iraq	26.0	51.9	24.7	21.4	13.5	9.2	31.5	28.4	22.1	19.3
Jordan	54.1	47.1	24.9	20.3	16.7	30.9	31.1	25.4	21.8	18.3
Kuwait	34.8		28.6	27.4	22.0	33.9	26.5	24.4	23.8	25.5
Lebanon	20.1		38.7	28.4	21.9	23.7	49.0	42.9	31.4	26.5
Oman*	37.5		13.7	9.3	6.7	41.6	30.9	22.1	13.7	7.7
Qatar*	28.0		11.9	8.1	4.1	39.1	50.3	13.8	7.9	4.7

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Country	r^y_{1990}	Hendricks	r^{15-24}_{1990}	r^{25-34}_{1990}	r^{35-44}_{1990}	r^y_{2000}	Schoellman	r^{15-24}_{2000}	r^{25-34}_{2000}	r^{35-44}_{2000}
Saudi Arabia	57.4		17.4	15.7	11.4	53.8	34.7	24.9	16.8	13.6
Syria	50.5	65.9	33.6	25.7	17.9	42.9	37.9	34.4	26.4	23.4
UAE	52.0		30.2	23.9	16.6	31.4	42.9	36.7	25.7	21.8
Yemen	22.1		15.1	12.1	8.5	21.0	30.2	21.2	14.8	10.3
average	35.7	54.0	25.0	19.9	13.2	30.8	34.6	27.7	20.6	17.0
Algeria	26.9		24.8	17.3	12.8	18.0	46.9	35.3	22.4	15.6
Egypt	18.3	65.5	29.3	19.5	16.3	20.0	46.1	38.9	25.9	17.8
Libya*	24.3		32.0	25.0	17.7	11.9	46.5	36.9	26.6	22.8
Morocco	18.5		15.9	14.0	11.8	15.0	21.1	16.8	15.0	12.2
Tunisia*	24.6		26.5	20.7	17.7	25.4	40.7	32.7	23.3	19.1
average	18.3	65.5	29.3	19.5	16.3	18.5	40.1	32.6	22.6	16.4
overall relative hc average	22.6	61.5	39.4	30.3	22.3	19.8	42.9	38.8	31.6	27.2

Notes: * Not in Schoellman (2012) sample.

Table A3: Relative Output per Worker, Human Capital, and Predicted School Quality Measures

Country	r^y_{2010}	Predicted Schoellman	r^{15-24}_{2010}	r^{25-34}_{2010}	r^{35-44}_{2010}
Australia	77.3	89.2	81.8	75.6	70.3
Austria	75.8	80.1	78.3	72.6	63.3
Belgium	85.6	79.0	81.5	77.6	71.1
Canada	74.0	94.9	89.3	92.6	86.2
Denmark	72.3	113.4	91.4	83.1	80.6
Finland	75.2	106.4	84.1	80.0	72.7
France	75.2	72.0	76.1	71.4	62.3
Germany	64.7	88.6	82.3	78.5	71.1
Iceland*	63.6	129.6	86.1	78.6	76.9
Ireland	75.4	73.8	79.0	75.0	71.8
Luxembourg*	178.9	53.9	67.7	62.0	59.2
Netherlands	74.0	80.7	84.4	82.9	80.0
New Zealand	58.6	112.0	91.3	80.0	73.8
Norway	83.4	89.9	84.5	79.8	71.6
Sweden	77.9	97.1	82.3	75.5	70.5
Switzerland	72.7	78.1	78.5	74.6	64.0
United Kingdom	76.6	89.4	86.8	76.5	73.5
average	73.2	86.6	82.9	78.2	71.9
Cyprus	56.7	60.1	44.6	34.6	27.7
Greece	51.0	103.5	77.7	69.9	61.5
Israel	78.0	77.6	61.0	42.8	42.4
Italy	72.2	97.7	79.8	69.0	61.6

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Country	r^{y}_{2010}	Predicted Schoellman	r^{15-24}_{2010}	r^{25-34}_{2010}	r^{35-44}_{2010}
Malta*	59.8	68.8	62.2	55.8	45.2
Portugal	45.9	75.2	69.9	58.1	48.9
Spain	53.6	82.6	76.7	70.9	65.4
Turkey	37.3	47.6	52.2	43.8	34.0
average	54.3	77.0	69.2	60.3	52.8
Albania*	19.1	50.1	35.6	18.7	16.5
Armenia*	39.2	50.0	40.1	22.6	20.0
Azerbaijan	27.6	55.6	49.9	27.2	24.1
Belarus	46.2	86.2	56.5	32.8	29.0
Bulgaria	31.4	73.9	53.8	37.1	32.8
Czech Republic	42.1	74.6	51.8	35.2	31.2
Estonia*	60.9	88.9	62.1	47.8	42.3
Georgia	21.5	61.2	57.1	37.4	33.1
Hungary	31.3	81.2	51.4	43.2	31.5
Kazakhstan*	34.7	66.7	57.4	35.1	31.1
Kyrgyzstan*	10.4	63.3	49.1	37.0	32.7
Latvia	37.7	87.1	61.2	44.9	39.8
Lithuania	36.1	90.3	61.7	47.5	42.0
Moldova*	14.5	51.8	20.9	30.5	27.0
Poland	36.6	85.1	51.5	44.9	29.8
Romania	15.8	73.7	48.3	31.9	28.2
Russia	26.1	78.9	58.5	58.9	37.0
Slovak Republic	40.0	71.1	46.9	24.4	21.6
Tajikistan*	7.2	52.6	21.4	16.4	29.8
Turkmenistan*	18.2	40.4	53.4	38.2	19.7
Ukraine	15.4	89.4	61.6	36.0	20.4
Uzbekistan	23.2	52.9	50.0	30.2	12.9
Yugoslavia	27.8	45.0	27.9	13.0	11.5
average	26.6	75.3	54.4	44.3	30.0
Hong Kong	94.9	80.9	66.9	60.7	52.5
Japan	74.9	75.9	82.0	79.0	77.3
Singapore	86.5	52.9	65.7	57.3	49.6
South Korea	75.6	106.3	73.5	62.7	52.6
Taiwan	78.0	76.8	68.0	56.6	47.8
average	76.5	82.5	77.5	71.6	66.8
Afghanistan	5.0	32.1	15.1	10.5	8.9
Bangladesh	4.3	23.5	16.8	14.3	12.0
Bhutan*	6.8	23.4	11.7	7.3	4.6
Cambodia	7.3	29.3	22.3	18.1	15.0
China	22.1	50.2	41.6	32.8	24.6

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Country	r^y_{2010}	Predicted Schoellman	r^{15-24}_{2010}	r^{25-34}_{2010}	r^{35-44}_{2010}
Fiji	22.1	40.0	40.1	32.3	29.1
India	14.0	30.5	39.1	34.1	27.5
Indonesia	15.9	42.0	47.8	39.3	32.4
Laos	6.0	24.7	20.4	17.0	14.2
Malaysia	39.5	48.4	52.4	46.0	35.0
Mongolia*	3.9	65.2	51.7	38.0	33.5
Myanmar	13.1	25.3	31.2	26.4	21.0
Nepal	3.5	21.4	27.5	24.9	18.4
North Korea*	3.2	26.6	43.1	42.8	40.8
Pakistan	11.1	18.7	13.0	11.3	9.1
Papua New Guinea*	6.4	13.4	13.6	14.7	15.0
Philippines	12.1	48.4	63.5	59.6	55.2
Sri Lanka	21.4	44.8	58.9	52.4	45.4
Thailand	25.5	48.7	52.7	43.1	37.3
Vietnam	8.9	32.7	41.0	31.5	26.1
average	17.3	40.4	39.6	32.7	25.9
Angola*	7.1	14.4	10.7	9.3	9.4
Benin*	6.0	27.8	20.3	13.2	10.5
Botswana*	15.1	41.8	34.5	25.8	18.4
Burkina Faso*	4.2	17.6	9.8	7.4	5.8
Burundi*	1.6	22.2	13.9	11.4	8.1
Cameroon	4.8	28.6	25.7	22.8	19.1
Cape Verde	8.9	33.1	26.5	19.8	15.5
Central African Republic*	2.0	15.8	12.9	11.8	10.9
Chad*	3.2	18.1	12.7	10.3	7.7
Comoros*	3.6	29.8	18.7	13.1	12.9
Congo*	9.0	29.3	29.1	29.3	30.9
Djibouti*	6.5	14.7	9.7	7.9	7.2
Equitorial Guinea*	62.5	23.0	19.6	14.7	13.4
Eritrea	2.2	13.1	7.9	6.8	5.4
Ethiopia	3.2	24.4	12.0	7.9	6.4
Gabon*	16.5	33.6	32.5	27.8	21.3
Gambia*	4.2	26.2	17.7	12.7	8.9
Ghana	7.5	33.6	26.4	20.5	18.1
Guinea*	2.6	25.3	14.6	9.3	7.1
Guinea-Bissau*	2.7	24.1	15.2	10.5	8.8
Ivory Coast*	5.6	18.9	16.2	13.8	11.7
Kenya	5.0	42.9	38.4	30.7	26.9
Lesotho*	7.2	30.5	29.1	26.4	23.1
Liberia	4.1	25.1	19.5	12.5	9.6
Madagascar*	2.2	20.8	17.9	16.9	15.3

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Country	r^{y}_{2010}	Predicted Schoellman	r^{15-24}_{2010}	r^{25-34}_{2010}	r^{35-44}_{2010}
Malawi*	2.5	31.9	21.9	15.4	12.2
Mali*	4.9	23.2	12.2	7.8	5.9
Mauritania*	5.8	22.4	15.0	10.4	7.6
Mauritius*	52.7	52.3	40.7	34.1	29.2
Mozambique*	9.0	18.5	12.5	9.5	8.7
Namibia*	18.3	38.8	33.6	28.8	22.8
Niger*	2.5	13.0	8.6	7.0	6.0
Nigeria	10.0	23.9	16.7	12.6	10.7
Reunion*	15.9	42.2	45.8	43.0	35.5
Rwanda*	3.6	33.8	27.0	18.8	13.8
Senegal	5.8	21.9	14.7	11.4	8.9
Seychelles*	20.6	44.7	46.2	47.7	35.4
Sierra Leone	3.0	32.1	23.2	13.8	9.9
Somalia	5.1	9.7	8.1	7.3	6.8
South Africa	22.5	49.0	40.4	31.4	23.4
Sudan	15.8	19.7	12.4	9.2	7.3
Swaziland*	14.8	33.9	33.9	29.6	24.7
Tanzania	2.6	23.4	17.2	12.4	12.7
Togo*	2.1	29.1	25.2	21.0	20.2
Uganda	4.6	28.5	19.8	14.8	10.3
Zaire*	1.1	22.9	3.1	2.1	7.8
Zambia*	3.2	33.0	28.7	24.1	18.2
Zimbabwe	2.4	32.8	25.1	19.3	17.1
average	6.6	26.3	18.1	13.9	12.0
Argentina	37.6	76.1	56.3	39.5	36.4
Bahamas	40.5	51.4	47.2	40.1	40.2
Barbados	35.6	65.8	55.2	37.1	33.8
Belize	17.4	42.4	42.5	33.2	29.6
Bolivia	11.8	60.2	39.2	27.2	22.7
Brazil	21.6	53.1	40.4	29.7	25.9
Chile	45.1	71.3	53.5	38.4	34.4
Colombia	24.1	46.2	34.4	24.8	20.8
Costa Rica	27.2	43.8	38.3	28.9	26.8
Cuba	13.6	60.7	44.7	31.8	28.6
Dominican Republic	19.8	48.1	38.6	28.8	24.6
Ecuador	18.0	46.7	41.2	30.3	29.0
El Salvador	11.6	52.8	40.4	29.4	24.1
Guatemala	18.9	35.2	25.7	18.9	15.4
Guyana	13.9	49.1	42.7	31.3	29.3
Haiti	2.7	29.8	19.1	17.3	13.8
Honduras	10.1	34.3	28.2	22.2	20.2

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Country	r^y_{2010}	Predicted Schoellman	r^{15-24}_{2010}	r^{25-34}_{2010}	r^{35-44}_{2010}
Jamaica	13.3	49.7	43.7	33.1	30.7
Mexico	29.2	50.4	40.0	29.7	25.8
Nicaragua	6.9	35.0	30.9	24.6	22.7
Panama	25.1	51.9	45.6	35.3	33.5
Paraguay	12.3	41.2	34.9	27.1	26.5
Peru	18.7	50.6	43.2	32.5	28.3
Puerto Rico	62.7	89.9	54.2	40.1	38.7
Suriname*	26.0	39.6	39.4	30.7	25.4
Trinidad	61.6	47.2	45.8	35.3	32.5
Uruguay	38.1	75.1	51.5	35.8	31.1
Venezuela	35.7	66.1	39.3	28.3	23.8
average	24.6	53.7	40.7	29.9	26.2
Bahrain*	13.8	56.7	50.0	36.5	30.6
Iran	31.5	48.4	32.7	22.9	18.5
Iraq	11.4	32.8	29.9	24.0	20.1
Jordan	34.8	53.1	32.2	22.6	20.0
Kuwait	52.2	41.4	31.3	22.6	22.2
Lebanon	21.7	58.7	45.9	33.5	29.6
Oman*	38.3	38.6	24.8	18.5	11.9
Qatar*	26.4	47.4	13.8	9.1	4.7
Saudi Arabia	46.9	54.5	31.0	21.7	14.9
Syria	48.9	42.1	37.8	28.1	24.8
UAE	36.9	52.8	40.1	29.6	23.8
Yemen	18.4	35.1	25.1	18.6	13.0
average	32.1	46.2	32.3	23.4	18.6
Algeria	18.2	53.8	38.8	27.8	20.3
Egypt	20.2	48.9	40.3	30.2	23.7
Libya*	13.5	70.2	42.3	30.0	24.9
Morocco	18.8	29.8	20.4	16.0	13.4
Tunisia*	29.1	63.2	37.6	27.4	21.4
average	19.8	47.9	35.9	26.7	20.8
overall relative hc average	24.1	47.7	42.7	35.6	29.2

Notes: * Not in Schoellman (2012) sample.