THE ROLE OF CAPITAL AND PRODUCTIVITY IN ACCOUNTING FOR INCOME DIFFERENCES SINCE 1913

Daniel Gallardo-Albarrán* iD

Wageningen University

Robert Inklaar iD

Groningen University

Abstract. This paper studies the proximate determinants of differences in output per worker across countries since 1913. We provide a new long-term perspective by developing a novel dataset with information on produced capital for 33 countries that covers most of the global income distribution. Using development accounting analysis, we find a large shift in the proximate determinants of cross-country income inequality during the 20th century. The contribution of produced capital to cross-country income variation declined from 29% to 11%, while that for productivity rose from 47% to 72%. Thus, the current predominant role of productivity in accounting for income differences is quite exceptional from a historical perspective. We draw on these findings to review various strands of the literature and offer some hypothesis about the rising relative importance of TFP for comparative economic performance. We conclude that differences in technological adoption rates and efficiency are the primer drivers of the decreasing relative importance of capital deepening for cross-country income inequality, rather than factor input mismeasurement.

Keywords. development accounting; income inequality; 20th century; physical capital

1. Introduction

Large income differences between rich and poor countries and the availability of relevant data for most countries around the world has led to a thriving literature aiming to account for those income differences. A typical development accounting analysis starts from an aggregate production function where differences in income per person or per worker are accounted for by differences in the availability of produced and human capital, and (residual) differences in productivity (Caselli, 2005; Hsieh and Klenow, 2010). The basic model is then extended, for instance, to account for additional types of capital (Chen, 2018; Freeman *et al*., 2020) or to take an alternative approach to measuring human and productive capital (Lagakos *et al*., 2018; Inklaar *et al*., 2019), to assess whether these extensions help account for a greater fraction of income differences. Overall, these studies indicate that differences in productivity are the dominant factor accounting for cross-country income variation (Jones, 2016).

* Corresponding author contact email: daniel.gallardoalbarran@wur.nl; Tel: (+31) 0317-487581.

This literature is primarily focused on contemporaneous income differences, with the year of analysis in the mid-1980s or later. One argument in favour of this is that current income differences are a reflection of past growth differences (Hall and Jones, 1999, p. 85). Another is that data sources such as the Penn World Table (Feenstra *et al*., 2015) cover only the period since 1950. However, a focus on recent periods misses a substantial part of the long-term trajectory of income divergence and its proximate determinants since the 19th century (Pritchett, 1997). Therefore, for a better understanding of how the current large income differences opened up, it is also important to study what can account for income gaps at earlier points in time.

Our aim in this paper is to provide this long-run perspective, by constructing and analysing a dataset of output and factor inputs covering the 20th and 21st centuries for a group of 33 countries spanning the global income distribution. This allows us to review various explanations in the literature about the proximate determinants of economic development and their evolution over the long term. Given the lack of comparable data on productive capital for the time period considered, we have made a substantial effort in compiling a new dataset on investment and capital stocks that improve on the existing literature. First, we cover a substantial number of economies, including various important lower-income countries such as India and Indonesia. As a result, the analysis is informative for global income differences. Second, our data tracks (to the extent possible) separate movements in the share and prices of investment in structures versus equipment. Therefore, and in contrast to the literature (Bergeaud *et al*., 2016; Madsen and Farhadi, 2018), our measure of the capital stock measure does not depend on the chosen base year.

Our cross-country approach complements growth accounting studies such as the work of Bergeaud *et al*. (2016), who provide a long-run perspective on productivity growth across 13[1] advanced economies and, more generally, the literature reviewed by Crafts and O'Rourke (2014) and Crafts and Woltjer (2020) on the sources of economic growth over the twentieth century. With our dataset, we are able to track the importance of differences in the levels of produced and human capital in accounting for income differences throughout the 20th century. Compared to growth accounting studies for the same period, an advantage of this development accounting analysis is that we can more readily relate investments in produced capital and in schooling to income differences, and thus trace the extent to which these investments lead to convergence in inputs and income. A further contribution of our analysis is that by stretching our analysis back to 1913, when cross-country income differences were already substantial (Bolt and van Zanden, 2014), we can help shed light on the proximate factors that had opened up those income differences during the 19th century. In this way, we can also put the findings of the development accounting literature focusing on recent periods into the long-term trajectory of income divergence (Pritchett, 1997).

Our new dataset exhibits several interesting patterns about the process of capital accumulation. First, contrary to one of the stylized facts of Kaldor (1961), we identify a long-term rising trend in capital-output ratios. On average, these increased from 1.6 to almost 3.5 during the analysed period. Second, we find that as the level of income rises, the share of machinery and equipment in total capital at current prices falls due to the decline of their price relative to that of structures. This is especially the case after the 1970s when relative prices fell by 2% per year or more, suggesting faster efficiency improvements in their production (e.g. Moore's Law) relative to structures as the main driving force. Consequently, developed economies experienced a stronger decline in the share of machinery and other equipment.

Our development accounting analyses point to a large shift in the proximate determinants of between-country income inequality during the analysed period. In 1913, the contribution of produced and human capital to income variation was 29% and 24%, respectively. Consequently, cross-country income differences could be almost equally accounted for by differences in factor inputs and productivity. By 2011, though, productivity emerged as the dominant contributor accounting for 72% of income variation, mostly as a result of the lower contribution of produced capital (11%). From a historical perspective, the much greater importance of productivity relative to produced capital for cross-country income inequality is quite exceptional.

The shift in the relative importance of capital and productivity, which tend to mirror each other, has not been steady over time. The decreasing trend for produced capital began in the first half of the 20th century, when its contribution to income variation fell from 29% to 20%. For this period, our analysis attributes half of the decline in the variance of GDP per worker to a decline in the variance of the contribution from produced capital, making this a period of investment-driven convergence. Up to the 1970s, the relative importance of capital remained constant before starting a second and sharper fall that would last until the early 2000s. The magnitude of this decline was remarkable, since the contribution of capital to income differences fell from 25% in 1975 to 4% in 2003. Interestingly, produced capital is making a comeback in the last years since its contribution to income variation nowadays is comparable to that of the 1980s. Overall, produced and human capital were drivers of further convergence between 1955 and 2011, but given their small variance by 2011, most of the variation in GDP per worker can thus be attributed to variation in productivity.

What explains these trends? To answer this question, we review various strands of the literature and offer some hypotheses related to patterns of technology diffusion, efficiency differences in how technologies are applied in distinct local contexts and mismeasurement of factor inputs in level accounting frameworks. We suggest that differences in technological adoption rates and efficiency are the prime drivers of the decreasing relative importance of capital deepening for cross-country income inequality.

The remainder of this paper is structured as follows. First, we will outline our methodology and present our data sources as well as how we constructed our novel dataset on produced capital. Next, we will discuss the main features of the dataset, present our results and offer some hypotheses that may explain them and conclude.

2. Method and Data

A common starting point in development accounting frameworks is the following aggregate production function:[2]

$$Y_m = A_m f(K_m, H_m) \tag{1}$$

stating that country m produces GDP, Y, using production function f with input of capital (K) and human capital-augmented labour ($H_m = L_m h_m$, where L is the number of workers and h is their average human capital in the form of education),[3] and productivity (A). Assuming a Cobb–Douglas production function with constant returns to scale, we have:

$$Y_m = A_m K_m^{\alpha} H_m^{1-\alpha} \tag{2}$$

where α is the output elasticity with respect to capital. We then divide quantities by the number of workers (L_m) and express them relative to the USA. In this way, for instance, relative GDP per worker is defined as: $\tilde{y}_m = \frac{Y_m/L_m}{Y_{US}/L_{US}}$. Doing this for all elements in equation (2), we decompose GDP per worker in country m relative to the USA into relative differences factor inputs (human and productive capital) and productivity:

$$\tilde{y}_m = \tilde{A}_m \tilde{k}_m^{\alpha} \tilde{h}_m^{1-\alpha} \tag{3}$$

Using this equation to account for differences in GDP per worker answers the following hypothetical question: if one of the factor inputs or productivity were to increase, holding constant the other two elements, by how much would GDP per worker increase. Assuming one of the terms does not change while the other one does can be plausible when comparing growth over a short period of time, since the

economy may not have yet moved from one steady state to another. In a cross-country setting, though, Hsieh and Klenow (2010) argue that a more sensible hypothetical would be:

$$\tilde{y}_m = \tilde{A}_m^{\frac{1}{1-\alpha}} \left(\frac{\tilde{k}_m}{\tilde{y}_m} \right)^{\frac{\alpha}{1-\alpha}} \tilde{h}_m \tag{4}$$

This production function rearranges equation (3) in intensive form by expressing the contribution of produced capital to production in capital-output terms ($\frac{\tilde{k}_m}{\tilde{y}_m}$). This form allows capital per person to adjust if total factor productivity or labour input per worker were to change, thus taking into account that part of the differences in capital per worker are an endogenous response to differences in productivity and labour input (Caselli, 2005).

We calculate the relative importance of each element in accounting for differences in (relative) GDP per worker in equation (4) by estimating the following regressions:

$$\frac{1}{1-\alpha} \log \left(\tilde{A}_m \right) = \beta^A \log \left(\tilde{y}_m \right) + \varepsilon_m^A \tag{5}$$

$$\frac{\alpha}{1-\alpha} \log \left(\frac{\tilde{k}_m}{\tilde{y}_m} \right) = \beta^K \log \left(\tilde{y}_m \right) + \varepsilon_m^K \tag{6}$$

$$\log \left(\tilde{h}_m \right) = \beta^H \log \left(\tilde{y}_m \right) + \varepsilon_m^L \tag{7}$$

Given that the sum of the dependent variables equals the independent variable, the coefficients (β^A, β^K and β^H) add up to one and can be interpreted as the relative importance of each term in accounting for differences in GDP per worker across countries.[4]

2.1 Measuring Capital

An important contribution of our paper concerns the construction of a new dataset on produced capital that spans more than a century and covers 33 countries.[5] Our measure of capital refers to produced assets that are used repeatedly in the production process such as nonresidential structures, machinery and equipment or software, as defined in the most recent version of the System of National Accounts (SNA08). Thus, we do not include land, inventories and other forms of intangible capital.

To create a consistent and comparable series for the number of countries and long time span we cover, the available data only allowed for disaggregating total capital into two groups: structures (residential and nonresidential) and machinery, equipment and other assets. Our measure of the quantity of capital input in equation (4) is based on estimated net capital stocks. These stocks are obtained applying the perpetual inventory method, which accrues past investment (I) in asset i and subtracts depreciated capital at a given rate δ, as follows:

$$K_{i,t} = (1 - \delta_i) K_{i,t-1} + I_{i,t} \tag{8}$$

One advantage of our capital series is that we account for changes in the relative price between structures and machinery and equipment over the long time period considered to construct a current cost measure of a country's total net capital stock:

$$p_t^K K_t = \sum_i p_{i,t}^K K_{i,t} \tag{9}$$

where $p_{i,t}^K$ is the price index of asset i at time t. Ideally, we would like to use asset rental prices for a measure of capital services in the production process, as done by Inklaar et al. (2019) for the

post-1950 period. However, lack of data does not allow using this method consistently for the broad range of countries and years considered.[6]

Based on equation (9), we are able to compare the current-price capital-output ratio, $p^K K / p^Y Y$, across countries and over time. Yet implementing equation (4) requires the real capital-output ratio, K/Y, so adjusting equation (9) for differences in the relative price of the capital stock and of GDP across countries:

$$\frac{K}{Y} = \left(\frac{p^K K}{PPP^K} \right) / \left(\frac{p^Y Y}{PPP^Y} \right) \equiv \frac{p^K K}{p^Y Y} \times \frac{PPP^Y}{PPP^K} \tag{10}$$

where PPP^K is the purchasing power parity for the capital stock and PPP^Y the purchasing power parity for GDP. From the 2018 version of the Maddison Project Database (see below), we can infer information on the (implied) PPP for GDP, but we cannot recover similar estimates of the PPP for the capital stock. Estimates for both are available from 1950 onwards in the Penn World Table and in version 9.1, the cross-country average of the $\frac{PPP^Y}{PPP^K}$ ratio is close to one and there is no clear relationship between the ratio and GDP per capita. This suggests that using $p^K K / p^Y Y$ rather than K/Y based on equation (10) would not bias our development accounting results. In our sensitivity analysis we also return to this.

To implement our development accounting calculations in equation (4), we draw on the multiple-benchmark series introduced in the 2018 version of the Maddison Project Database for data on income per capita (Bolt *et al.*, 2018). The main alternative to relying on multiple relative price comparisons and interpolating between subsequent comparisons is to rely on a price comparison in a single year to construct a benchmark income comparison and extrapolating using growth rates of GDP per capita (Maddison, 2006). For our analysis, we argue that the multiple-benchmark series is the most appealing choice, because we are making repeated cross-country comparisons and the relative prices observed in those years or closest to those years would likely be more relevant than a temporally distant price comparison.[7]

Data on years of schooling are taken from Barro and Lee (2016).[8] For employment, we use data from Penn World Table (PWT) 9.1 for the post-1950 period (Feenstra *et al.*, 2015), and a range of other sources specified in Appendix B for the earlier years.

To construct our measure of capital or net capital stocks, we use investment flows from PWT 9.1 for the post-1950 period, and link them to the sources specified in Appendix B. Finally, we assume a geometric depreciation rate of 2% for structures and 15% for machinery, equipment and other assets following Feenstra *et al.* (2015);[9] and adjust our stocks when damage due to wars take place, when such information is available (see Appendix B).

3. Stylized Patterns in the Capital Data

Given the novelty of the capital dataset, it is informative to first discuss some relevant features of these data. The first is related to the ratio of productive capital to GDP. One of the stylized facts of Kaldor (1961) is that capital per unit of output (at current prices) is approximately constant over the long run. More recently, Jones (2016) shows that evidence for the USA is consistent with this fact. Yet other long-run studies have shown that in Spain (Prados de la Escosura and Roses, 2010) and the Netherlands (van Ark and de Jong, 1996), the capital-output ratio follows an upward trend over time. The scope of our dataset, with a coverage of 33 developed and developing countries over a period of 100 years, makes it possible to provide more comprehensive evidence.

We regress capital-output ratios at current prices, $p^K K / p^Y Y$, on country and year dummies, and plot the year dummy coefficients with the 95% confidence interval in Figure 1. The outcome of this exercise shows that the long-term evolution of capital-output ratios followed three distinct phases. The first comprises the period 1913–1950 and it is characterized by a slight rising trend. Interestingly, the first
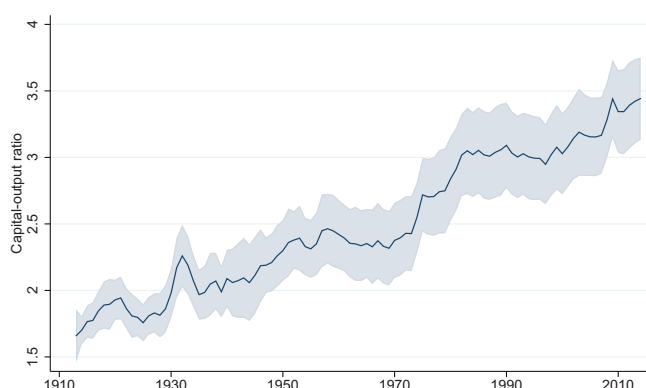
Figure 1. Capital-Output Ratios over Time at Current Prices. [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: The figure charts the year dummy coefficients from a regression of capital-output ratios at current prices on country and year dummies. The shaded area is the 95% confidence interval based on robust standard errors, clustered by country.

years of the Great Depression witnessed a significant increase in capital-output ratios, as GDP shrank due to the immediate effects of the economic crisis. By the mid-1930s, capital-output ratios returned to their long-term increasing trend that would continue until the early 1950s. The second phase in the development of the series exhibits a temporary halt during the two decades after the Second World War. If we consider the 1960s, capital-output ratios even experienced a small decline. The last phase lasts until today and it is marked by a strong increase in capital-output ratios. Despite the temporary halt of the series during the 1980s and 1990s, the rise in capital-output ratios during this period is more pronounced than that for the period 1913–1950. Overall, we can conclude that increasing capital-output ratios are the dominant pattern during the hundred-year period considered, thus supporting Prados de la Escosura and Roses (2010) and van Ark and de Jong (1996). The average capital-output ratio has risen from 1.7 to 3.4 between 1913 and 2014.[10] If we split the sample in half according to countries income per capita levels, we find the same broad trends for both subsamples (see Figure 1A). Furthermore, as a preview of the development accounting results that will follow, we observe the largest increases in capital-output ratios in low-income countries.

A second aspect of our data that can be analysed relates to how the composition of capital stocks differs by income level, and how this has changed over time. To cover the number of countries we do, it is only feasible to distinguish the stock of structures (residential and nonresidential) and machinery, equipment and other assets. Certainly, this aggregation of assets means that much heterogeneity is not covered. For instance, Caselli and Wilson (2004) and Inklaar *et al*. (2019) find that, in recent periods, higher-income countries invest more in high-quality types of machinery and equipment. However, our broad two-asset split can be informative of the process of long-term capital accumulation across the global income distribution.

Table 1 shows the relationship between the share of machinery, equipment and other assets in the total current-cost net capital stock and the relative income level. Column (1) presents the results of regressing the share of machinery on GDP per worker and a time trend. The lack of significance of both coefficients indicates that there is no systematic difference by level of GDP per worker in the share of machinery, equipment and other assets, and or evidence of a downward trend. But interacting the level of GDP per worker and the time trend, in column (2), shows that higher-income countries experienced

Table 1. The Relationship the Share of Machinery, Equipment and Other Assets and GDP per Worker over Time.

	(1)	(2)
Log of GDP per worker	−0.459	3.778
	(2.095)	(2.436)
Year	−0.0437	−0.113***
	(0.0265)	(0.0322)
Year × (log of GDP per worker)		−0.0771**
		(0.0332)
Observations	3319	3319

Notes: The dependent variable is the share of the total current-cost net capital stock of machinery, equipment and other assets, in percent. GDP per worker is computed relative to the GDP per worker level of the USA in every year. The Year variable is set equal to 0 in 1913 so that the coefficient on log of GDP per worker in column (2) reflects the relationship between income level and the share of machinery, equipment and other assets in 1913. Each specification includes country fixed effects. Robust standard errors, clustered by country, are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

a decline relative to lower-income countries in this share over the subsequent century. In other words, lower-income countries have been shifting investment towards machinery. The point estimates show that initially higher-income countries had higher shares and that by the early 1960s, the point estimates are equal.[11]

One possible interpretation for these findings is that lower-income countries followed the investment patterns of higher-income countries over this period (Young, 1995). Another could be that investment in infrastructure, part of investment in structures, started to require ever greater outlays in high-income countries. However, it is unclear why the relative importance of this factor may have changed over time. An explanation that may be able to account for both the declining share across all countries and the faster decline in high-income countries is the decline in relative prices of machinery and equipment. As widely documented (Jones, 2016, p. 13), machinery and equipment have become much cheaper relative to other goods and services due to rising productivity in the manufacturing sector. This is especially the case in recent decades as Moore's Law led to rapidly falling prices of semiconductors and thus of information and communication technologies (ICT). From a historical perspective, the speed and magnitude of the decline in real prices of ICT equipment is unprecedented when compared with other general purpose technologies, such as steam and electricity (Crafts and O'Rourke, 2014, p. 301). Therefore, falling prices for investment goods leads to a decrease in the share of machinery and other equipment at a given investment level at current prices.

To investigate the evolution of relative prices in our set of countries, we compare the price deflator for machinery and equipment to the price deflator for structures. We set the relative price of machinery to one in 2011 and regress it on country and year dummies. Then, we plot the coefficients for the year dummies and their 95% confidence intervals in Figure 2. Overall, our results indicate that machinery and equipment prices declined considerably over the period, relative to those of structures. This decline has not been steady over time. It started during the first two decades of the 20th century, coinciding with important declines in the price of electricity equipment (Crafts and O'Rourke, 2014). Then, after a break between the 1930s and 1960s, the fall in the price of machinery and other equipment became especially pronounced, with relative prices falling by 2% per year or more.

The confidence interval in the figure implies that there is considerable cross-country variation in these price changes over time. At the same time, this variation has remained stable throughout the analysed
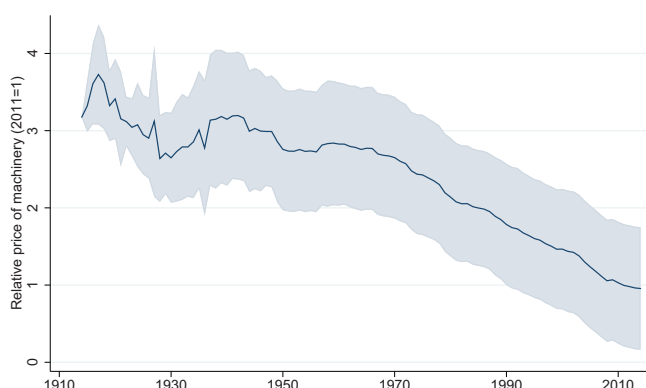
Figure 2. The Relative Price of Machinery and Equipment over Time. [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: The figure charts the year dummy coefficients from a regression of price deflator for machinery and equipment relative to the price deflator for structures on country and year dummies. Both price deflators are set equal to 1 in 2011. The shaded area is the 95% confidence interval based on robust standard errors, clustered by country. Portugal is omitted from the regression due to extreme relative price estimates in the early decades of the period. For some countries, the GDP deflator is used for (part of) the time series for both assets; those years are omitted.

period, which indicates that the relative price declines for machinery and equipment are a feature shared by most countries in our sample. This common pattern is expected given that manufacturing of machinery and equipment has mostly been concentrated in a limited number of advanced economies (Eaton and Kortum, 2001). The implications for the subsequent development accounting analysis may thus be limited, since such a common trend will not lead to large cross-country differences in the productivity of the capital stock.

4. Development Accounting

Combining our new dataset on capital stocks with information on education and economic performance, we are now in a position to assess how cross-country differences in produced capital and human capital can account for differences in GDP per worker over time by using equations (5)–(7). Figure 3 presents the results for 1913 and shows the contributions of differences in produced capital, human capital and productivity to differences in GDP per worker. The best-fit lines indicate the extent to which each factor accounts for variation in GDP per worker. Productivity differences is the most important factor, with a slope coefficient of 0.47, followed by produced capital (0.29) and human capital (0.24), although all three sources contribute substantially. If we compare these findings with those for 2011 in Figure 4, an interesting pattern emerges. Contrary to 1913, most of the variation in produced capital has disappeared, while the variation in relative GDP per worker (along the horizontal axis) has not changed much. The same process of convergence applies to educational attainment, although to a lesser extent, as noted by Lee and Lee (2016). As a result, productivity differences in 2011 account for, by far, the largest variation in GDP per worker. The slope coefficients reflect this, since the they amount 0.11, 0.17 and 0.72 for produced capital, human capital and productivity, respectively. Our result for TFP is very similar to that reported by Jones (2016, p. 44) using a 128-country sample.
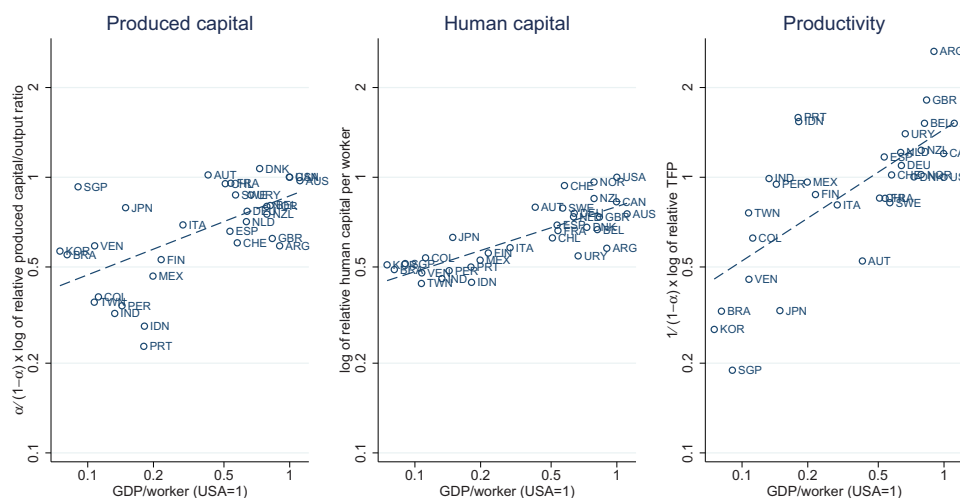
Figure 3. Development Accounting for 1913. [Colour figure can be viewed at wileyonlinelibrary.com]
Notes: The figures show the development accounting decomposition from equations (5)–(7) (for each of the panels) for the 32 countries with data for 1913. The contribution from differences in produced capital, $\frac{\alpha}{1-\alpha} \log[\frac{K_m/Y_m}{K_{USA}/Y_{USA}}]$ is shown in the left figure; the contribution from relative human capital per worker, $\log[\frac{H_m}{H_{USA}}]$, in the middle figure and the contribution from differences in relative productivity, $\frac{1}{1-\alpha} \log[\frac{A_m}{A_{USA}}]$ in the right figure. All these contributions are plotted against relative GDP per worker, $\log[\frac{Y_m/L_m}{Y_{USA}/L_{USA}}]$. The dashed line is the linear best fit regression line. The coefficients are 0.29 (produced capital), 0.24 (human capital) and 0.47 (productivity).

This enormous shift, especially the much lower variation in produced capital, is a key finding of our paper.

These two sets of figures represent two snapshots almost a century apart, so it is useful to exploit the full time series to see when these changes occurred. For this purpose, we plot in Figure 5 the development accounting coefficients for each year for which we have data for all 33 countries, plus 1913 where the data cover 32 countries (capital data for Honduras is available from 1925 onwards). Although data for the first half of the 20th century is scarcer than for the post-1950 period, we are able to cover some key benchmarks of the period such as 1913 and a few years prior and after the Great Depression (1934–1937). For human capital, the figure shows a peak of approximately 0.35 in the 1930s before starting a gradual decline until the 0.18 at the end of the period. The timing of this decline is in line with the rapid catch up in terms of educational attainment noted by Prados de la Escosura (2015) between developed and developing countries starting in the 1930s. In the last decades, the decreasing trend in the relative importance of human capital has stopped.

For produced capital, the decreasing trend in its relative importance began in the first half of the 20th century, since its coefficient falls from 0.29 in 1913 to 0.2 in the 1950s. In the two decades after the end of the Second World War, the coefficients fluctuate around 0.2 before starting a second sharp fall that would last until the early 2000s. The magnitude of this decline is remarkable, since the coefficient for produced capital fall from 0.25 in 1975 to 0.04 in 2003. Interestingly, produced capital is making a comeback in the last years since its contribution to income variation nowadays is comparable to that of the 1980s.

As a result of the trends in produced and human capital, the relative importance of productivity exhibits a clear rising trend between 1929 and the mid-20th century as well as between the mid-1970s and
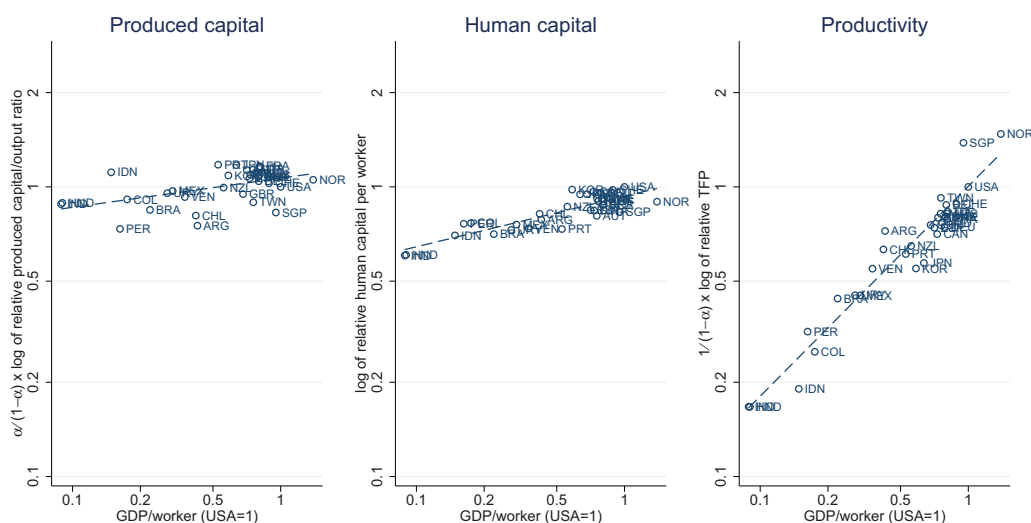
Figure 4. Development Accounting for 2011. [Colour figure can be viewed at wileyonlinelibrary.com]
Notes: The figures show the development accounting results from equations (5)–(7) for 2011 for all 33 countries. See notes to Figure 3 for further explanation. The coefficients are 0.11 (produced capital), 0.17 (human capital) and 0.72 (productivity).

early-2000s. In the last decades, the coefficient for productivity has remained at a high level, between 0.7 and 0.8, a finding that has been echoed by a substantial body of research in the development accounting literature (Klenow and Rodríguez-Clare, 1997; Caselli, 2005; Jerzmanowsky, 2007; Hsieh and Klenow, 2010). Our results show that this is a rather abnormal phenomenon from a historical perspective, since such coefficients for productivity are unprecedented at least since the early 20th century, and probably during the last part of the 19th century given the large share of income variance accounted for by physical capital in 1913.

Aside from these long-run trends, the high-frequency movements in the produced capital and productivity coefficients are mirror images. This is most notable during the Great Depression, when the coefficient on productivity drops from 0.4 in 1930 to 0.25 in 1934 and the coefficient on produced capital rises from 0.28 to 0.40. During this period, GDP fell in many countries, especially amongst the higher-income group, and (mechanically) their capital-output ratios rose. Given the extraordinary nature of the Great Depression, the results for those years should not take on too great a significance, especially because the trends between 1913 and 1929 are stable and the post-1950 years do not show such rapid swings.

Until now, we have focused on the relation between variation in GDP per worker and the variation in produced and human capital, and productivity. However, it is also informative to provide a variance decomposition for each of those four separately, similar in spirit to those discussed by Caselli (2005). Table 2 does this by showing the variance of the log of relative GDP per worker, the variance of each of the three contribution terms and the sum of the covariances between the three contribution terms.

For the group of countries analysed, Column 1 shows that variation in GDP per worker has declined by approximately one-third percent over the full period, with most of the decline taking place before 1955. The variation in the contribution from produced capital has declined by almost 90%, with a large decline between 1930 and 1955 and another notable decline between 1980 and 2011. The contribution from human capital showed approximately constant variation until 1955 with, subsequently, the sharpest
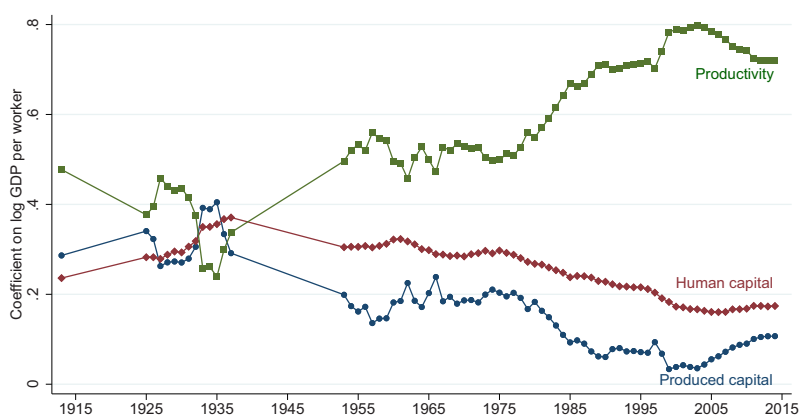
Figure 5. Development Accounting Coefficients for the Period 1913–2014. [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: The figure shows the slope coefficients on produced capital, human capital and productivity for each year with complete data for all 33 countries plus 1913 (32 countries). Each marker indicates the results from a separate development accounting decomposition.

Table 2. Variance of GDP per Worker and Development Accounting Contributions.

	Log GDP/worker (1)	Variance of the contribution from:			
		Produced capital (2)	Human capital (3)	Productivity (4)	Covariances (5)
1913	0.64	0.14	0.06	0.29	0.15
1930	0.43	0.14	0.06	0.26	−0.03
1955	0.44	0.04	0.07	0.20	0.12
1980	0.45	0.04	0.05	0.18	0.19
2011	0.41	0.02	0.02	0.23	0.15

Notes: The table shows, for selected years for the 33 countries (32 in 1913) in the sample, the variance of the log of GDP per worker, the variance of the contributions from produced capital, human capital and productivity from equations (5)–(7) and the sum of the covariances between the contributions from produced capital and human capital, human capital and productivity and produced capital and productivity.

decline between 1980 and 2011. Finally, the variation in the contribution from productivity declined until 1955 and then showed more fluctuations. The sum of the covariance terms is fairly constant, with the exception of 1930, which is helpful for the discussion because these are not straightforward to give an interpretation to.

For the pre-1955 period, we can thus attribute half of the decline in the variance of GDP per worker to a decline in the variance of the contribution from produced capital, making this a period of investment-driven convergence. Between 1955 and 2011, produced and human capital were also drivers of further convergence. But given the small variance in produced and human capital that remains by 2011, most of the variation in GDP per worker can thus be attributed to variation in productivity. The results in Table 2 for 1913 also suggest that the variation in productivity was an important proximate driver of income divergence during the 19th century in 1913, since it accounts for around 45% of variation in GDP per

worker. However, its relative importance is much lower than we would be able to infer from recent periods because produced and human capital account directly (i.e. without taking into account covariances) for almost a third of income differences at the beginning of the 20th century.

5. Discussion

What explains the rising relative importance of TFP during the 20th century? Although somewhat imperfect, TFP estimates from level accounting exercises are interpreted as a measure of technological differences across countries (Caselli, 2005). Thus, the long-term developments shown in Figure 5 may be explained by cross-country patterns of technological diffusion. Indeed, the increasing relative importance of TFP after the interwar period follows the wave of productivity growth during the 1930s and 1940s in the USA identified by Gordon (2016).[12] Efficiency improvements resulted from the refinement of technologies stemming from the second industrial revolution (e.g. electricity or internal combustion engine), and disembodied technological change due to better factory organization and increasing returns to scale (Inklaar *et al.*, 2011). This technological wave then diffused beyond the USA contributing to TFP growth in Europe and Japan during the second half of the 20th century (Bergeaud *et al.*, 2016). American technologies were then more congruent with European conditions due to a larger availability of natural resources, larger markets following the economic integration of European nations, high rates of investment and the shift from protectionist to open policies towards trade (Crafts and O'Rourke, 2014).

On the other hand, the convergence process experienced in East Asia after the mid-20th century was driven by factor input accumulation. In countries such as Singapore, South Korea or Taiwan investment rates rose from about 10% at mid-century to 30% during the 1970s and 1980s (Young, 1995). In Japan, postwar economic development relied on importing foreign machinery and equipment (Odagiri and Goto, 1996). Although there is discussion about the precise role of capital accumulation in East Asia (Hsieh, 2002), Crafts and Woltjer (2020) conclude that TFP contributed relatively little to catch-up growth, as compared with the experience of Southern European countries at similar initial levels of labour productivity. In Latin America, both TFP and capital deepening account for economic development between 1960 and 1980, although these along with output per worker plummeted until 2000 (Bosworth and Collins, 2003).

Comin and Mestieri (2018) analysed the long-term global diffusion of specific technologies by considering their cross-country adoption lags and intensity of use. They show that the mean adoption lag of recent technologies (e.g. Internet) is much lower than that of earlier technologies, such as spindles or railways. However, while adoption lags have converged between rich and poor countries, the intensity of use of adopted technologies have diverged. This uneven diffusion pattern could be explained by the 'appropriateness' of technologies in different contexts. If innovations happen at high-end technologies, economies working with low-end technologies will not benefit from technological change in developed countries (Atkinson and Stiglitz, 1969; Basu and Weil, 1998). In line with this theory of 'appropriate technology', Kumar and Russell (2002) argue that the world production possibility frontier has shifted outward at relatively high levels of capital per worker between 1965 and 1990. This suggests that new capital-intensive technologies are more likely to benefit and be adopted by relatively rich countries with higher levels of factor endowments and social capabilities and institutions than in developed countries.[13] Allen (2012) shows this phenomenon holds over the long term, since technologies from the first and second industrial revolution raised productivity at increasingly high levels of capital intensity.

Part of the rising relative importance of TFP may be related to efficiency differences with which technologies are used. Applying frontier analysis, Jerzmanowsky (2007) decomposes the contribution of TFP into differences in technology and efficiency. His results show that both factors account for a similar fraction of output per worker differences in 1960. More recently, efficiency differences have become increasingly important, while the world technology frontier has shifted out faster at input

combinations close to those of developed economies (Kumar and Russell, 2002; Timmer and Los, 2005). Similarly, Timmer *et al*. (2016) find that efficiency differences, rather than applied techniques, explain labour productivity gaps between Germany and the USA in innovative industries (e.g. chemicals) at the beginning of the 20th century. One reason why efficiency differences may emerge is related to management practices affecting firms' economic performance. Bloom *et al*. (2017) calculate that this accounts for about 30% of cross-country income variance. At the beginning of the 20th century, though, Wolcott and Clark (1999) suggest that management practices in India do not explain the relatively weak performance of its textile sector. Another important element can be that factor inputs are not put to their most productive use. This can be due to distortions in labour or financial markets that prevent firms or industries from operating at the production possibility frontier. Using firm-level data, Hsieh and Klenow (2009) show that part of the relatively low levels of aggregate TFP in China and India are due to substantial differences in the marginal product of capital and labour. Gollin *et al*. (2014) show that labour productivity is lower than in nonagriculture particularly in lower-income countries, implying that reallocating workers to the nonagricultural sector would increase overall productivity. While these studies suggest that the efficiency factor is more important than technology in explaining cross-country income variation in the last decades, it is unclear what their relative importance during the first half of the 20th century was. Ziebarth (2013) does show that the extent of resource misallocation in the USA of the late 19th century was very similar to that seen in China and India today, in Hsieh and Klenow (2009), but Inklaar *et al*. (2017) show that Hsieh/Klenow-type misallocation is not systematically worse in lower-income countries today. This suggests that much is not yet known on the role of resource misallocation, but further research in this area could well be quite fruitful.

Another argument that could be made is that a large manufacturing sector is particularly important for aggregate productivity growth. This fits the evidence presented by Rodrik (2013) that productivity convergences unconditionally in manufacturing but not in nonmanufacturing. But as Rodrik (2016) argues, the combination of labour-saving technological progress and globalization has led to premature deindustrialization. While at their peak in the 1960s and 1970s. the manufacturing industries of (currently) high-income countries employed 20%–30% of the workforce, peak manufacturing employment in Latin America and Asia occurs at only 10%–20% of the workforce. So even if these manufacturing sectors are showing strong productivity growth (as per Rodrik, 2013) this would translate into smaller aggregate growth today compared to earlier in the 20th century.

A different explanation for our findings refers to the mismeasurement of certain types of capital input, thus challenging the idea that differences in technology or efficiency drive the changing relative importance of TFP. An example is intangible capital, which is more prevalent in for high-income economies (Caselli and Wilson, 2004). Chen (2018) estimates that up to 16% of income variation between countries in 2011 can be attributed to the increasing reliance of developed economies on brand equity or scientific research and development.[14] Though sizeable, we think the 20th-century trends of TFP are unlikely to be explained by this factor. In a frontier economy such as the USA most of the increase in intangible capital happened after 1973 (Corrado *et al*., 2009), and the upward TFP trend started much earlier, during the second quarter of the 20th century (see Figure 5). Another measurement issue influencing our calculations refers to the use of capital stocks instead of services. Inklaar *et al*. (2019) show that using a measure of capital services increases the relative importance of capital deepening, though TFP remains the main driver of cross-country income inequality. Moreover, Prados de la Escosura and Roses (2010) do not find significant differences between using a stock- or service-based measure of capital input to account for the sources of Spanish economic growth since 1850.

Our measure of human capital only considers educational attainment without taking into account potential quality changes. If quality-adjusted human capital became increasingly unequal across countries during the 20th century, the relative importance of TFP would be overstated in our analyses. One aspect we do not consider is health, which influences workers' cognitive skills and working effort. Gallardo-Albarrán (2018) draws on the methodology developed by Weil (2007) and shows that

differences in health, as measured by life expectancy, account for a sizeable fraction of cross-country income differentials at the beginning of the 20th century. However, health convergence after the mid-20th century reduced its relative importance for between-country income inequality, while that of TFP followed the exact opposite trend. Another factor influencing the quality of human capital relates to workers' experience. Lagakos *et al.* (2018) argue that developed countries have steeper wage-experience profiles than less developed economies due to lower human capital accumulation and search-and-matching frictions in the labour market. Their results suggest that differences in workers experience account for a third of cross-country income inequality. To the extent that wage-experience profiles are related to human capital accumulation, we suspect they would be less important during the early part of the 20th century; however further research is needed to confirm our intuition.

Overall, we think the shifting relative importance in the proximate determinants of international income inequality during the 20th century is unlikely to be driven by mismeasurement. Rather, technological diffusion patterns and the efficiency with which new production techniques are applied in different contexts can explain why the returns to capital deepening have greatly declined since 1913. However, further research is needed in this area to disentangle their relative importance before the mid-20th century.

6. Sensitivity Analyses

In this section, we discuss the sensitivity of our results to three features of our dataset and analysis. First, we discuss how the results for our set of 33 countries relate to income differences and (for the later period) productivity differences for the broader range of countries around the world. Second, to achieve coverage of the period since 1913, we could not apply conceptually superior measurement methods, in particular we compare capital stocks rather than productive capital services across countries. Third, we rely on the multiple-benchmark real GDP measure provided in the Maddison Project Database 2018 (Bolt *et al.*, 2018). We discuss how our results would change if we were to rely on alternative real GDP measures, such as the 1990 relative income benchmark of (Maddison, 2006) or the relative prices of ICP 2011.

6.1 *Country Coverage*

The results in the previous section have been obtained within the context of the sample of 33 countries for which capital stocks could reliably be estimated. That raises the question to what extent these results are informative of more general patterns of variation in GDP per worker or GDP per capita and the degree to which produced and human capital can account for this variation. Figure 6 provides a first indication by plotting the variance of GDP per worker for our 33-country sample against two broader samples. The first (red line) is for GDP per capita for all countries with data in the Maddison Project Database (MDP) since 1913 (Bolt *et al.*, 2018), which is for up to 56 countries. The second is the set 114 countries for which PWT provides data since 1965 (Feenstra *et al.*, 2015). As the figure shows, the cross-country variance in our 33-country sample is approximately stable around 0.5, while variance in the broader MPD sample doubles from 0.5 to over 1 between 1939 and 2000. The PWT sample has higher variance still, starting around 1 in 1965 and peaking at 1.6 around 2000.

The main reason for these differences is that, especially in the later period, our sample excludes many of the poorer countries, such as in Sub-Saharan Africa. In the year 2000, the average income level in our 33-country sample was 48% of the US level, while in the PWT sample, the average income was only 17% of the US level. Similarly, of the 56 countries in the MPD, the group without data to estimate reliable capital stocks had a lower relative income level in 1913.

The increasing variance of GDP per capita during the second half of our analysed period may raise concerns related to the robustness of our results using a larger sample containing more middle- and low-income countries. Indeed, if the proximate determinants of cross-country income inequality among
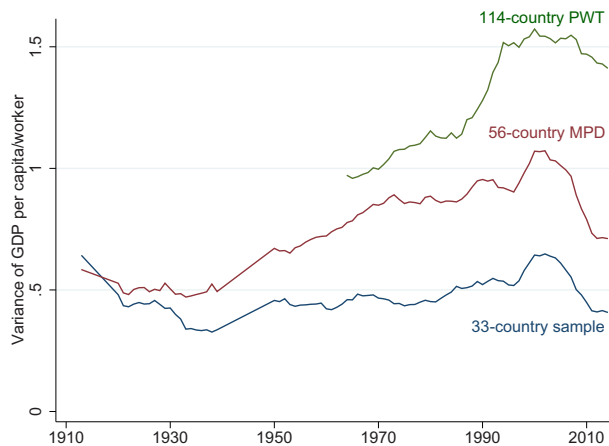
Figure 6. Variance of GDP per Worker/Capita since 1913 across Datasets and Samples. [Colour figure can be viewed at wileyonlinelibrary.com]

Notes: The figure plots the cross-country variance of GDP per worker for the 33 countries from the dataset in this paper, the variance of GDP per capita for the (up to 56) countries with data in the Maddison Project Database 2018 (MDP, Bolt *et al*., 2018) from 1913 onwards and the variance of GDP per worker for the 114 countries with data from 1965 onwards in the Penn World Table version 9.1 (PWT, Feenstra *et al*., 2015). Between 1913 and 1950, MPD data coverage varies with a minimum country coverage of 41. For MPD, the variance in the variable *CGDPpc* is computed; for PWT the variance in *CGDPo*/*POP*.

those missing countries is significantly different from those in our sample, our results would not hold for the post-1950 period. It is not feasible to extend our analysis for the full period to a larger number of countries than the current 33, but we can perform development accounting exercises for the 107 countries (out of a maximum of 114) for which PWT 9.1 provides the necessary data since 1965. For this purpose, we apply the same methodology as on our 33-country sample, so relying on capital stocks and a constant output elasticity of capital of 0.4 – see below for a discussion of the sensitivity of our results to these methodological choices.

Table 3 reports the development accounting coefficients for our baseline 33 countries and for the 107 countries for selected years, in Panel A and B respectively. For 1965, the 107-country sample shows a larger coefficient on produced capital, indicating greater variation than in our 33-country sample, and a smaller human capital coefficient. Between 1965 and 2011, the decline in the produced-capital coefficient is even stronger in the 107-country sample than in our 33-country sample, while the human-capital coefficient does not show a clear decline. The net result of these differences is a set of coefficients on productivity that are very comparable across the two samples and that exhibit the same trends. Therefore, while the overall income variation in the two samples differs substantially (see Figure 6), Table 3 shows much greater similarity in how the (proximate) sources of those income differences have evolved over time: from a larger role for differences in produced capital to a larger role for differences in productivity.

6.2 *Capital Measurement Methodology*

To cover the entire period since 1913, several methodological simplifications had to be made, in particular for measuring capital but also in terms of productivity measurement. As discussed in Inklaar *et al*. (2019), we would ideally construct a measure of relative capital services, based on a detailed set of produced

Table 3. Development Accounting Coefficients for 33 Countries and 107 Countries.

	Produced capital	Human capital	Productivity
Panel A: Baseline – 33 countries			
1913	0.29	0.24	0.47
1930	0.28	0.29	0.43
1955	0.16	0.31	0.53
1965	0.20	0.30	0.50
1980	0.18	0.27	0.55
2011	0.10	0.17	0.72
Panel B: PWT 9.1 – 107 countries			
1965	0.30	0.24	0.46
1980	0.25	0.25	0.50
2011	0.08	0.22	0.70

Notes: The table reproduces the baseline development accounting coefficients for the 33-country sample and adds the coefficients computed from a 107-country sample from PWT 9.1. The methodology for computing productivity is the same as for the 33-country sample and therefore this does not rely on the standard PWT 9.1 measure of productivity but instead a measure computed based on capital stocks and a constant output elasticity of capital of 0.4.

capital assets and compare these across countries based on estimates of relative rental prices. We would also like to apply the translog function, a flexible functional form, for the aggregate production function to allow for differences in the output elasticities of the various produced capital assets and human capital. This requires information on the share of income accruing to labour and estimates of the required rate of return on produced capital. In Penn World Table version 9.1 (Feenstra *et al.*, 2015), this more sophisticated measurement approach has been adopted.

In Table 4, we compare the development accounting coefficients based on our dataset for selected years since 1955 and the coefficients based on PWT 9.1 data for the same set of 33 countries and the same years. The main difference between the two datasets is that the coefficient for produced capital is higher based on PWT than based on the current dataset and the coefficient on productivity is correspondingly smaller.[15] This is in line with the results of Inklaar *et al.* (2019), who show that especially the adoption of a capital services measure as compared to the capital stock approach taken in the current data, leads to produced capital accounting for a larger fraction of cross-country differences in GDP per worker. This is because shorter-lived assets, such as ICT assets, are weighted more heavily in the capital services approach and high-income countries tend to invest more in these assets.

The difference between the produced capital coefficient based on our data and based on PWT 9.1 increases over time, especially between 1980 and 2011. This reflects that ICT assets have gained prominence in this last period and that rental prices for ICT assets are so much higher than for other assets due to the rapid depreciation and price declines of those assets. As a result, the rise in the coefficient on productivity is more muted than in the baseline case, though the rise is still substantial and in line with the main conclusion of this paper.

For the post-1955 period, the results in Table 4 also shed light on the impact of our choice of parameters such as the output elasticity of capital (set at 0.4 here) and the depreciation rates chosen (2% for structures, 15% for machinery, equipment and other assets). In PWT, the output elasticity of capital varies across countries and over time as it is based on estimates of (one minus) the share of labour income in GDP. Changes over time, such as the broad decline in labour shares, are thus taken into account. Similarly, changes in depreciation rates due to changes in the composition of assets within our broad categories are also accounted for.

Table 4. Sensitivity of Development Accounting Coefficients to Capital Measurement Methodology – This Paper versus PWT 9.1.

	Produced capital	Human capital	Productivity
Baseline			
1913	0.29	0.24	0.47
1930	0.28	0.29	0.43
1955	0.16	0.31	0.53
1980	0.18	0.27	0.55
2011	0.10	0.17	0.72
PWT 9.1			
1955	0.20	0.31	0.50
1980	0.23	0.27	0.50
2011	0.16	0.20	0.64

Notes: This table shows the development accounting coefficients for years since 1955 for the 33 countries covered in this paper based on the data constructed here (baseline) and based on the Penn World Table (PWT) version 9.1 (Feenstra *et al*., 2015).

Table 5. Sensitivity of the Productivity Development Accounting Coefficient to Alternative Real GDP Series.

	Multiple benchmark	2011 price benchmark	Maddison 1990
1913	0.47	0.46	0.43
1930	0.43	0.47	0.39
1955	0.53	0.60	0.55
1980	0.55	0.57	0.50
2011	0.72	0.72	0.71

Notes: The table shows the coefficient on productivity in development accounting for alternative real GDP series. The 'multiple-benchmark' series is the *CGDPpc* series from the Maddison Project Database 2018 (MPD, Bolt *et al*., 2018) and corresponds to our baseline results. The '2011 price benchmark' series is the *RGDPNApc* series from the MPD 2018 and the 'Maddison 1990' series is the *GDPpc* series from the MPD1990 data file. All series are available at www.ggdc.net/maddison [accessed on 25 January, 2020].

A question that is more difficult to answer is how the results before 1955 would be affected. Given the very large decline in the capital coefficient between 1913–1930 and 1955 – from 0.28–0.29 to 0.16 – and the less drastic differences in rental prices between assets in the early period, it seems highly unlikely that a more sophisticated capital measurement methodology would overturn our finding of a declining relevance of produced capital and an increased relevant of productivity in accounting for differences in GDP per worker. Confirming this suspicion is harder. Òscar *et al*. (2019) provide data on the rate of return on equity and bonds, which can be used to construct a measure of the required rate of return on produced capital (see e.g. Inklaar, 2010). However, their data is only available for 15 of our 33 countries. Across those (mostly) high-income countries, differences in produced capital do not account for a statistically significant fraction of differences in GDP per worker. Adopting the less data-intensive assumption of a common real required rate of return across all countries leads to very similar contributions from produced capital in accounting for differences in GDP per worker as our current data. However, assuming an equal rate of return assumes away most of the differences between our current capital measure and a capital

services measure, because the user cost of each asset (defined as the required real rate of return on produced capital plus the asset depreciation rate) is then assumed to be identical across countries.

6.3 *Real GDP Series*

To compare GDP per worker levels across countries, our baseline results rely on the multiple-benchmark series introduced in the 2018 version of the Maddison Project Database (MDP, Bolt *et al.*, 2018). Alternatively, we could rely on a price comparison in a single year to construct a benchmark income comparison and extrapolating using growth rates of GDP (per capita) as done by Maddison (2006).[16] To assess the impact of different real GDP series on our development accounting results, Table 5 compares the development accounting coefficient for productivity of our baseline series, the multiple-benchmark real GDP series from the MPD, to two alternative series – the real GDP series extrapolated from the 2011 price benchmark and the real GDP series extrapolated from Maddison's 1990 income benchmark. All three series lead to a very similar trend on the importance of productivity differences in accounting for differences in GDP per worker. For the years 1913 and 1930, the 'Maddison 1990' series imply a somewhat smaller role for productivity differences and the '2011 price benchmark' a somewhat larger role in 1930 and 1955, but the overall picture is more one of similarity than differences.

7. Conclusions

Why is output per worker much higher in some countries than in others? According to a large body of studies in the development accounting literature, the answer lies in the enormous productivity gaps across countries. Differences in produced and human capital are simply not large enough to account for the high degree of cross-country income variation.

Our paper builds on this body of literature and asks whether the dominance of productivity differences in accounting for income differences has been a constant feature throughout the process of income divergence that has characterized the unequal onset of modern economic growth since the 19th century. Then, we use our results to examine the explanations put forward by various branches of the literature on the relative importance of factor input accumulation and total factor productivity over the long term.

This question has received little attention in the past due to a focus on current income differences, as a reflection of past long-term performance, and lack of data to carry out development accounting analyses for a large number of historical benchmarks in a consistent manner.

Our paper fills this knowledge gap by creating a new dataset on produced capital for 33 countries that allows examining the proximate determinants of cross-country income inequality since 1913 until the present. In this way, our study is better positioned to understand how the current large income differences opened up, and what can account for income gaps at earlier points in time.

The newly developed data set presents three interesting patterns about the process of capital accumulation. First, we identify a long-term rising trend in capital-output ratios that does not support one of Kaldor's (1961) stylized facts: capital per unit of output is approximately constant over the long run. On average, these increased from 1.6 to almost 3.5 between 1913 and 2014. Second, we find that the share of machinery and other equipment in total capital at current prices has fallen over time, and that the magnitude of this fall was higher in richer countries. Seeking for an explanation for the stronger decline in the share of machinery and other equipment among developed economies, we find that the price index of machinery has declined to a larger extent than that for structures. This is especially the case after the 1970s when relative prices fell by 2% per year or more, suggesting Moore's Law as the main driving force.

Our development accounting analyses point to a substantial change in the proximate determinants of income inequality during the 20th century. Between 1913 and 2011, the contribution of produced and human capital to income variation declined from 29% and 24%, respectively, to 11% and 17%. As a result, the relative importance of productivity has risen during the analysed period from 47% to 72%.

This shift has not been steady over time. The decreasing trend for produced capital began in the first half of the 20th century, when its contribution to income variation fell from 29% to 20% between 1913 and the early 1950s. Up to the 1970s, the relative importance of capital remained constant before starting a second and sharper fall that would last until the early 2000s, and a further increase afterwards.

We discuss how factor input mismeasurement could affect our calculations but conclude that they are not likely to account for the rising relative importance of TFP. Instead, we highlight two strands of the literature on the determinants of productivity differences. The first suggests that the intensity of use of productive technologies is very unequal across countries, possibly because technological change takes place in countries with a mix of factor inputs and institutional and social environments that cannot be replicated everywhere. The second explanation puts more emphasis on the efficiency with which technologies are used, rather than their mere application. Differences in management practices or bad policies promoting capital and labour misallocation prevent an economy from reaching its full productive potential.

Overall, we conclude that the current large importance of productivity for cross-country income inequality seems quite exceptional from a historical perspective. For more than a century, many developing countries have experienced investment-driven growth, matching or exceeding high-income countries in investing in machinery and equipment, but this had somewhat disappointing effects on levels of GDP per worker. Indeed, the interplay and changing relative importance of the proximate determinants of income divergence is more complex than hitherto thought and deserve further investigation.

Acknowledgements

Notes

1. Now extended to 23 countries, see http://www.longtermproductivity.com/ [accessed on September 14, 2019].
2. This methodological section draws on Inklaar *et al*. (2019).
3. Human capital can also be measured in terms of health. See Gallardo-Albarrán (2018) for an analysis of its historical importance in accounting for cross-country income differences.
4. As discussed in Inklaar *et al*. (2019), this variance decomposition, unlike that of Caselli (2005), does not require allocating the covariances between inputs and productivity. For comparison purposes, we also present a variance decomposition similar to the one by Caselli (2005).
5. Our sample consists of the following countries: Argentina, Australia, Austria, Belgium, Brazil, Canada, Switzerland, Chile, Colombia, Germany, Denmark, Spain, Finland, France, United Kingdom, Honduras, Indonesia, India, Italy, Japan, South Korea, Mexico, the Netherlands, Norway, New Zealand, Peru, Portugal, Singapore, Sweden, Taiwan, Uruguay, the USA and Venezuela.
6. In our sensitivity analysis, we consider the quantitative impact of this limitation.
7. We show below that our results are robust to using single-benchmark real GDP series.
8. Lee and Lee (2016) provide human capital estimates using a single rate of return to an additional year of schooling. On the other hand, Hall and Jones (1999) take into account that returns to schooling vary by education level and use $h_m = e^{\varphi_i(s)}$, where s is average years of schooling and φ is piecewise linear with different slopes: 0.134 if years of schooling are less or equal than 4 years; 0.1 if they are larger than 4 and less or equal than 8 and 0.07 if they are larger than 8. We follow the latter approach, although the differences between the two procedures are rather small on average (Lee and Lee, 2016, p. 167).

9. The rate for machinery and other equipment is an average for 'Transport equipment' and 'Other machinery and assets', and the rate for structures is an average for residential and nonresidential structures (Online Appendix, Feenstra *et al*., 2015).

10. This is not to say that our dataset contradicts Jones (2016) for the USA. We find that the US capital-output ratio increased from 2.8 in 1913 to 3.3 in 2011, in line with the modest increases shown by Jones (2016, p. 11).

11. The interaction between log of GDP per worker and Year × log of GDP per worker is statistically significant at the 10% confidence level.

12. Although Bakker *et al*. (2019, p. 2280) argue that the highest TFP growth rates in the USA happened during the third quarter of the 20th century, their figures show fast productivity growth in the 1920s and 1930s (between 1.6 and 1.8 percentage points annually).

13. Factor input accumulation may be driven in turn by economic growth. Restuccia and Vandenbroucke (2013) show that productivity changes influenced educational attainment during the period 1940–2000 in the USA.

14. A different, but related, issue concerns the cross-country composition of capital investment. Caselli and Wilson (2004) show that accounting for differences in investment patterns affects TFP estimates, since high-income countries invest in higher-quality types of machinery and equipment. We discuss this issue below.

15. PWT also relies on a combination of schooling data from Barro and Lee (2013) and from Cohen and Leker (2014). Lee and Lee (2016) is identical to Barro and Lee (2013) for the post-1950 period.

16. Even though we favor a multiple-benchmark approach, we acknowledge that comparing prices across countries is challenging for conceptual and practical reasons, see e.g. Deaton and Heston (2010). Furthermore, most experts would agree that the international price comparison in 2011 was superior to earlier comparisons on both conceptual and practical grounds (Deaton and Aten, 2017). In a measurement framework with potential errors in the cross-country comparison and potential errors in the growth rates (Rao *et al*., 2010), it could be the case that errors in the early cross-country comparisons are so large that relying on the 2011 benchmark and extrapolating using growth rates would be more reliable than relying on multiple benchmarks. However, using this technique, as done by Maddison, to obtain relative income levels further back in the past can be even more challenging and sometimes involved adjusting the time series of real growth for specific countries, as in his famous adjustments of Chinese growth (Maddison and Wu, 2008), or tweaking the benchmark income level.

References

Allen, R.C. (2012) Technology and the great divergence: Global economic development since 1820. *Explorations in Economic History* 49(1): 1–16.

Atkinson, A.B. and Stiglitz, J.E. (1969) A new view of technological change. *The Economic Journal* 79(315): 573–578.

Bakker, G., Crafts, N.F.R. and Woltjer, P.J. (2019) The sources of growth in a techonologically progressive economy: the United States, 1899–1941. *The Economic Journal* 129(622): 2267–2294.

Barro, R.J. and Lee, J.-W. (2013) A new data set of educational attainment in the world, 1950–2010. *Journal of Development Economics* 104: 184–198.

Lee, J.-W. and Lee, H. (2016) Human capital in the long run. *Journal of Development Economics* 122: 147–169.

Basu, S. and Weil, D.N. (1998) Appropriate technology and growth. *The Quarterly Journal of Economics* 113(4): 1025–1054.

Bergeaud, A., Cette, G. and Lecat, R. (2016) Productivity trends in advanced countries between 1890 and 2012. *Review of Income and Wealth* 62(3): 420–444.

Bloom, N., Sadun, R. and van Reenen, J. (2017) *Management as a technology*? NBER Working Paper No. 22327. Retrieved from: https://www.nber.org/papers/w22327.pdf [accessed on 25 January, 2020].

Bolt, J., Inklaar, R., de Jong, H. and van Zanden, J.L. (2018) *Rebasing 'Maddison': new income comparisons and the shape of long-run economic development*. Groningen Growth and Development Center Research Memoranda Nr. 174. Retrieved from: https://www.rug.nl/ggdc/html_publications/memorandum/gd174.pdf [accessed on 24 January, 2020].

Bolt, J. and van Zanden, J.L. (2014) The Maddison project: collaborative research on historical national accounts. *The Economic History Review* 67(3): 627–651.

Bosworth, B.P. and Collins, S.M. (2003) The empirics of growth: an update. *Brookings Papers on Economic Activity* 2: 113–206.

Caselli, F. (2005) Accounting for cross-country income differences. In P. Aghion & S. N. Durlauf (eds.), *Handbook of Economic Growth*, Vol. 1A (pp. 679–741). Amsterdam: Elsevier.

Caselli, F. and Wilson, D.J. (2004) Importing technology. *Journal of Monetary Economics* 51(1): 1–32.

Chen, W. (2018) Cross-country income differences revisited: accounting for the role of intangible capital. *Review of Income and Wealth* 64(3): 626–648.

Cohen, D. and Leker, L. (2014) *Health and education: another look with the proper data*. CEPR Discussion Paper no. DP9940. Retrieved from: https://cepr.org/active/publications/discussion_papers/dp.php?dpno=9940 [accessed on 25 January, 2020].

Comin, D. and Mestieri, M. (2018) If technology has arrived everywhere, why has income diverged? *American Economic Journal: Macroeconomics* 10(3): 137–178.

Corrado, C., Hulten, C. and Sichel, D. (2009) Intangible capital and U.S. economic growth. *Review of Income and Wealth* 55(3): 661–685.

Crafts, N.F.R. and O'Rourke, K.H. (2014) Twentieth century growth. In P. Aghion & S. N. Durlauf (eds.), *Handbook of Economic Growth*, Vol. 2A (pp. 263–346). Amsterdam: Elsevier.

Crafts, N.F.R. and Woltjer, P.J. (2020) Growth accounting in economic history: findings, lessons and new directions. *Journal of Economic Surveys*. https://doi.org/10.1111/joes.123 48.

Deaton, A. and Aten, B. (2017) Trying to understand the PPPs in ICP 2011: why are the results so different? *American Economic Journal: Macroeconomics* 9(1): 243–264.

Deaton, A. and Heston, A. (2010) Understanding PPPs and PPP-based national accounts. *American Economic Journal: Macroeconomics* 2(4): 1–35.

Eaton, J. and Kortum, S. (2001) Trade in capital goods. *European Economic Review* 45(7): 1195–1235.

Feenstra, R.C., Inklaar, R. and Timmer, M.P. (2015) The next generation of the Penn world table. *American Economic Review* 105(10): 3150–3182.

Freeman, D., Inklaar, R. and Diewert, W.E. (2020) Natural resources and missing inputs in international productivity comparisons. *Review of Income and Wealth*. https://doi.org/10.1111/roiw.12451

Gallardo-Albarrán, D. (2018) Health and economic development since 1900. *Economics & Human Biology* 31: 228–237.

Gollin, D., Lagakos, D. and Waugh, M.E. (2014) The agricultural productivity gap. *The Quarterly Journal of Economics* 129(2): 939–993.

Gordon, R.J. (2016) *The Rise and Fall of American Growth: The U.S. Standard of Living since the Civil War*. Princeton: Princeton University Press.

Hall, R.E. and Jones, C.I. (1999) Why do some countries produce so much more output per worker than others? *The Quarterly Journal of Economics* 114(1): 83–116.

Hsieh, C.-T. (2002) What explains the industrial revolution in East Asia? Evidence from the factor markets. *American Economic Review* 92(3): 502–526.

Hsieh, C.-T. and Klenow, P.J. (2009) Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics* 124(4): 1403–1448.

Hsieh, C.-T. and Klenow, P.J. (2010) Development accounting. *American Economic Journal: Macroeconomics* 2(1): 207–223.

Inklaar, R. (2010) The sensitivity of capital services measurement: measure all assets and the cost of capital. *Review of Income and Wealth* 56(2): 389–412.

Inklaar, R., de Jong, H. and Gouma, R. (2011) Did technology shocks drive the great depression? Explaining cyclical productivity movements in US manufacturing, 1919–1939. *The Journal of Economic History* 71(4): 827–858.

Inklaar, R., Lashitew, A.A. and Timmer, M.P. (2017) The role of resource misallocation in cross-country differences in manufacturing productivity. *Macroeconomic Dynamics* 21(3): 733–756.

Inklaar, R., Woltjer, P.J. and Gallardo-Albarrán, D. (2019) The composition of capital and cross-country productivity comparisons. *International Productivity Monitor* 36(Spring): 34–52.

Jerzmanowsky, M. (2007) Total factor productivity differences: appropriate technology vs. efficiency. *European Economic Review* 51(8): 2080–2110.

Jones, C.I. (2016) The facts of economic growth. In J. B. Taylor & H. Uhlig (eds.), *Handbook of Macroeconomics*, Vol. 2A (pp. 3–69). Amsterdam: Elsevier.

Kaldor, N. (1961) Capital accumulation and economic growth. In D. C. Hague (ed.), *The theory of capital* (pp. 177–222). London: Palgrave Macmillan.

Klenow, P.J. and Rodríguez-Clare, A. (1997) The neoclassical revival in growth economics: has it gone too far? In B. S. Bernanke & J. Rotemberg (eds.), *NBER Macroeconomics Annual 1997, volume 12* (pp. 73–114). Cambridge: MIT Press.

Kumar, S. and Russell, R.R. (2002) Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence. *American Economic Review* 92(3): 527–548.

Lagakos, D., Moll, B., Porzio, T., Qian, N. and Schoellman, T. (2018) Life-cycle wage growth across countries. *Journal of Political Economy* 126(2): 797–849.

Lee, J.-W. and Lee, H. (2016) Human capital in the long run. *Journal of Development Economics* 122: 147–169.

Maddison, A. (2006) *The World Economy: A Millennial Perspective*. Paris: OECD.

Maddison, A. and Wu, H.X. (2008) Measuring China's economic performance. *World Economics* 9(2): 13–44.

Madsen, J.B. and Farhadi, M. (2018) International technology spillovers and growth over the past 142 years: the role of genetic proximity. *Economica* 85(338): 329–359.

Odagiri, H. and Goto, A. (1996) *Technology and Industrial Development in Japan*. Oxford: Oxford University Press.

Òscar, J., Knoll, K., Kuvshinov, D., Schularick, M. and Taylor, A.M. (2019) The rate of return on everything, 1870–2015. *The Quarterly Journal of Economics* 134(3): 1225–1298.

Prados de la Escosura, L. (2015) World human development: 1870–2007. *Review of Income and Wealth* 61(2): 220–247.

Prados de la Escosura, L. and Roses, J.R. (2010) Capital accumulation in the long run: the case of Spain, 1850–2000. *Research in Economic History* 27: 141–200.

Pritchett, L. (1997) Divergence, big time. *The Journal of Economic Perspectives* 11(3): 3–17.

Rao, P.D.S., Rambaldi, A. and Doran, H. (2010) Extrapolation of purchasing power parities using multiple benchmarks and auxiliary information: a new approach. *Review of Income and Wealth* 56(1): S59-S98.

Restuccia, D. and Vandenbroucke, G. (2013) The evolution of education: a macroeconomic analysis. *International Economic Review* 54(3): 915–936.

Rodrik, D. (2013) Unconditional convergence in manufacturing. *The Quarterly Journal of Economics* 128(1): 165–204.

Rodrik, D. (2016) Premature deindustrialization. *Journal of Economic Growth* 21(1): 1–33.

Timmer, M.P. and Los, B. (2005) The 'appropriate technology' explanation of productivity growth differentials: an empirical approach. *Journal of Development Economics* 77(2): 517–531.

Timmer, M.P., Veenstra, J. and Woltjer, P.J. (2016) The Yankees of Europe? A new view on technology and productivity in German manufacturing in the early twentieth century. *The Journal of Economic History* 76(3): 874–908.

van Ark, B. and de Jong, H. (1996) Accounting for economic growth in the Netherlands since 1913. *Economic and Social History in the Netherlands* 7: 199–242.

Weil, D.N. (2007) Accounting for the effect of health on economic growth. *The Quarterly Journal of Economics* 122(3): 1265–1306.

Wolcott, S. and Clark, G. (1999) Why nations fail: managerial decisions and performance in Indian cotton textiles, 1890–1938. *The Journal of Economic History* 59(2): 397–423.

Young, A. (1995) The tyranny of numbers: confronting the statistical realities of the East Asian growth experience. *The Quarterly Journal of Economics* 110(3): 641–680.

Ziebarth, N.L. (2013) Are China and India backward? Evidence from the 19th century U.S. census of manufactures. *Review of Economic Dynamics* 16(1): 86–99.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A. Supplementary material
Appendix B. Dataset construction