Convergence or Divergence?

A Cross-Country Analysis with Updated Data

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Abstract

By replicating earlier research in convergence theory, this thesis is seen as complement by applying updated data to different approaches. I will present the results by Baumol (1986), De Long (1988), Barro (1991) and Pritchett (1997) to see if their results are robust to new revisions of the data.

Baumol introduced a univariate growth regression and found a pattern of convergence for 16 advanced economies, which provided evidence of growth convergence in a unconditional manner. The updated data contain a larger time and country coverage, and by running the same regression I find no evidence in the data of effects of GDP per capita on growth.

Due to issues of selection bias and a concern with measurement error in the GDP estimates in the data, De Long analysed different magnitudes of such measurement error. Using his framework, I found that allowing for errors in the estimates created a positive and significant effect of GDP per capita on growth. Baumol did not account for such error, which created a downward bias in his original results that favoured convergence. If allowing for estimate errors, then there is no evidence of convergence in the new data. This is supported by Pritchett, who introduces a method to construct new income distributions. I find that such an approach provides evidence of increased cross-country income variations in the last 100 years.

Assuming a univariate specification, might result in omitting different country-specific or time-variant effects. In a conditional sense, controlling for human capital in a cross-sectional regression provides positive and statistically significant effects of human capital on growth. This coincide with Barro's findings that convergence is conditional. It also strengthens the idea that Baumol's regression and findings are unsatisfactory in generalising growth patterns across countries.

Preface

I found working on this thesis both inspiring and instructive. After enrolling in the 5-year program in economics at the University of Oslo, I have been able to put to use acquired insight from over the years. I feel that working on this thesis has helped me to improve my interest and understanding in this particular field in social sciences.

After a semester studying abroad, I gained increased interest for development economics. The background for this thesis is a lecture held at the university by Debraj Ray in March 2015. He talked about the theory of convergence and discussed two views of underdevelopment. I express my gratitude towards my supervisor Andreas Müller, who suggested that the topic of Ray's lecture could have reference for the thesis. His contribution to the thesis has been invaluable, providing me with insight and suggestions. He has always offered his assistance when needed.

I would also like thank my fellow students for a great time at the university, making the time here more enjoyable. I feel grateful for all the valuable help and support with regard to the thesis, either directly through comments or indirectly through moral support. An extra thank you is handed; Stian, Eyo, Jens, Silje, Mats and Eirik for their much appreciated comments.

The estimation of the models in this thesis is performed in STATA. Any inaccuracies and errors that might occur, I am solely responsible for. In case the reader would like to validate my results; data and do-files applied are available upon request.

Oslo, May 2016
Sindre Eilertsen

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1 Introduction

Looking at the richest economies in the world, we see a steady growth in GDP per capita over the last 150 years. In the pre-modern era humans lived simple and relied on hunting and agriculture for subsistence. Living standards were fairly stable for thousands of years until the modern economic era in the 19^{th}-century (Jones, 2015). Modern theories regarding economic growth, such as Solow (1956) and Romer (1990) seek to analyse the rapid growth over the last two centuries. Growth models enables us to analyse the transition from that stagnant pre-modern living to today's modern era. An important assumption in many growth models is Malthusian diminishing returns. In a simple example of an economy with a fixed supply of land, larger populations occupying that land will lead to a reduction in marginal productivity of labour. For constant levels of technological progress, this reduction in marginal productivity will reduce living standards. In combination with a subsistence level of consumption, everything ties down to the fact that better technology can support larger populations.

In the seminal contribution by Solow (1956), the emphasis of average growth relies on the concept of diminishing returns. In other words, an increase in capital increases output, but the marginal effect is diminishing. He argues that by saving a fraction of the countries output, then the capital stock will increase. A central idea is that capital accumulation, enables countries to reach an equilibrium, or a steady-state. This is a stable state, due to the fact which the rate of new investment in capital is equal to the depreciation of existing capital. If a group of otherwise similar countries have different levels of capital per labour, then these countries should converge to the same steady-state level. The idea is that countries with lower levels of capital, being further from their steady state, is expected to grow faster than those closer to the steady-state. In a basic Solow model unconditional convergence is predicted. Empirically, this was the case for Germany and Japan after World War II. Subsequently, they grew faster than any other industrialised country in the immediate post-war period. The Solow model and other similar growth models are often baseline models for empirical analysis.

The theory of unconditional convergence is tested empirically by Baumol (1986). He performed a univariate growth regression and analysed real per capita incomes from 1870 to 1979 for 16 industrialised countries. He found that there has been growth in productivity, gross domestic product per capita, and exports. In this thesis, I will replicate the analysis by Baumol, and complement these findings with other important work, such as De Long (1988), Barro (1991) and Pritchett (1997). Their research are of importance due to their critique of Baumol's initial results.

The scope of the thesis is to investigate whether their results are robust to recent revisions to the data. By applying the same methodology, I will try to find evidence of convergence across countries. Baumol's univariate growth regression is the baseline reference for this thesis. The former growth research suffers from issues of unreliable cross-country data coverage and time horizons, when applying theory to empirical data. Debraj Ray (1998) discuss the difficulty in finding reliable estimates stretching back more than a century. This problem has introduced a trade-off between longer time horizons with less reliable data coverage, or shorter and more recent analysis with larger cross-country data. Full data coverage on GDP per capita estimates for the developing world are not sufficiently detailed before 1950 (Bolt & van Zanden, 2014).

In line with the discussion of conditional convergence by Barro (1991), I expand my baseline regression and include controls for human capital. I will also complement my findings, with regard to convergence, with a development accounting exercise. This exercise seeks to assess the relative contribution of differences in factor quantities, such as capital intensity and human capital, and differences in productivity, to differences in income per worker across countries. The development accounting exercise will follow the research of Hall & Jones (1999) and Caselli (2005).

The structure of the thesis will be the following. Section 2 will provide some short background literature. In Section 3, I will present my data and provide a comparison to the data used by the other researchers. Section 4 will contain the results from the replication analysis. In this section I will also introduce the methodology of each replication. Section 5 will provide a more in-depth discussion of my results. Section 6 will contain the simple development accounting exercise and a discussion of that exercise is given in Section 7. In Section 8 I will provdie some concluding remarks. References of literature and the appendix are provided in Section 9 and 10, respectively.

2 Background literature

2.1 Convergence analysis

Baumol (1986) finds it difficult to dismiss the fact which forces accelerating the growth of nations that were latecomers to industrialisation, give rise to a long-run tendency towards convergence of levels in such per capita factors. This is shown in a simple univariate growth regression and he finds a high inverse correlation between the growth rate and GDP per work hour in 1870. Such results underlines the fact that the higher a country's productivity levels were in 1870 the slower they grew in the following century.

Even though Baumol (1986) finds evidence suggesting convergence for 16 industrial countries, he finds it difficult to draw collective inference. Using data on 72 countries for a 30-year period from 1950 to 1980, he is able to strengthen his analysis on GDP per capita growth. For the full sample case he finds no evidence of convergence, but by grouping countries he argues that the 16 industrialised countries in his initial regression is not the only group that have converged; suggesting more than one convergence club.

De Long (1988) agrees with Baumol only to some degree. De Long does not fully believe in Baumol's argument that since the 16 industrialised countries converged, then every country once they acquire a foundation of technological literacy will follow this pattern. His main critique is that Baumol use an ex post sample of countries that have already successfully converged.

"*Convergence is thus all but guaranteed in Baumol's regression, which tells us little about the strength of the forces making convergence among nations in 1870 belonged to what Baumol calls the "convergence club".*" (De Long, 1988:1139).

He makes stronghold of the fact that Maddison in his data has excluded those countries that have not yet converged, which biases Baumol's results. If instead a regression ran on a ex ante sample of countries that in 1870 seemed likely to converge, then and only then, a conclusion of convergence can be inferred. De Long finds no such evidence.

As stated earlier and discussed in great detail in Bolt & van Zanden (2014), there are unsatisfactory historical data for many of the less developed economies, due to the lack of infrastructure to provide precise estimates. Pritchett (1997) introduced a method simply placing a reasonable lower bound on what GDP per capita could have been in 1870 for any economy. The argument is that if such a lower bound can be found, then one can draw reliable conclusions about the historical growth rates and convergence in the cross-country distribution of income levels. He argues for a lower bound of $250 per capita by introducing some criteria. The current estimates of relative incomes and the historical estimates of incomes for the poorest economies cannot be below the lower-bound threshold of $250 per capita at any point. If so is the case, then Pritchett reaches the conclusion that in the last 150 years there is evidence of divergence.

Robert Barro (1991) also find inconsistent evidence of cross-country convergence. He analyses 98 countries over the period from 1960 to 1985, and finds a positive correlation between growth and income in 1960. He argues that poorer countries tend to catch up with richer countries if the poorer countries have a high level of human capital per capita, relative to per capita GDP. He controls other different factors and finds that political instability are inversely related to growth, while there is also a lot of unexplained results for the relatively weak growth performance of countries in sub-Saharan Africa and Latin America. Barro & Sala-i-Martin (1992) put even stronger emphasis on conditional convergence and discuss the fact that in a neoclassical growth model, the balanced growth path will depend on technology parameters which might differ across countries. This would force convergence to be conditional on such parameters.

"*Thus, poor countries tend to catch up with rich countries if the poor countries have high human capital per person (in relation to their level of per capita GDP), but not otherwise.*" (Barro, 1991:437).

2.2 Development Accounting

The aim of a development accounting exercise is to analyse cross-country data on output and inputs at one point in time (Caselli, 2005:681). Caselli (2005) tries to find out whether or not observed differences in the factors employed in production explain most of the cross-country income variations. He concludes with no. This is justified by improving the measurement of human capital; allowing for differences in the quality of schooling and in the health status of the population. He also takes into account the age composition of the capital stock and sectoral disaggregation of output. He finds that the observed factors employed in production only explain 39% of total production. Hall & Jones (1999) reaches a similar conclusion. They argue that the large variation in output per worker across countries are only partially explained by the differences in physical and human capital.

Other work on the matter, like Hsieh & Klenow (2010), reaches the conclusion that human capital accounts for 10-30%, 20% is due to physical capital, and residual total factor productivity, being the most important factor, accounts for around 50-70% of cross-country income differences. Córdoba & Ripoll (2009) show that a standard one-sector accounting exercise will introduce a systematic bias in estimating total factor productivity levels, meaning that the estimates by Hsieh & Klenow are somewhat unreliable. They find evidence that this bias is larger in poorer economies, which indicates that poorer countries are not well represented in development accounting exercises.

Using estimated experience-wage profiles, Lagakos et. al. (2012) show that human capital due to experience is positively correlated with income and cross-country dispersion, in a similar magnitude as the dispersion of human capital due to schooling. By combining experience and a measure for the level of schooling as a proxy for human capital, they find that physical and human capital account for around 60% of income differences, which is a 20% increase compared to Caselli. These findings can enable us to understand the different forces behind income differences across countries. Most of the literature provide strong evidence suggesting that unexplained factor productivity is the main factor in accounting for such income differences.

3 Data

In the following subsections, I will present the data sources that I will use in each replication in this thesis. I will also provide a general and short introduction to the data used by the authors I am replicating. I find it important to stress the fact that I use different versions of the data in every replication, compared to them. This structure is the same for all of my data sources; Maddison data, Penn World Tables, Barro & Lee data, and World Development Indicators.

3.1 Maddison data

Angus Maddison have had a huge impact on collecting estimates of GDP for as many countries as possible in a historical context. The data published in "Phases of Capitalist Development" in 1982 is a contribution to empirical study of long-term economic movements. He reported estimates of economic aggregates for 16 major capitalist countries in 1820-1980. In March 2010 the Maddison Project was launched with the aim to find an effective way of cooperation between scholars, and to increase the data coverage of historical GDP estimates even further. The most recent update and the main data source in this thesis is the the newest version from January 2013.

The 2013 revision of the data provide estimates on GDP per capita, while estimates for productivity and volume of exports are no longer presented. Bolt & van Zanden (2014) discuss the extension in coverage and problems with the precision of the estimates. This revision has included an extension for many European countries in the pre-1850 period, while eastern European countries still miss data coverage before 1950. Australia and USA have full coverage in 19^{th}-century. The data provide estimates for the rest of Oceania from 1870 and also eight Latin American countries have data reported in 1870. The rest of the Americas have full data coverage from 1920. East and West Asia have full country coverage from 1950, while countries in the former USSR and Middle Asia lack estimates before 1990. Countries from the African continent have sufficient coverage from 1950.

I am able to use estimates for 65 countries in a period from 1870 to 2008, while there are 163 countries available in 2008. The full country coverage is presented in Table A1-A4 in the appendix. My sample ends in 2008, even though the data is reported all the way to 2010, due 43 countries missing estimates for 2009 and 2010. The estimates are calculated in 1990 international dollars.

Baumol (1986)

Baumol (1986) bases his analysis of convergence of economic growth using the 1982 Maddison data. Baumol analyse a sample of 16 countries over a from 1870 to 1979. The estimates are calculated in 1970 international dollars.

De Long (1988)

De Long (1988) also use the 1982 Maddison data, but he analyses estimates of GDP per capita in both 1870-1979 and 1913-1970. He includes, compared to Baumol, Ireland, Argentina, Chile, East Germany, New Zealand, Portugal and Spain (De Long, 1988:Table A4).

Pritchett (1997)

In his attempt to calculate credible 1870 GDP per capita estimates, Pritchett's historical data analysis is mostly based on 1995 Maddison data. His data report GDP per capita estimates for 56 countries over a period from 1820 to 1992. The estimates are calculated in 1990 international dollars.

3.2 Penn World Tables

The Penn World Tables (PWT) provide a thorough source for real national accounts data, which is adjusted for a common currency across countries, namely U.S. dollars. It has for over four decades been one of the main sources for yearly cross-country data on real GDP. The first version of of PWT was constructed by Robert Summers and Alan Heston from University of Pennsylvania in 1988, in cooperation with Irving Kravis. The PWT database includes information on relative levels of output, inputs and productivity for different countries and year coverage. The most recent version is PWT8.1, which was published in April 2015. This data set provide estimates on 143 countries in 1970 and 167 countries in 2010. The estimates of interest in this data is given in current PPPs, 2005US$ millions.

PWT version 8.1 will be the main source in the replication analysis of Barro (1991), and also in the development accounting exercise. To increase precision, real GDP estimates have been separated to distinguish between the expenditure side and the productivity side of an economy. Countries with strong terms of trade will have higher real GDP on the expenditure side as a result. The real GDP per capita estimate will be an average of the two real GDP estimates. These estimates are provided to analyse the data across countries and time. Because of combining data sets, I will only be able to analyse 17-115 countries. These countries are presented in in Table A5 and A6 in the appendix.

In the development accounting exercise, I will collect estimates for output, capital and the labour force. PWT8.1 does not provide a capital stock estimate that is good in comparing across both country and time, so my real GDP per capita estimate in this exercise is distinguished from the estimate in the Barro replication. Output is still calculated as the average of the expenditure side and productivity side, but for a single point in time. I will, as Caselli (2005), not correct for inputs such as revenues from resources as oil. If we correct for oil, then other revenues from other resources should be excluded as well. I will analyse 132 countries in 1985, 1995 and 2010, which is presented in Table A7 in the appendix.

Baumol (1986)

To discuss the possibility of convergence clubs, Baumol uses the Summers and Heston (1984) data, or PWT version 3, analysing 72 countries. He analyses a 30-year period from 1950-1980. The estimates are calculated in 1975 international dollar price measure.

De Long (1988)

Estimates of 1979 GDP per capita used in De Long (1988) are based on the estimates from Summers and Heston (1984) - PTW version 3. He uses this data to achieve greater data coverage for 1979.

Pritchett (1997)

Pritchett (1997) analyses growth from 1960-1990 using PWT version 5. This gives him coverage of 108 developing countries, and the estimates are calculated in 1985 international dollars.

Barro (1991)

The PWT version 4, which was released in 1988 provides data on 130 countries. Barro (1991) analyses 118 countries, with an in-depth analysis of 98 countries from 1960-1985. The drop of country coverage in the in-depth analysis stems from combining other data sources, such as data on educational attainment from Barro & Lee.

Development accounting exercise

Hall & Jones (1999) collect their estimates from PWT version 5.6, which are calculated in 1985 international dollars. They analyse a set of 127 countries in 1988, where the numbers of workers are used to measure labour input. They correct for inputs such as natural resources to get as precise estimates of productivity as possible. Physical capital is calculated using investment data going back at least to 1970, and the capital stock is calculated using the first year of available investment data. The growth in the capital stock is calculated as the average geometric growth rate from 1960 to 1970 of the investment series. They assume a 6% depreciation rate.

On the other hand, Caselli (2005) uses PWT version 6.1. Where Hall & Jones (1999) look at the world income distribution of the late 1980s, Caselli is able to update the basic result to mid-90s. He analyses 94 countries in 1996, extracting output, capital, and the number of workers. Using the same method as Hall & Jones, he is able to calculate an estimate for the capital stock. In a direct comparison to my 132-country data, six of these 94 countries are missing. They are highlighted in Table A8 in the appendix.

3.3 Barro & Lee data

The Barro-Lee data provides estimates from 1950 to 2010 in 5-year intervals. I will use the most recent update from February 2016. It contains data on educational attainment of the adult population over age 25 for 146 countries. It is grouped into seven classes of schooling, being: no formal education, incomplete primary, complete primary, lower secondary, upper secondary, incomplete tertiary, and complete tertiary. The Barro-Lee data also provide estimates of average years of schooling at all the levels. This variable is of importance in the development accounting exercise.

In replicating Barro (1991), my focus will be on the complete primary and secondary level groups; creating variables for the enrolment ratio for these two groups. My year of focus will be in 1970, in which the data cover 115 countries.

For the development accounting exercise, I will use the average year of schooling for the population aged 25 and over in 2010, to estimate the effect of human capital. I will explain this in detail in Section 6.1.1.

Barro (1991)

In analysing the effect of human capital on economic growth, Barro (1991) introduces two proxies for human capital; school enrolment rates and student-teacher ratios at the primary and secondary level in 1960. These estimates are from the data by Barro & Wolf (1989) and contain 98 countries.

Development accounting exercise

In Hall & Jones (1999) the data on educational attainment is measured in 1985 for the population aged 25 and over using the 1993 Barro & Lee data. The measure for human capital is constructed using a function, $\phi(E)$, which is piecewise linear and following survey evidence from Psacharopoulos (1994). Caselli (2005) uses the same approach as Hall & Jones, but with the 2001 Barro & Lee data.

3.4 World Development Indicators

The World Development Indicators (WDI) is a collection of development indicators compiled from official and secure sources published by the World Bank. It includes 214 economies and the coverage extends from 1960 to 2015. It is published together with different sources such as the Educations Statistics, UNESCO Institute for Statistics, African Development Indicators, Health Nutrition and Population Statistics.

In my replication of Barro (1991), I will focus on student-teacher ratios at primary and secondary level with 1970 as the year of interest. This data does not provide sufficient coverage; only sporadic estimates across countries and years. I will not spend too much thought on these estimates, due to the lack of data. The variable for student-teacher ratio at primary level in 1970 provide only estimates for 26 countries, while the student-teacher variable at secondary level contains 17 countries. These countries are displayed in Table A6 in the appendix.

Barro (1991)

Barro (1991) analyses the average from 1965 to 1985 of fertility and mortality, combined with student-teacher ratios in 1960 at both primary and secondary level. He also includes a variable for adult literacy in 1960. These estimates are collected from the 1979 World Bank data, which contains data coverage in a range of 60 to 98 countries.

4 Convergence or Divergence?

In this section, I will apply different approaches to test the convergence theory. I will investigate the simple univariate regression from Baumol (1986) applying a updated cross-country data coverage, and prolong the analysis by replicating the research of De Long (1988), Pritchett (1997) and Barro (1991). For each replication, I will present the methodology specification and my results. Section 10.2 in the appendix present a more detailed explanation of variables in each replication.

4.1 Baumol replication

4.1.1 Methodology

A comparison of the country with the highest GDP per capita for 1870 and 2008 to other countries in the sample is calculated by constructing a ratio. It is the average of this ratio and its standard deviation that interests me. The development of the average ratio and its standard deviation, enables me to infer on cross-country income variation over time. The ratio is given as

$$ratio_{j,i} = \frac{GDP_j}{GDP_i} \tag{1}$$

where j represents the richest country and i is any other country, for a given year.

I will also run a univariate cross-country regression of per capita income growth. First, I will run the regression on 1870-2008 growth comparing the 16 countries from Baumol (1986) to the full sample data. By changing time periods of interest I am able to analyse larger cross-country samples. The growth regression will be ran on 1870-2008, 1950-2008, 1960-2008 and 1990-2008, in which I will compare the original 16-country sample to the full sample in each period. The growth rate is calculated using log differences between the years of interest

$$Growth_{i,x-y} = ln(\frac{GDP_{i,y}}{GDP_{i,x}})$$

An example of such a simple univariate regression is

$$Growth_{i,1870-2008} = \alpha_i + \beta \times lnGDP_{i,1870} + \epsilon_i \tag{2}$$

where I analyse 1870-2008 growth. This regression is the baseline regression of this thesis. α_i is a constant included in the regression, β is the coefficient for the logarithm of GDP per capita for country i in 1870, and ϵ_i is the disturbance term in the regression.

4.1.2 Results: Cross-country income variation

In 1870 Australia is estimated to have had the highest GDP per capita, while Japan was reported to have had the lowest. When applying Equation (1), we can see from Table C1 in the appendix, that Australia's GDP per capita in 1870 was 4.4 times larger than Japan's, 2.1 as large as Italy's and 1.3 times as large as United States'. For the full sample of 67 countries in 1870, New Zealand is now among the top five richest countries with a reported GDP per capita fairly close to Australia's. There is also evidence of changes in the rankings of countries in the income distribution, which can be seen in Table C2 in the appendix. None of the initial 16 countries were actually among the five poorest countries in 1870. North and South Korea, together with Nepal, had the three lowest GDP per capita estimates in the full sample. In comparison to Australia, the ratio show that the Australian economy was 9.7 times larger than North and South Korea and 8.2 times larger than Nepal, in 1870.

Table 1: Average ratio for 1870 and 2008

	1870		2008	
	(1)	(2)	(3)	(4)
	16-sample	Full-sample	16-sample	Full-sample
Mean	1.9	4.1	1.3	13.5
Standard deviation	0.9	2.1	0.1	17.4
Number of countries	16	65	16	163

The average of the 1870 ratio, as presented in Table 1, show that in the 16-country sample Australia was on average 1.9 times larger than any other country, with a reported standard deviation of 0.9. A smaller standard deviation implies a lower income variation across countries, or in other words a more equal cross-country income distribution. This indicates that the 16 countries that Baumol analysed actually did not differ that much in 1870. In comparison to the full sample, the average ratio increased to 4.1. There is also an increase in the standard deviation of the full sample as well, clearly indicating increased income variation in 1870 compared to the original assessment.

By evaluating 2008, we see a clear development in the average ratio of cross-country incomes. In Table C3 in the appendix, United States was reported to have the largest economy in 2008. In the 16-country sample, Italy had the lowest. It is worth noticing that Japan almost caught up with Australia, who in 2008 was only the fifth richest country in per capita terms. In the full sample analysis, Hong Kong and Singapore are among the five richest countries. This is due to experiencing heavy growth post World War II. Meanwhile, countries from the African continent are heavily represented among the poorest countries. In 2008 the US had a GDP per capita 126 and 65 times bigger than Congo-Kinshasa and Burundi, respectively, being the two poorest countries in 2008.

There is a reduction in the sample average in the 16-country sample compared to 1870. The average ratio is 1.3 in 2008, which is a reduction in the ratio of 0.6 compared to the 1870. There is also a reduction in the standard deviation, now being 0.1. The income distribution for the 16 countries has shown to be more narrow in 2008 compared to 1870. This implies that the poorer countries, among the 16 in 1870, has caught up with the richer countries in this 138 year period.

In the full sample analysis for 2008, the average ratio has increased drastically compared to 1870, now being 13.4. The standard deviation of this average, which is 17.3, show that there has been a large increase in cross-country income variation from 1870 to 2008. Due to differences in sample sizes, it is difficult to compare these averages directly. But they provide evidence suggesting that the original 16 Baumol countries were fairly similar in 1870 and have all converged. A generalisation on the 16 Baumol countries might therefore not be constructive.

4.1.3 Results: β - convergence

Table 2: 1870-2008 growth: 16-country sample vs Full sample

	(1) 1870-1979 Baumol (1986)	(2) 1870-2008 growth	(3) 1870-2008 growth	(4) 1870-2008 growth
lngdp1870	-0.996***	-0.931***	-0.199	0.052
	(0.09)	(0.05)	(0.15)	(0.14)
Constant	8.457***	9.583***	3.843***	1.923*
	(-)	(0.35)	(1.11)	(0.98)
R^2	0.880	0.925	0.063	0.001
N	16	16	29	65

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Are there any tendencies in the data augmenting that poorer countries actually grow faster than richer countries? A negative sign of β in the univariate cross-country regression, is commonly referred to as β-convergence. If so is the case then this would provide evidence that countries at lower initial income levels grow faster. The 1870-2008 growth regression analysing both the 16-country sample and a full sample, is presented in Table 2. The results from Baumol (1986) are presented in Column 1, while the results from the updated data are presented in Column 2-4.

By running the regression on the same 16-country sample as Baumol, a direct comparison of the development for these countries for larger time periods, are possible. This is displayed in Column 2. In the full sample regression, there is a distinction between two full samples. This comes from the fact that only 29 countries in the sample actually contain a full time-series coverage from 1870 to 2008. The additional 38 countries, shown in Column 4, has estimates only sporadically presented between 1870 and 2008. Again, I refer to Table A1 in the appendix for greater details regarding the countries in the different samples.

A slope coefficient of -1 would provide evidence that the countries analysed have similar levels of factors affecting growth, which would prove the unconditional convergence theory. Baumol found an estimate of -0.995, while my results does not differ that much when analysing the same 16 countries. Even though my time coverage is wider, I find a coefficient which is relatively close (-0.931). This coefficient is also statistically significantly different from zero at a 1% level. A 1% increase in GDP per capita in 1870 would on average reduce 1870-2008 growth by 0.931%, in the 16-country sample. This result coincide with the findings from the development in variation in incomes in the 16-country sample case. This proves that the poorest countries in Baumol's sample grew faster on average than the richer countries.

In the full sample my results differ. A loss of statistical significance occurs in the full sample. We also see increased standard errors of the coefficient. There is a large reduction in R^2 as well. The increase in the coefficient, in combination with larger standard errors unables us to conclude with any significant effect of 1870 GDP per capita on growth.

4.1.4 Results: Shorter time periods, more countries

Table 3: Growth: 16-country sample; Different time periods

	(1) 1870-2008 growth	(2) 1950-2008 growth	(3) 1960-2008 growth	(4) 1990-2008 growth
lngdp1870	-0.931***			
	(0.05)			
lngdp1950		-0.822***		
		(0.06)		
lngdp1960			-0.761***	
			(0.09)	
lngdp1990				-0.258
				(0.22)
Constant	9.583***	8.574***	7.964***	2.830
	(0.35)	(0.54)	(0.84)	(2.16)
R^2	0.925	0.945	0.837	0.086
N	16	16	16	16

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4: Growth: Full sample analysis

	(1) 1870-2008 growth	(2) 1950-2008 growth	(3) 1960-2008 growth	(4) 1990-2008 growth
lngdp1870	-0.199			
	(0.15)			
lngdp1950		-0.015		
		(0.09)		
lngdp1960			0.007	
			(0.08)	
lngdp1990				0.041
				(0.03)
Constant	3.843***	1.176*	0.785	-0.016
	(1.11)	(0.67)	(0.61)	(0.25)
R^2	0.063	0.000	0.000	0.011
N	29	139	145	163

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

I ran the univariate cross-country regression on 1950-2008 growth, 1960-2008 growth and 1990-2008 growth as well, to increase the country coverage in the analysis. The tendency of lower time coverage in the 16-country sample regression is displayed in Table 3. The coefficient of initial income increases for each column. The new time-period regressions evaluating the effect of initial income for 1950, 1960 and 1990 on average growth, are displayed in Column 2, 3 and 4, respectively.

There is a tendency in the results that shorter time coverage dampens the absolute effect of initial income. A 1% increase in GDP per capita in 1950 is associated with a 0.8% reduction in average growth between 1950-2008. This effect drops marginally for the 1960-2008 growth regression. Both of these coefficients are statistically significantly different from zero, while in the case of 1990-2008 growth inference on the initial effect of 1990 per capita GDP is no longer constructive. This is due to loss of significance. These results do suggest that shorter time coverage affects the β-coefficient in the 16-country sample, mostly leading to a smaller relative effect of initial GDP per capita on growth.

In the full sample analysis in Table 4, the largest country and time coverage is estimated. Interestingly, we are unable to conclude with any significance of initial income on growth, in either time specification. By comparing Table 3 and 4 directly, we see a large drop in R^2 for the full sample analysis. We also see that in the full sample regressions the standard errors have increased in relative magnitude. By keeping the same specification in the univariate regression, while only changing the data coverage across country and time, we might ignore both country-specific and time-variant effects.

When applying an updated data with a larger cross-country sample, these results show that the univariate growth regression performs poorly. The relatively larger standard errors and drop of R^2 might come from changes in the behaviour of the unexplained residuals in the regression. But, it strengthens the point that the initial 16 countries that Baumol analysed actually did not differ that much.

4.2 De Long (1988) replication

When applying the updated data, I find no evidence in the full sample regression of any statistical significant effect of initial GDP per capita on growth. This corresponds to De Long's main argument in his critique of Baumol. He argued that the sample of countries, ex post, showed that those 16 countries had already converged, which in turn provided biased results. Instead, an ex ante sample should be considered. This is in fact what I did in the previous section, which strengthens De Long's argument. De Long (1988) also made a point out of the fact that the 1870 GDP per capita estimates, presented in the data, were measured with error. To account for this error he introduced a method, with the aim of correcting for this bias. In this section, I will again run the univariate growth regression applying his his method.

4.2.1 Methodology

De Long argues that the measurement error in the 1870 income estimate increases the variance of the regression, which would force a pattern of convergence. De Long modified Baumol's original model, to correct for this bias. The new and modified model is

$$Growth_{i,1870-2008} = \alpha_i + \beta \times lnGDP^{True}_{i,1870} + \epsilon_i \tag{3}$$

$$GDP^{Estimated}_{i,1870} = GDP^{True}_{i,1870} + \eta_i \tag{4}$$

where we in Equation (4) we see how the measurement error, η_i, is taken into account. Instead of running the regression on estimated GDP per capita, but rather on the "true value", the argument is that it will provide more accurate coefficients and therefore lower the bias in the regression.

We are unable to know the magnitude of such measurement error. It is also problematic to find an instrument that could increase the precision of the estimated GDP per capita. De Long's approach is to correct for this error by constructing a ratio of the variances of the two disturbance terms. There is, however, a catch to this approach. To get an identified system of equations, we have to assume that ϵ_i and η_i are uncorrelated. If so, then system of equations are identified. The ratio of the variances is

$$\rho = (\frac{\sigma_\eta^2}{\sigma_\epsilon^2}) \tag{5}$$

By fixing different values for ρ we are able to manipulate the magnitude of measurement error. In the case were ρ is equal to zero, the measurement error disappears and we are back to the initial univariate regression in Equation (2). Larger ρ's implies either a larger variance of the measurement error, or lower variance in the disturbance of the regression. This method is not introduced to calculate more "true" GDP per capita estimates, but rather to give increased focus to the manner in which measurement error in the estimates might occur. For fixed values of ρ, we can solve the system of equations, (3), (4) and (5), using

$$\hat{x}_i = \frac{(1 + \rho + \rho\hat{\beta})y_i + \rho(1 + \hat{\beta})g_i}{1 + \rho(1 + \hat{\beta})^2} \tag{6}$$

$$\hat{\beta} = \frac{\sum \hat{x}_i(y_i + g_i)}{\sum \hat{x}_i^2} - 1 \tag{7}$$

y_i represents the log of estimated 1870 income from and x_i represents the log of true 1870 income. g_i is the the estimated growth.

Table 5: Growth: Correcting for sample bias

	(1)	(2)	(3)	(4)	(5)	(7)
	1870-1979	1870-2008	1870-2008	1950-2008	1960-2008	1990-2008
ρ	De Long (1988)	16-sample	Full sample	Full sample	Full sample	Full sample
0	-0.566***	-0.931***	-0.199	-0.015	0.007	0.043
	(0.14)	(0.07)	(0.15)	(0.07)	(0.07)	(0.03)
0.5	-0.292	-0.806***	0.165	0.207***	0.182***	0.067***
	(0.19)	(0.12)	(0.10)	(0.05)	(0.04)	(0.02)
1	0.110	-0.659***	0.253***	0.236***	0.205***	0.068***
	(0.28)	(0.15)	(0.07)	(0.03)	(0.03)	(0.02)
2	0.669	-0.396**	0.287***	0.227***	0.196***	0.062***
	(0.46)	(0.18)	(0.05)	(0.02)	(0.02)	(0.01)
∞	1.381	0.167	0.261***	0.147***	0.122***	0.036***
	(0.76)	(0.15)	(0.04)	(0.00)	(0.01)	(0.01)
N	22	16	29	139	145	160

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

This system will, by repeated calculations, enable us to construct new GDP per capita estimates that accounts for the fixed ratio.

"*When there is assumed that there are no measurement error in 1870 income, there is a large negative slope to the regression line. But even in this case the residual disturbance term is large. When measurement error variance is assumed equal to half disturbance variance, the slope is slightly but not significantly negative.*" (De Long, 1988:1145).

4.2.2 Results: Correcting for measurement error in estimates

The results of applying De Long's correction method is shown in Table 5. The first column show the results from De Long (2008) directly, while my results are presented in Column 2-7. In the case for ρ equal to zero the results are equal to Table 3 and 4. It is interesting that De Long, for ρ equal to zero, also gets a larger coefficient for 1870 GDP per capita compared to Baumol. This coincide with previous results that larger cross-country samples, for similar time periods analysed, increases the coefficient.

If we fix ρ equal to one, then the measurement error of the estimated initial GDP per capita is equal to the size of the regression disturbance. If measurement error actually exists, then our results will be biased downward. The true parameter will in such a scenario be larger, or less negative, than the estimated parameter, which implies that our previous results would favour convergence. De long finds this to be the case. By fixing ρ equal zero, his parameter is -0.566, which is more negative than the parameter found when assuming ρ equal to one (0.110).

My results confirms this trend as well. If we allow for larger measurement error in the GDP per capita estimates or lower variance in the regression disturbance, the coefficients are biased downward, if not accounted for. In the case of the polarised scenarios, ρ equal to zero and infinity, the trend in every regression is that the coefficients increase for larger ρ's. In the 16-country sample, when analysing growth between 1870 and 2008, a larger ρ increases the standard error of the coefficient. The coefficient itself also drop in absolute terms, resulting in a insignificant effect of GDP per capita in 1870 on growth.

In the full sample regression of 1870-2008 growth, the standard errors of the coefficient is reduced when allowing for measurement errors. In some sense, this provides evidence that this method increases the precision of initial

GDP per capita in 1870 on growth compared to the initial regression. The same trend in standard errors are found in the other full sample regressions as well. The coefficients, in most cases, increases for larger ρ's. We see that every coefficient in the full sample, by allowing ρ to approach infinity, provide positive and statistically significant GDP per capita coefficients.

This suggests divergence instead of convergence in the full sample, which coincide with what the results found when analysing the cross-country income variation in Section 4.1.2. In applying De Long's, I was able to manipulate the measurement error of the estimates of GDP per capita and the disturbance in the regression. If we believe in the assumption that there are no correlation between the two disturbances in Equation (3) and (4), then we would need a large ρ and a negative estimate to be assured of β-convergence. My results show no evidence of this.

4.3 Pritchett (1997) replication

Another method that focuses on the flaws of the GDP per capita estimates is a method introduced by Pritchett (1997). By assuming a lower bound (US$) for GDP per capita in any economy in 1870, he constructed a method that enabled him to generate new cross-country income distributions based on a recent income distributions that contain richer data coverage. In my analysis, I will replicate this approach by constructing a new income distribution for 1870 based on the ranking in 2008.

"*This technique "smushes" the distribution back into the smaller range between the top and bottom while maintaining all cross country rankings.*" (Pritchett, 1997:Footnote 11).

4.3.1 Methodology

The idea is to calculate estimates such that the poorest country in 2008 reached the assumed lower bound in 1870. Each country's constructed GDP per capita estimate in 1870 is assumed to be a weighted average of the poorest country compared to USA, which was the richest country in 2008. This is in line with Pritchett, who also chose USA as a reference country. The weighted average depends on a scaled distance from the poorest country to the richest in 2008. The constructed estimates for GDP per capita in 1870, based on the weighted average (w_i), is constructed as follows

$$GDP_i^{1870} = GDP_i^{2008} \times (\frac{1}{w_i}) \tag{8}$$

where the weighted average is

$$w_i = (1 - \alpha_i) \times \frac{min(GDP^{2008})}{\$LB} + \alpha_i \times \frac{GDP_{USA}^{2008}}{GDP_{USA}^{1870}} \tag{9}$$

and the scaled distance (α_i) is defined

$$\alpha_i = \frac{GDP_i^{2008} - min(GDP^{2008})}{GDP_{USA}^{2008} - min(GDP^{2008})} \tag{10}$$

This method is purely mathematical. By assuming a lower bound (LB) in Equation (9), we can create a system of equations that only contains one unknown parameter, namely GDP per capita for country i in 1870. These new estimates will be the basis in performing an analysis of the average ratio from Equation (1).

4.3.2 Results: Change in dispersion

Pritchett (1997) assumes a lower bound of \$250 per capita in 1870. He justifies it by the fact that there has never been reported a lower GDP per capita estimate in the past. He adds robustness checks to this assumption as well, which will not be discussed here. The lowest GDP per capita estimate reported in the 2013 Maddison data, is Congo in 2001. In Table C4 in the appendix, we see that Congo is reported to have had a GDP per capita of \$203. I have not taken into account any differences that might occur due to how these estimates are calculated. I refer to Section 3 to check for the differences in the data.

Instead, an inclusion of two lower bounds, \$200 and \$150, is complemented. As already mentioned in Section 4.1.2, USA had the highest income per capita (\$31251) in 2008, while Congo-Kinshasa had the lowest reported GDP per capita (\$249). Pritchett's mathematical approach enables us to convert the 2008 income distribution to 1870. In other words, Congo-Kinshasa, being the poorest country in 2008, will also be the poorest country in the newly constructed 1870 income distribution. We have 163 cross-country GDP

Table 6: 1870 values: Different lower bounds

Boundary (P$)	250	200	150
USA (P$)	2445	2445	2445
Poorest (P$)	250	200	150
Average Ratio:	1.9	2.1	2.5
Standard deviation: Ratio	1.22	1.56	2.13
N	163	163	163

per capita estimates in 2008, so this method will therefore enable us to construct as many GDP per capita estimates for 1870.

By calculating the average of the richest-to-poorest ratio in 1870, Table 6 display the results for different lower bounds. We see that for "lower" lower bounds the average ratio of GDP per capita compared to the United States increases. This comes from the fact that the constructed 1870 income estimates for USA are the same, while the estimates for Congo-Kinshasa are assumed poorer for lower bounds.

An assumed lower bound of P$200 per capita show that the US, on average, was 2.1 times larger than the other countries in the sample. We can also see an increase in the standard deviation, since assumed lower lower bounds increases the variation in the cross-country income distributions, due to the poorer being assumed even poorer.

"*The magnitude of the change in the absolute gaps in per capita incomes between rich and poor countries is staggering. From 1870 to 1990, the average absolute gap in incomes of all countries from the leader had grown by an order of magnitude, from $1,286 to $12,662, as [...]*" (Pritchett, 1997:12).

A closer look at the lower bound of P$250, even though there are reports of of lower GDP per capita estimates in the data, is produced. Pritchett (1997) compares richest-to-poorest ratios directly for different years, while I continue to analyse the average rich-to-poor ratio and report the standard deviation of that average. There is no loss in inference by doing so, since a larger rich-to-poor ratio is equivalent to a larger standard deviation of the average ratio. Both are simple constructions in explaining the development in income variation over time.

Table 7: Divergence since 1870

	(1) 1870	(2) 1960	(3) 1990	(4) 2008
USA (P$)	2445	11329	23201	31251
Poorest (P$)	250	392	434	249
	(Assumption)	(Guinea)	(Chad)	(Congo-Kinshasa)
Average Ratio	1.9	8.8	11.8	13.5
Standard deviation: Ratio	1.22	6.94	11.92	17.35
Average GDP/capita	1651	3108	5532	8206
Standard deviation: GDP/capita	623	4434	5379	8047
Number of countries	163	146	164	163

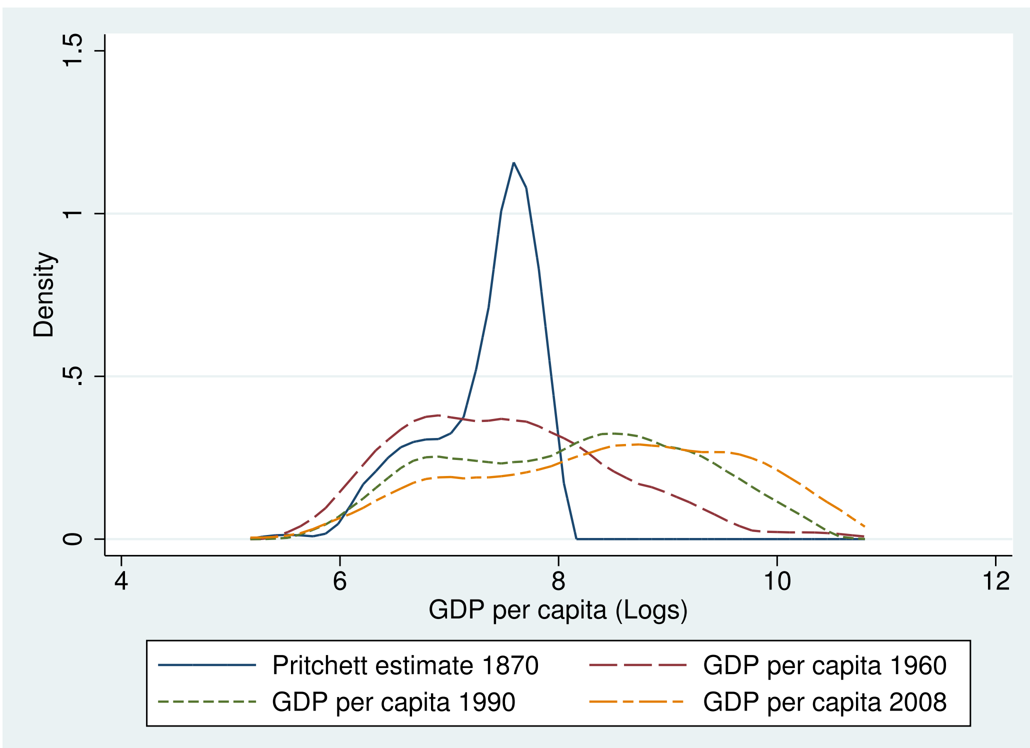

Figure 1: Kernel estimation: Income dispersion since 1870

In Table 7, 1960, 1990 and 2008 is included as years of interest and provided from the data. By assuming a lower bound of P$250 for 1870 GDP per capita, the average ratio increases closer to present day. Analysing the fixed lower bound and the constructed income distribution, we see that the average ratio is 1.9. In other words, the US was on average 1.9 times larger that any other country in my mathematically constructed sample.

Analysing the data we get that the US was on average 8.8 times larger than any other country in 1960, and 11.8 and 13.5 times larger in 1990 and 2008, respectively. There is also a trend that the standard deviation of the average ratio increases for each year of interest. In 1870 we find a standard deviation of 1.22, while there was a significant increase if comparing to 1990 and 2008. This again just proves the point that we cannot find any evidence of convergence since 1870.

Figure 1 provide a simple graphical presentation of the development in the income variation since 1870. The horizontal axis are the log of GDP per capita, while the vertical axis are the density. By smoothing the income distribution, using kernel estimation, we see a compressed and widened density for more present years. This non-parametric density estimation are performed using an Epanechnikov kernel. Any discussion regarding size of bandwidth, or the trade-off between the variance and bias created by such smoothing, will be presented in this thesis. I find it beyond the scope of the thesis. This figure is only displayed to provide a rough overview of the development in the income distribution.

We can see the clear tendency that the income dispersion in 2008 was higher, than for the other years of interest. The figure also show the income distribution going from positive to negative skewness the closer we get to present day. Compared to the distribution in 1870, we can clearly see that there are more rich countries in 2008. There is also fewer poor countries, relative to 1870, but those countries that are poor are on the other had relatively poorer. We can see an increase in the middle-income group.

4.4 Barro (1991) replication

Up until now β-convergence has tested by running a univariate cross-country regression of per capita income of growth. This specification has also been modified to account for possible presence of measurement error in the estimates in the reported data. This specification has provided us with no evidence of β-convergence for different full sample analysis. This might come from the fact that this regression ignores both country-specific and time-variant effects.

In the following section, a change in the specification is analysed, which accounts for differences in country-specific effects. The new model is not necessarily formally derived from any particular growth model, but includes other explanatory variables associated with technological progress. As suggested by Nelson and Phelps (1966), a follower country with a large human capital stock tend to grow faster because it is able to catch up with the leader. In turn, a larger stock of human capital makes it easier for countries to accumulate products and ideas invented elsewhere. In standard macroeconomics a higher level of human capital tend to lead to higher levels of investment in human and physical capital, which again leads to higher income growth.

"*A poor country tends to grow faster than a rich country, but only for a given quantity of human capital; that is, only if the poor country's human capital exceeds the amount that typically accompanies the low level of per capita income.*" (Barro, 1991:409).

Allowing for different conditioning variables, provides a test of conditional convergence. This enables us to account for some country-specific effects. The availability of different statistical data also plays an important role. It works as a sort of boundary on our conditioning. The idea is that such conditioning variables can affect technological and income gaps across countries. Such variables are typically variables of educational attainment, capital accumulation, imports of technological products, measures of institutional development, an so on.

4.4.1 Methodology

In this last part of the convergence and divergence analysis, proxies for human capital in the growth regression are included. This is in line with Barro (1991), who pioneered the analysis of conditional convergence. The different proxies for human capital are school enrolment rates and student-teacher ratios at primary and secondary level. By conditioning on these variables, I am able to analyse the effect of such proxies on growth in relation to GDP per capita. The new cross-country growth regression is

$$\begin{aligned} Growth_{i,1970-2010} = \alpha_i + \beta_1 lnGDP70_i + \beta_2 PRIM70_i + \beta_3 SEC70_i + \\ \beta_4 STTEAPRI_i + \beta_5 STTEASEC_i + \epsilon_i \end{aligned} \tag{11}$$

where the growth rate is calculated using a standard macroeconomic approach

$$Growth_{i,1970-2010} = (\frac{GDP_{i,2010}}{GDP_{i,1970}})^{1/40} - 1$$

Every conditioning variables are analysed for the year of 1970, where lnGDP70 is the logarithm of GDP per capita, PRIM70 and SEC70 are school enrolment rates at primary and secondary level, while STTEAPRI and STTEASEC are the student-teacher ratios at primary and secondary level.

Table 8: Growth: 1970-2010, including proxies for human capital

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
lnGDP70	-0.000	-0.002	-0.004**	-0.006***	-0.009*	-0.014**	-0.022***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.005)	(0.006)	(0.005)
PRIM70		0.027***		0.028***	0.017	-0.029	-0.019
		(0.007)		(0.007)	(0.020)	(0.036)	(0.029)
SEC70			0.049***	0.050***			0.187***
			(0.015)	(0.013)			(0.052)
STTEAPRI					-0.001**	-0.002**	-0.001
					(0.001)	(0.001)	(0.001)
STTEASEC						0.000	-0.000
						(0.001)	(0.001)
Constant	0.022*	0.024**	0.047***	0.049***	0.129**	0.206**	0.211***
	(0.013)	(0.012)	(0.013)	(0.013)	(0.055)	(0.071)	(0.063)
R^2	0.00	0.01	0.11	0.21	0.28	0.37	0.63
N	115	115	115	115	26	17	17

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

4.4.2 Results: Human capital proxies

I have analysed the effect of primary and secondary school enrolment rates and student-teacher ratios in 1970 on growth from 1970 to 2010. A first glance at Table 8 show one obvious weakness with the student-teacher ratios; namely the lack of data coverage. Some of these estimates must therefore be handled with great care.

Column 1 display the familiar univariate cross-country regression that from previous sections. Compared to my previous results, inference does not change. We do not find any evidence in the data suggesting that 1970 income has any statistically significant effect on growth. In Column 2, a parameter for the school enrolment rate at primary level is included. The income parameter is still not significant, while we see that the enrolment rate is statistically significantly different from zero. The estimate for enrolment rate in primary school show that a 1% increase in primary enrolment rate is associated with a 2.7% increase in GDP per capita growth.

If we shift interest towards the school enrolment rate at a secondary level, there is an even larger effect on growth than the effect found at the primary level. This is seen in Column 3. A 1% increase in increase in enrolment at secondary level is associated with a 4.9% increase in GDP per capita growth, which also is statistically significantly different form zero. It is also interesting to see that controlling for school enrolment rates at secondary level made the coefficient for 1970 income becomes statistically significantly different from zero at a 5% level. In this regression, an increase in 1970 income of 1% is associated with a reduction in growth of 0.004%. This result is in line with Barro (1991), who find evidence that countries with a high level of human capital compared to their income level grow faster on average compared to similar countries.

It is interesting that by including both of the enrolment rates, then the estimates are still highly significant. We see that enrolment rate at secondary level provide an even larger effect on growth than the enrolment rate at a primary level. This might come from the fact that people that actually enrolled at a secondary level, also enrolled at the primary level.

If we include the student-teacher ratios, we get a problem with low cross-country data coverage in 1970. The reason for this is that the estimates from the World Bank are only presented sporadically for different years. By controlling for the student-teacher ratio at a primary level only 26 countries can be analysed, due to the lack of data. This inclusion leads to an insignificant effect of school enrolment rate at primary level, while the student-teacher ratio is statistically significant at a 5% level. A marginal increase in in the student-teacher ratio at a primary level in associated with a reduction in growth of 0.1%.

If we look at the countries in this sample, we can see in Table A6 in the appendix that this sample contains mostly countries from the developing world. In this simple model we see that lowering the student-teacher ratio for developing countries has a positive effect on growth, and there is a pattern of convergence in growth. The student-teacher ratio at a secondary level has no significant effect in either specification. A further discussion of these results will therefor not be provided.

By including every control variable, we see in Column 7 that 1970 income is highly significant and negative. We also see that the human capital proxy for school enrolment at a secondary level is still significant. This is intuitive since people enrolled at the secondary level often have enrolled at the primary level, as well. But the results from Column 1-4, which is more reliable due to the data coverage, we see that conditioning do matter in enabling us to analyse patterns of convergence.

5 Discussion: Convergence or Divergence?

"*A group of economies are converging in the sense of σ if the dispersion of their real per capita GDP levels tend to decrease over time.*" (Sala-i-Martin, 1996a:1020)

If we can find that the GDP levels of two economies become more similar over time, then it must be the case that the poor economy is growing faster. This is the general principle of β-convergence discussed in this thesis. Sala-i-Martin (1996a) argues that if poorer countries grows faster, then β-convergence usually generates what he calls a convergence in σ. He does not find any evidence in the data suggesting that the distribution of world GDP between 1960 and 1990 has narrowed, which disproves his idea σ-convergence.

In my analysis the income variation for different years has increased. I find no evidence in the updated data suggesting any convergence in the overall level. I found that the mean of the rich-to-poor ratio has increased from 1870 to 2008, and even more interesting is the fact that the standard deviation of this average ratio increased as well. These findings are in stark contrast to Baumol. A direct comparison to Baumol's results, which might not be that constructive, since his analysis is based on a much smaller sample. He (Baumol, 1986) reports that the leader in 1870 was about eight times larger than the lowest income country, while the same ratio decreased to about two in 1979. My findings coincide with Baumol's for the 16-country sample analysis, while in the full sample analysis the story differs; the average has increased from 4.1 to 13.5. This brings concern to the any generalisation from Baumol's results, due to the small sample analysed.

In my results, for the full sample case, the average ratio was not constructed on the same sample size. Inference based on those numbers will not give me a satisfactory story, since it does not consider the differences in rankings of countries over time. Therefore, I find Pritchett's method useful. His method enabled me to generate a new income distribution in 1870 based on the 2008 distribution. In other words; Congo-Kinshasa which was the poorest country in 2008 are also the poorest country in 1870, equal to the fixed lower bound of $250. The newly constructed income distribution contains the same sample of countries, which makes inference more fruitful. By fixing a lower bound of $250, being what he believes is the lowest GDP per capita value possible in 1870, he (Pritchett, 1997) finds that the ratio of GDP per capita of richest to poorest country increases from 8.7 in 1870 to 45.2 in 1990. My findings are similar to Pritchett's, and they also complement my previous results. From Table 7, we saw that the average ratio and the standard deviation of that ratio increased over time, which suggests a tendency of richer countries becoming richer and poorer countries becoming relatively poorer over the last 100 years.

There are however some weaknesses in Pritchett's approach. It relies heavily on the fact that the lower bound is close to the actual income of the poorest country in 1870, so a there is a problem with the precision of the fixed lower bound. By including additional lower bounds, I was able to analyse the different effects of such changes. I found that lower lower bounds, not surprisingly, increased the average ratio and its deviation. If in fact the GDP per capita in 1870 was larger than the actual lower bounds analysed, then this would bias my results, putting an even greater weight on divergence in incomes. So if I had chosen a lower bound lower than $250 per capita, then my result would only favour divergence even more.

Baumol (1986) ran a univariate cross-country regression, where he reached a result close to a case of unconditional convergence. In this regression every factor is assumed equal, except for the income level in 1870. In his cross-country analysis of the 16 countries by Maddison, he found a inverse relation between GDP per capita and growth. By performing the same univariate regression on the same 16-country sample, but with updated data, I find a fairly similar result to Baumol.

The new data also enabled me to evaluate larger cross-country samples for a longer time period compared to Baumol. My results in Table 2, 3 and 4 show that only in the 16-country sample case when evaluating growth for 1870-2008, 1950-2008 and 1960-2008 do I find that GDP per capita has an effect statistically significant effect on growth. It is obvious that larger data coverage has had an effect. This is also easily seen in Table 3, where shorter time coverage leads to more positive coefficients for GDP per capita, compared to the 16-sample case.

Baumol does not overlook the problem of a small sample of countries. He analyses a larger cross-country income sample, for a 30 year period from 1950 to 1980. Baumol (1986) finds no tight relationship between 1950 income and growth on an overall level, which is is in line with my full sample replication. In Table 4, I found that none of the estimates are statistically significantly different from zero. Inference from the effect of GDP per capita on growth in a univariate regression are therefore not constructive in the full sample. Baumol's model is therefore not a satisfactory predictor of the effect of income per capita on growth. The drop in significance is due to the change in sample, which suggests that the original 16 countries can not be generalised to the full sample.

Important factors are omitted in the univariate regression. This univariate regression assumes that every country in the sample obey some sort of common linear specification, assuming that the countries in the data are somewhat identical except for their initial income level. It does not take into account any country-specific or time-variant effects. My results supports the fact that the 16 Baumol countries did not differ that much except for their initial income. I find this to be the reason why I get significant effects of income on growth for these countries.

Compared to the full sample where none of the coefficients are statistically significant, we found an increase, in relative magnitude, in the standard errors of those coefficients. This holds for every specification of the univariate regression in the full sample. I checked the residual behaviour for the different regressions based on different cross-country samples. By analysing residual plots, I found no pattern in the residuals in the 16-country sample, for any year. This supports my inference that initial income works well at explaining the difference in growth for these countries.

When analysing the full sample data, I find there to be a non-linear tendency in the residuals. Some of these plots are presented in Section 10.4 in the appendix. This might suggest that increased precision in analysing convergence would have been found by changing the specification of the model. These plots show that in the full sample regression, the residuals from low income countries follow a fairly similar residual pattern, while the larger economies tend to have a bias in the residuals. I am not going to provide any in depth discussion about these findings, but I find this to be evidence that the univariate regression is misspecified in the full sample case. As De Long (1988) points out there might also be a problem with sample selection bias. One, being the fact that Baumol analysed a to small ex post data sample of countries, that had already converged. By applying the updated data, we find insignificant coefficients in the full sample regression, proving De Long's point. The relative increase in the standard errors might also come from errors in measuring precise GDP per capita estimates.

De Long provided a method, which took this into account. The method relies on the fact that the error terms in Equations (3) and (4) are uncorrelated. This is a problematic assumption. One reason being that countries that provide less precise estimates might have a lower level of institutional quality, due to for example corruption. Mauro (1995) finds that corruption leads to lower investment, which has a negative effect on growth. The closing argument being that there might occur some correlation between the two disturbances. I still find De Long's method appealing, because it enables us to analyse to which degree such measurement error influence the effect of initial GDP per capita on growth. I found that different fixed values of ρ, which implies either a large measurement error in the estimates or lower variance in the disturbance term, had an effect on the initial income coefficient.

Baumol omitted to account for such measurement error in his estimates. If such measurement error exists, then his results is biased downward and in favour of convergence. This tendency is also present in my results. In Table 5, a higher ρ led to an increase in the coefficient of GDP per capita, compared to ρ equal to zero. Increased ρ also generated positive and significant parameters, which is a tendency evident in my full sample analysis for any year specified in the regression. When ρ approached infinity, every parameter in the full sample analysis had a positive and significant parameter. The development in significance comes from the fact that these parameters have fairly similar standard errors for each column.

De Long's approach show that if the possibility of errors of measurement in the GDP per capita is not taken into account, then at least Baumol's results was biased downward. It is important to mention that Baumol agrees with De Long's critique to some extent and in a reply to De Long, Baumol & Wolff (1988) discuss the problem of the selection bias that was omitted in the original analysis. But where De Long argues for divergence in an overall cross-country analysis, Baumol & Wolff still believe that some groups have converged.

This inference is contributed in another paper by Sala-i-Martin (1996b), where he includes different regions. He finds evidence proving convergence across regions of the US, Japan, Europe, Spain and Canada for different time periods. His main result is that the speed at which regions containing different countries converge over different time periods are surprisingly similar; at around 2% per year. This is also found in Barro & Sala-i-Martin (1992), who focuses on different states in USA over various periods from 1840 to 1988. They find convergence in the sense that economies grow faster in per capita terms the further away from the steady-state position they are. This holds even if they do not hold other variables than income per capita constant. So an extension to my analyses, would be to check for such regional differences; therefore proving or disproving the idea of convergence clubs.

In both the replication of Baumol and De Long, I have only analysed the impact of initial GDP per capita on economic growth. As frequently mentioned, I find the univariate regression to be unsatisfactory. The residual behaviour might stem from the fact that there is need of some controls in the model. The choice of such a set of conditioning variables depends on the nature of the economic processes in the group of economies that I would like to analyse. Such conditioning should in fact reflect the presence of a factor that supports the closing of income gaps. It is fair to assume that other factors matter, with convergence being conditional rather than unconditional.

Barro & Sala-i-Martin (1992) show this conditional convergence by holding variables such as initial school enrolment rates and the ratio of government consumption to GDP, constant. By doing this they find that the estimated rates of convergence are only slightly smaller than 2%. While Hobjin & Franses (2001) on the other hand, find that convergence in real GDP per capita does not imply convergence in other social indicators. They provide evidence, by analysing different social indicators, that the persistent gap between the rich and poor are not only accounted for in real GDP per capita, but also in living standards. Such indicators are factors such as life expectancy, infant mortality rates, daily calorie and protein supply. In stark contrast to Hobjin & Franses, Neumayer (2003) find strong evidence for convergence in aspects of living standards. He states that by suggesting divergence rather that convergence in living standards, you deny the fact that there has been a development in living standards in the last century.

So different specifications of the growth regression model do matter. Barro (1991) added a squared term of initial income, a linear combination of the school enrolment rates, and other parameters such as government consumption to GDP ratio, assassination measure, a measure for revolutions. He finds evidence that poor countries tend to catch up with richer countries if the poor country have a high level of human capital per person, relative to per capita GDP, but not otherwise. Political instability is inversely related to growth, and there is also a lot of unexplained results for the relatively weak growth performance of countries in sub-Saharan Africa and Latin America.

My extension of the univariate regression include proxies for human capital, such as school enrolment rates and student-teacher ratios at primary and secondary level. In Table 8, I found that the coefficient for GDP per capita becomes statistically significantly different from zero after controlling for human capital trough school enrolment rates at secondary level. Conditioning on school enrolment at both primary and secondary level combined, provides a statistically significant GDP per capita coefficient, while the effect is largest at the secondary level. I find this reasonable since students who enrolled at secondary level, for a large part have also enrolled at the primary level.

I find it interesting that Barro finds negative and significant dummy variables for Africa and Latin America. With regard to the convergence club discussion of Baumol, such significant dummies reduce the conclusion in favour of unconditional convergence and strengthens the idea that some groups of countries in fact have converged, while the less developed countries actually have become relatively poorer. Barro also argues that this regional significance is there even when the human capital are included in the regression; making a point out of the fact that such proxies might in fact be imperfect.

"*The variables SEC60 and PRIM60 are imperfect proxies for the level of human capital, which is especially low in Africa. But, since these proxies are imperfect, it may be that continent dummies - especially the one for Africa - retain some explanatory power for human capital and hence for the rate of economic growth. If this interpretation is correct, a better proxy for human* *capital would eliminate the AFRICA dummy as a significant influence on growth.*" (Barro, 1991:436).

In regard to the possibility of convergence clubs, a method of clustering would prove fruitful. Durlauf & Johnson (1995) analyses cross-country growth and finds evidence of multiple regimes, in other words groups countries that can obey the same model. While Franses & Hobjin finds that high and low income economies do not converge towards one another, but they do converge to different limits (Durlauf & Quah, 1999). Mankiw (1995) discusses different types of methodological problems in cross-country growth regressions. One being issues of simultaneity. It is difficult to separate causes and effects. Another, is the issue of multicollinearity, that correlation between determinants of growth can arise.

In this thesis my focus has been purely on cross-sectional differences, where any assumption regarding the error term has totally neglected any time-specific effects. Such disregard might make the model failing at accounting for any abnormal performance in the economy that may occur during the time coverage of the regression. Growth regressions such as the univariate regression introduced by Baumol, which calculate averages of growth over time, can be replaced by a panel-data approach which accounts for annual data. I am not going to discuss any advantages or disadvantages of other regression models in depth in this thesis, but rather point to the fact that my results, when applying the updated data, have shown that a generalisation cannot be made from a univariate growth regression model. I will instead complement my convergence analysis with a development accounting exercise.

6 Development Accounting Exercise

In a development accounting exercise the idea is to evaluate the effect of different factors on economic growth. I will try to estimate how differences in human and physical capital, and productivity among countries affect output on an aggregate level. The idea is to decompose differences in output per worker into differences in inputs and productivity. In this exercise I will follow the approaches from Hall & Jones (1999) and Caselli (2005).

6.1 Methodology

6.1.1 Hall & Jones (199)

Assume that output, Y_i, in country i has the following production function:

$$Y_i = K_i^{\alpha} \times (A_i H_i)^{1-\alpha} \tag{12}$$

where K_i is the stock of physical capital, H_i is the amount of human capital used in production, and A_i is a measure of productivity. α is given as 1/3. Human capital is constructed by

$$H_i = e^{\phi(s)} L_i \tag{13}$$

I will assume that labour L_i is homogeneous within a country and that each unit of labour has been trained with s years of schooling. The function $\phi(s)$ is piecewise linear, corresponding to the average Psacharopoulos (1994) reports for sub-Saharan Africa, specified as

$$\begin{aligned} \phi(s) = 0.134 \times s \ \ if \ s \leq 4, \\ \phi(s) = 0.134 \times 4 + 0.101 \times (s-4) \ \ if \ 4 < s \leq 8, \\ \phi(s) = 0.134 \times 4 + 0.101 \times 4 + 0.068 \times (s-8) \ \ if \ 8 \leq s. \end{aligned}$$

The function for $\phi(s)$ specifies the efficiency of a unit labour with s years of schooling, compared to a situation with no schooling (ϕ(0)=0). To be able to decompose the differences in output per worker across countries into differences in factors, I will re-write Equation (12) in output per worker terms, y $\equiv$ Y / L

$$y_i = (\frac{K_i}{Y_i})^{\alpha/(1-\alpha)} h_i A_i \tag{14}$$

This equation will allow me to analyse the effect of human and physical capital, and productivity, on output. It is important to stress that the estimates for productivity is given as a Solow residual, being that it is unobservable in the data. For simplification, each decomposition of factors are compared to the US in 2010.

6.1.2 Caselli (2005)

By analysing the magnitude of the unexplained residual variation in total factor productivity, I will follow the method from Caselli (2005) and construct two measures of success. They portray how successful the known factors h and k are at explaining cross-country income differences. I will again re-write Equation (12) in per labour terms

$$y = Ay_{KH} \tag{15}$$

where $y_{KH} = k^{\alpha}h^{1-\alpha}$. Both y and y_{KH}, which is the factor-only model, are observables in the data. k is defined as capital per worker, ($k \equiv K_i/L_i$), and h is human capital per worker, ($h \equiv H_i/L_i$), following from equation (13).

By taking the logarithm of Equation (15) and then calculate the variance, we can if we assume constant productivity across countries, create a counterfactual scenario to see how much of the variance in y that is explained by the variance of the factor-only model. From equation (15) we get

$$var[log(y)] = var[log(y_{KH})] + var[log(A)] + 2cov[log(A), log(y_{KH})]$$

where var[log(A)] = cov[log(A),log(y_{KH})] = 0 by assumption. This will enable us to construct the first measure of success, $success_1$;

$$success_1 = \frac{var[log(y_{KH})]}{var[log(y)]} \tag{16}$$

Caselli (2005) discuss a drawback with this measure of success, due to the fact that the variances are sensitive to outliers. I will therefore also include a measure of the inter-percentile differential

$$success_2 = \frac{y^{90}_{KH}/y^{10}_{KH}}{y^{90}/y^{10}} \tag{17}$$

This measure is less sensitive to outliers, but more sensitive to smaller samples. I will not focus to much on this measure, due to the fact that my sample contains a larger country coverage. $success_2$ compares the 90th-to-10th percentile ratio for counterfactual scenario that productivity are the same across countries, to the actual value. My main success measure in the exercise is $success_1$. Caselli (2005) performs his analysis analysing 1996, while Hall & Jones (1999) analyse 1988. I will complement their analysis and report results for 1985, 1995 and 2010.

6.2 Results: Productivity

Table 9: Ratios to U.S values: 2010

Country	Y/L	Contribution from $(K/Y)^{\alpha/(1-\alpha)}$	H/L	A
United States	1	1	1	1
Singapore	1.022	1.005	0.827	1.231
Hong Kong	0.996	1.005	0.849	1.168
France	0.802	1.175	0.828	0.825
Italy	0.772	1.227	0.768	0.820
Germany	0.738	1.080	0.951	0.720
United Kingdom	0.741	1.010	0.928	0.791
Canada	0.729	0.956	0.943	0.808
Japan	0.681	1.220	0.879	0.635
Argentina	0.407	1.066	0.765	0.499
Russia	0.391	0.961	0.891	0.457
Mexico	0.341	0.926	0.707	0.520
China	0.150	1.083	0.659	0.210
India	0.099	0.815	0.531	0.228
Kenya	0.047	0.725	0.576	0.113
Congo	0.011	1.045	0.438	0.025
Average, 132 countries	0.372	0.949	0.693	0.508
Standard deviation	0.339	0.177	0.175	0.450
Correlation with Y/L (logs)	1.000	0.342	0.776	0.951
Correlation with A (logs)	0.951	0.091	0.602	1.000

Following Equation (14), output per worker is decomposed into three multiplicative terms; contribution from physical capital intensity, human capital per worker and productivity. This decomposition is displayed in Table 9 for a selection of countries in the data, as an illustration of differences in factors between countries. If we multiply the right-hand side of Equation (14), this will add up to the value for output per worker.

If we look at France as an example; France's output per worker was roughly 80% compared to the US in 2010. France had a larger level of capital intensity, around 17% larger, while the level human capital per worker and productivity were roughly 83% compared to the US. It is easily seen that it is the lower level of human capital per worker and productivity that are the main factor behind the output per worker differences compared to the US.

Other OECD countries such as Canada, Italy, Germany, United Kingdom, Mexico and Japan all have fairly high relative levels of capital intensity, in which Mexico is the only country exhibiting a lower ratio than one. All these countries also have a lower human capital per worker level compared to the US. Canada, United Kingdom and Germany are countries with similar level of human capital, around 90%. Other countries with relatively high levels of capital intensity and human capital are the Eastern and South-Eastern Asian countries, Hong Kong and Singapore. Russia also have a relatively high level of capital intensity and human capital. Interestingly, Singapore and Hong Kong were two of the richest countries in 2008, when we analysed the Maddison data. The reason why countries like Hong Kong and Singapore have grown so much since World War II (Jones, 2015), might be due to when compared to the American level, these countries actually had a higher capital intensity and productivity level.

In Table 9 we see that productivity contributes significantly to output. It is interesting to see that countries, such as Germany and Russia, who show close resemblance to the US are in fact less productive. This is a common factor for most of the countries in the table. It is even more visible if we analyse the underdeveloped countries; represented by Kenya and Congo. Kenya has a fairly high level of physical and human capital, relative to output, but they are only 11% as productive as the US. While Congo, who has a higher level of capital intensity, only produced a tenth compared to USA. This mainly driven by their low level of productivity, only 2.5% of the US level.

We see that output per worker are on average 37% of the American level, in this 132-country sample. I find it interesting that the contribution from capital intensity is on average fairly close to the US (95%). The average contribution from human capital per worker and productivity are, on the other hand, much lower. The contribution from productivity is on average around 50% of the US level, while the human capital per worker level is close to 70%. The standard deviation for the average output per worker is 34%, which is in line with my results from Section 4. As discussed in Sections 4.1.2 and 4.3.2, there is a large variation in output in recent years. In this exercise, I find that this spread is mostly due to differences in human capital and productivity. This is also apparent in the standard deviation of the average productivity, being 45%; underlining the large variation in productivity across countries.

In the last two rows in Table 9, we see how the different factors are correlated with each other. Output per worker is highly correlated with productivity. As already discussed, countries such as Singapore and Hong Kong, who had a high level of productivity, are also the countries with the highest production level. It is also interesting to see that output per worker are relatively less correlated with the level of capital intensity. Again, countries such as France and Germany, and even Congo, who had a higher level of capital intensity compared to the US, but are even so, less productive. Interestingly there is almost no correlation between productivity and capital intensity.

6.3 Results: Measure of success

Table 10: Measure of success

	(1)	(2)
	$success_1$	$success_2$
1985	0.350	0.291
1995	0.284	0.242
2010	0.274	0.243

Table 11: $success_1$: Sub-samples, 2010

Sub-sample	Obs.	var[log(y)]	var[log(y_{KH})]	$success_1$
Above median	66	0.190	0.055	0.289
Below median	66	0.709	0.217	0.307
OECD	34	0.083	0.029	0.345
Non-OECD	98	1.322	0.335	0.253
Advanced economies	24	0.040	0.021	0.519
East Asia & Pacific	16	1.326	0.233	0.176
East Europa & Central Asia	18	0.405	0.071	0.176
Latin America & Caribbean	21	0.523	0.084	0.161
Middle-East & North Africa	15	0.653	0.177	0.274
South Asia	6	0.823	0.117	0.142
Sub-Saharan Africa	32	0.954	0.222	0.232
All	132	1.440	0.394	0.274

We have now seen how aggregate productivity affects the level of output. This effect can be strengthened even further by analysing the two measures of success from Equation (16) and (17). They are based on the counterfactual scenario that productivity is constant across countries. Caselli (2005) found, using $success_1$, that differences in intangible capital can account for 39% of the observed income. His $success_2$ measure is a little bit lower, 34%, providing the same story. Applying the same analysis to Hall & Jones (1999) data, he (Caselli, 2005) got a $success_1$ measure of 40%, and an equal $success_2$ measure.

My results show an even smaller effect in intangible capital. We see that differences in intangible capital can explain 27.4% of the observed income differences in 2010, while 24.3% is explained based on $success_2$. This is significantly lower than what Caselli got. The success measures for the two comparable years, 1985 and 1995, also show lower values of success. My $success_1$ is 0.35 in 1985 and 0.28 in 1995, while $success_2$ drops to 0.29 in 1985 and 0.24 for 1995. Compared to Caselli, these results puts even greater emphasis on unexplained total factor productivity differences. It is important to remember that my results are based on a revised and larger cross-country sample, which might be the cause of difference.

A more in-depth analysis of $success_1$ is provided in Table 11, where I have calculated the measure for different sub-groups in 2010. We see that countries above the median have a much lower dispersion in incomes (0.19) and a lower dispersion in observable factors (0.06), compared to countries below the median, 0.71 and 0.22, respectively. But relative to each other, differences in total factor productivity plays a larger role for countries above the median than below. When the differences in the variances of factor-only model are relatively smaller for the above median countries, compared to the below median countries, the success measure is driven down.

The dispersion in output per worker is also lower for sub-samples that tend to be richer on average, like the above median countries, OECD and advanced economies. I find that the largest variation in living standards, given by the variation in output, is found in East Asia & the Pacific and Sub-Saharan Africa. These findings are in line with those Caselli (2005).

"*It is indeed remarkable that, within the four continental groupings, the greatest variation in living standards is observed in Africa, a continent that is often depicted as flattened out by unmitigated and universal blight.*" (Caselli, 2005:690).

The success of the factor-only model is highest in the richer countries, like OECD and the advanced economies. Hence, it is easier to explain differences in income among richer countries than among the poorer countries. If we suppress the fact that my results show even larger unexplained differences in total factor productivity than what is found in Caselli, the main conclusion holds. The factor-only model is least applicable in parts of the world where we need it the most; that is, when applied to poor countries.

7 Discussion: Development Accounting

Table 12: Caselli data vs PWT8.1 in 1995

Sub-sample	Obs.	var[log(y)]	var[log(y_{KH})]	$success_1$
Above median	66	0.211	0.088	0.417
	47	0.176	0.109	0.620
Below median	66	0.685	0.241	0.351
	47	0.637	0.259	0.407
OECD	34	0.126	0.041	0.325
	26	0.091	0.055	0.602
Non-OECD	98	1.231	0.326	0.265
	68	1.030	0.365	0.354
Advanced economies	24	0.053	0.035	0.636
	22	0.075	0.048	0.645
East Asia & Pacific	16	1.428	0.316	0.221
	11	0.651	0.227	0.348
East Europa & Central Asia	18	0.406	0.047	0.116
	1	-	-	-
Latin America & Caribbean	21	0.412	0.098	0.237
	23	0.278	0.127	0.456
Middle-East & North Africa	15	1.074	0.397	0.370
	8	0.186	0.146	0.787
South Asia	6	0.530	0.111	0.210
	5	0.133	0.042	0.315
Sub-Saharan Africa	32	1.018	0.199	0.196
	24	0.785	0.270	0.345
All	132	1.450	0.411	0.284
	94	1.311	0.505	0.385

I found in my full sample analysis in Section 4.1.2, that the US had on average 13.5 times as large GDP per capita in 2008 compared to other countries, with a standard deviation of 17.4. This indicated a large variation in incomes in the 163-country sample. Table 9 provided us with a somewhat similar story. A direct comparison is not constructive, but we can from development accounting see that the average output per worker level was 37% compared to the US, with a standard deviation of 34%. This, as in Table 1, indicates a large dispersion in the income distribution in recent years.

The benefit of this exercise is the possibility to provide additional information about the aggregates of contributing factors discussed in the convergence-analysis. We have seen that factors of human capital, such as school enrolment at secondary level, had a positive effect on economic growth. The same is found in this exercise; the short story being that countries with higher levels of productivity and human capital usually have higher output, while the contribution from initial capital intensity is of lesser importance.

The significance of productivity-contribution to output is just being underlined by the replication of Caselli. I found that unexplained differences in total factor productivity accounts for around 70% of observed income differences. These results are even less optimistic, compared to similar research by Caselli (2005) and Lagakos et. al. (2012), who receive a measure of success of around 0.40. But like Caselli, I find that the observed factors have less impact in those areas of the world where it is needed. This raises a question of concern to why my results provide such big differences in the success measure. Is it due to my approach or is generated through the revision in data? As a robustness check, I have performed the same analysis using Caselli's data. A discussion in regard to the difference between the data is provided in Section 3. I analysed the PWT8.1 data in 1995 to Caselli's 1996 results, to get as close resemblance as possible.

The first thing I checked is whether my approach was correctly specified. Table 12 provide a direct comparison of the two data sets. My main results are presented in the first row, while my specification using Caselli's data is implemented and displayed in the second row for each category. My results does not differ from those of Caseli; $success_1$ is equal to 0.39. The reported variances are also similar to what Caselli got, therefore rejecting the possibility that my specification is incorrect.

A closer look at Table 12 reveals that the variance of output per worker estimate, in the new data, increased compared to the estimate in Caselli; 1.45 compared to 1.31. The variance of the factor-model, on the other hand, decreased compared to Caselli. We see a drop to 0.41 compared to 0.50. The revised data and larger country coverage has therefore increased the variance of the GDP per capita estimates, while the dispersion in the factor-model has been reduced. This give grounds for the mathematical reason why my reported results are significantly lower.

This trend is found in every case, except in the advanced economy and East Europa & Central Asia groups. The latter case is not useful to discuss, since Caselli only had one country in that group, while the new data contain 18 countries. I find it interesting that the advanced economy group display fairly similar result; 0.64 compared to 0.65. In the advanced economy case, both the variance of output per worker and the variance of factor-only model has decreased compared to Caselli. I find that the biggest differences in $success_1$ occur in Latin America & Caribbean, Middle East & North Africa, South Asia, and Sub-Saharan Africa.

When applying the new data, we see that some groups have changed significantly in sample size. The different countries in each group are displayed in Table A9-A10 in the appendix. Is this the reason for the reduced measure of success? In Middle East & North Africa, and for Sub-Saharan Africa there is an increase in the sample of 7 and 8 countries compared to the Caselli's data. At an aggregate level it is again difficult to conclude with which forces causes these differences in the variances. Is it due to the extra set of countries or due to the revisions of the estimates? For Latin America & Caribbean, and South Asia we also see a quite significant drop in the success measure, which is mostly driven by an increase in the variance of GDP per capita. For these two groups the sample sizes are fairly similar, which makes it more comparable.

We even see a reduction in the sample size for Latin America & Caribbean. This is due to the loss of Haiti and Nicaragua in my data set. For Latin America & Caribbean, removing two countries still increased the variance of GDP per capita, from 0.28 in the Caselli data to 0.41 in the new data. While in the case of South Asia, an additional country, increased the variance of GDP per capita from 0.13 to 0.53. These findings suggest that the changes in the success measure is mostly driven by the revision of the estimates, rather than changes in data coverage.

Table 13: Caselli data vs PWT8.1: 88 countries

	(1) var[log(y)]	(2) var[log(y_{KH})]	(3) $success_1$
Caselli	1.317	0.496	0.376
New data	1.481	0.422	0.285

To provide further robustness, I have analysed the 88 countries that are common in both of the data sets in 1995. The comparison is reported in Table 13. We see that the variance in GDP per worker is larger in the revised data compared to the Caselli, while the variance in the factor-only model is relatively similar in each data set. The success measure in Caselli's data drop to 0.3, compared to 0.39 in is 96-country sample. I find it interesting that the success measure in the revised data for this 88-country sample, which is 0.285, is fairly similar to my success measure in the full sample. I find it fair to conclude that most of the reduction in the success measure in my results are due to the revisions of the estimates in the data, rather than the increased country coverage. But either way, my results are qualitatively similar to Caselli, putting an even higher weight on unexplained productivity.

The results from the exercise also shows that countries have a fairly similar average aggregate contribution from capital intensity, compared to the American level, while the average contribution from human capital per worker is around 70% of the US level. The standard deviation of these averages are fairly small, at around 17% of the US; the contribution from capital intensity and human capital does therefore not differ that much in this analysis.

In relation, I found by controlling for human capital, a positive and significant effect of human capital on growth. This inclusion also assured convergence in a conditional manner. Barro (1991) argued that such proxies should in fact make his regional dummies insignificant, while he found that his dummies for Africa and Latin America had an effect on growth. In my exercise the human capital proxies, being the average years of schooling, show a small standard deviation of the average. But we see a fairly high correlation between output and human capital, which indicates the significance of human capital. I also find that the contribution from human capital differs across countries, so even though Barro argues that these human capital proxies are poor at explaining the effect of human capital on growth, we see from Table 9 that human capital indeed has an important role in contribution to output.

In my analysis of convergence, I have also overlooked the significance of productivity, by assuming that every country follows some sort of common linear specification. Even in a matter of conditioning, accounting for productivity is tougher than in the case of capital factors. I think that an developing accounting exercise, such as mine, is excellent at portraying the importance of productivity. There is a high correlation between output and productivity, and also human capital is significantly correlated with productivity.

I find it to be reasonable that the correlation between capital intensity and productivity is less severe. A higher level of human capital might imply a more educated population, which intuitively should be more productive. The fact that productivity is highly correlated with output, and substantially correlated with human capital, raises causality issues regarding the growth regressions from Section 4. This coincide with the fact that the specification of the growth regression is of importance and that the univariate regression that Baumol used, do not provide the full story.

8 Concluding remarks

This thesis has analysed different approaches to economic growth in the context of convergence. If we apply a univariate growth regression, as introduced by Baumol (1986), to updated data, I find no evidence suggesting β-convergence in a unconditional sense. By replicating the research by Baumol (1986), De Long (1988), Barro (1991) and Pritchett (19979, I find similar results to the latter three. In the univariate regression, I find a statistically significant effect of GDP per capita on growth when analysing the 16-country sample of Baumol. In addition to the results from replicating De Long and Pritchett, there is evidence suggesting that these countries did not differ that specifically in the first place, and that the countries is more likely to have diverged.

When applying the specification to the updated full sample data, I am unable to conclude with any effect of initial GDP per capita on growth for any time specification evaluated. This shows that generalisations based on the industrialised 16 country sample, proves not to be constructive. I find evidence suggesting a misspecification of the model, when the full sample is accounted for. I find evidence that countries tend to grow faster on average if their level of human capital per capita, relative to their income level, is high. This proves that controlling for country-specific effects matter, enabling us to see a pattern of convergence in a conditional manner. These findings are consistent with the findings from Barro (1991).

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10 Appendix

10.1 List of countries

Table A1: Maddison 2013 countries: 1870-2008

16 countries	29 countries(+13)	65 countries(+36)		
Australia	Brazil	Albania	Iraq	Thailand
Austria	South Africa	Algeria	Ireland	Tunisia
Belgium	Chile	Argentina	Jamaica	Vietnam
Canada	Colombia	Bulgaria	Jordan	Yugoslavia
Denmark	Greece	Burma	Lebanon	
Finland	Indonesia	China	Malaysia	
France	New Zealand	Cuba	Mexico	
Germany	Peru	Czechoslovakia	Morocco	
Italy	Portugal	Ecuador	Nepal	
Japan	Spain	Egypt	North Korea	
Netherlands	Sri Lanka	Philippines	Poland	
Norway	Uruguay	Ghana	Romania	
Sweden	Venezuela	Hong Kong	South Korea	
Switzerland		Hungary	Singapore	
UK		India	Syria	
USA		Iran	Taiwan	

Source: The Maddison-Project, 2013 version

Table A2: Maddison 2013 countries: 1950-2008

139 countries

Austria	Cuba	Lebanon	Namibia
Belgium	Dominican Republic	Oman	Niger
Denmark	Ecuador	Qatar	Nigeria
Finland	El Salvador	Saudi Arabia	Rwanda
France	Guatemala	Syria	Sao Tomé Principe
Germany	Haïti	UAE	Senegal
Italy	Honduras	Yemen	Seychelles
Netherlands	Jamaica	Algeria	Sierra Leone
Norway	Nicaragua	Angola	Somalia
Sweden	Panama	Benin	South Africa
Switzerland	Paraguay	Botswana	Sudan
UK	Puerto Rico	Burkina Faso	Swaziland
Ireland	Trinidad & Tobago	Burundi	Tanzania
Greece	China	Cameroon	Togo
Portugal	India	Cape Verde	Tunisia
Spain	Indonesia	Central African Repeublic	Uganda
Australia	Japan	Chad	Congo-Kinshasa
New Zealand	Philippines	Comoro Islands	Zambia
Canada	South Korea	Congo-Brazzaville	Zimbabwe
USA	Thailand	Côte d'Ivoire	
Albania	Taiwan	Djibouti	
Bulgaria	Bangladesh	Egypt	
Czechoslovakia	Burma	Equatorial Guinea	
Hungary	Hong Kong	Ethiopia	
Poland	Malaysia	Gabon	
Romania	Nepal	Gambia	
Yugoslavia	Pakistan	Ghana	
Former Yugoslavia	Singapore	Guinea	
FUSSR	Sri Lanka	Guinea Bissau	
Argentina	Afghanistan	Kenya	
Brazil	Cambodia	Lesotho	
Chile	Laos	Liberia	
Colombia	Mongolia	Libya	
Mexico	North Korea	Madagascar	
Peru	Vietnam	Malawi	
Uruguay	Bahrain	Mali	
Venezuela	Iran	Mauritania	
Bolivia	Iraq	Mauritius	
Costa Rica	Israel	Morocco	
Jordan	Mozambique	Kuwait	

Source: The Maddison-Project, 2013 version

Table A3: Maddison 2013 countries: 1960-2008

145 countries

Austria	Peru	Bahrain	Malawi
Belgium	Uruguay	Iran	Mali
Denmark	Venezuela	Iraq	Mauritania
Finland	Bolivia	Israel	Mauritius
France	Costa Rica	Jordan	Morocco
Germany	Cuba	Kuwait	Mozambique
Italy	Dominican Republic	Lebanon	Namibia
Netherlands	Ecuador	Oman	Niger
Norway	El Salvador	Qatar	Nigeria
Sweden	Guatemala	Saudi Arabia	Rwanda
Switzerland	Haïti	Syria	Sao Tomé Principe
UK	Honduras	UAE	Senegal
Ireland	Jamaica	Yemen	Seychelles
Greece	Nicaragua	Algeria	Sierra Leone
Portugal	Panama	Angola	Somalia
Spain	Paraguay	Benin	South Africa
Australia	Puerto Rico	Botswana	Sudan
New Zealand	Trinidad & Tobago	Burkina Faso	Swaziland
Canada	China	Burundi	Tanzania
USA	India	Cameroon	Togo
Albania	Indonesia	Cape Verde	Tunisia
Bulgaria	Japan	Central African Rep.	Uganda
Czechoslovakia	Philippines	Chad	Congo-Kinshasa
Hungary	South Korea	Comoro Islands	Zambia
Poland	Thailand	Congo-Brazzaville	Zimbabwe
Romania	Taiwan	Côte d'Ivoire	
Yugoslavia	Bangladesh	Djibouti	
Bosnia	Burma	Egypt	
Croatia	Hong Kong	Equatorial Guinea	
Macedonia	Malaysia	Ethiopia	
Slovenia	Nepal	Gabon	
Montenegro	Pakistan	Gambia	
Serbia	Singapore	Ghana	
Former Yugoslavia	Sri Lanka	Guinea	
FUSSR	Afghanistan	Guinea-Bissau	
Argentina	Cambodia	Kenya	
Brazil	Laos	Lesotho	
Chile	Mongolia	Liberia	
Colombia	North Korea	Libya	
Mexico	Vietnam	Madagascar	

Source: The Maddison-Project, 2013 version

Table A4: Maddison 2013 countries: 1990-2008

163 countries

Austria	Kazakhstan	Bangladesh	Equatorial Guinea
Belgium	Kyrgyzstan	Burma	Ethiopia
Denmark	Latvia	Hong Kong	Gabon
Finland	Lithuania	Malaysia	Gambia
France	Moldova	Nepal	Ghana
Germany	Russia	Pakistan	Guinea
Italy	Tajikistan	Singapore	Guinea Bissau
Netherlands	Turkmenistan	Sri Lanka	Kenya
Norway	Ukraine	Afghanistan	Lesotho
Sweden	Uzbekistan	Cambodia	Liberia
Switzerland	FUSSR	Laos	Libya
UK	Argentina	Mongolia	Madagascar
Ireland	Brazil	North Korea	Malawi
Greece	Chile	Vietnam	Mali
Portugal	Colombia	Bahrain	Mauritania
Spain	Mexico	Iran	Mauritius
Australia	Peru	Iraq	Morocco
New Zealand	Uruguay	Israel	Mozambique
Canada	Venezuela	Jordan	Namibia
USA	Bolivia	Kuwait	Niger
Albania	Costa Rica	Lebanon	Nigeria
Bulgaria	Cuba	Oman	Rwanda
Czechoslovakia	Dominican Rep.	Qatar	Sao Tomé Principe
Hungary	Ecuador	Saudi Arabia	Senegal
Poland	El Salvador	Syria	Seychelles
Romania	Guatemala	UAE	Sierra Leone
Yugoslavia	Haïti	Yemen	Somalia
Bosnia	Honduras	Algeria	South Africa
Croatia	Jamaica	Angola	Sudan
Macedonia	Nicaragua	Benin	Swaziland
Slovenia	Panama	Botswana	Tanzania
Montenegro	Paraguay	Burkina Faso	Togo
Serbia	Puerto Rico	Burundi	Tunisia
Former Yugoslavia	Trinidad & Tobago	Cameroon	Uganda
Czech Rep.	China	Cape Verde	Congo-Kinshasa
Slovakia	India	Central African Rep.	Zambia
e FCzechoslovakia	Indonesia	Chad	Zimbabwe
Armenia	Japan	Comoro Islands	
Azerbaijan	Philippines	Congo-Brazzaville	
Belarus	South Korea	Côte d'Ivoire	
Estonia	Thailand	Djibouti	
Georgia	Taiwan	Egypt	

Source: The Maddison-Project, 2013 version

Table A5: Barro replication: 1970-2010

115 countries

Albania	Ghana	Panama
Argentina	Greece	Paraguay
Australia	Guatemala	Peru
Austria	Honduras	Philippines
Bahrain	Hungary	Poland
Bangladesh	Iceland	Portugal
Barbados	India	Qatar
Belgium	Indonesia	Republic of Korea
Belize	Iran (Islamic Republic of)	Rwanda
Benin	Iraq	Saudi Arabia
Bolivia	Ireland	Senegal
Botswana	Israel	Sierra Leone
Brazil	Italy	Singapore
Brunei Darussalam	Jamaica	South Africa
Bulgaria	Japan	Spain
Burundi	Jordan	Sri Lanka
Cambodia	Kenya	Sudan
Cameroon	Kuwait	Swaziland
Canada	Lao People's Democratic Republic	Sweden
Central African Republic	Lesotho	Switzerland
Chile	Liberia	Syrian Arab Republic
China, People's Republic of	Luxembourg	Thailand
China: Hong Kong SAR	Malawi	Togo
China: Macao SAR	Malaysia	Trinidad and Tobago
Colombia	Maldives	Tunisia
Congo	Mali	Turkey
Costa Rica	Malta	Uganda
Cyprus	Mauritania	United Kingdom
Cote d'Ivoire	Mauritius	Tanzania
Denmark	Mexico	United States
Dominican Republic	Mongolia	Uruguay
Ecuador	Morocco	Venezuela
Egypt	Mozambique	Vietnam
El Salvador	Namibia	Zambia
Fiji	Nepal	Zimbabwe
Finland	Netherlands	
France	New Zealand	
Gabon	Niger	
Gambia	Norway	
Germany	Pakistan	

Source: PWT8.1. Barro & Lee, 2013. World Bank, 2016

Table A6: Barro replication: Including student-teacher ratio

26 countries		17 countries	
Argentina	Paraguay	Argentina	Malaysia
Nepal	Uganda	Paraguay	Tanzania
Luxembourg	Honduras	Indonesia	Brunei Darussalam
Brunei Darussalam	Peru	Brazil	Singapore
Panama	Guatemala	Guatemala	China, People's Republic of
Brazil	Botswana	Botswana	Panama
China of	Colombia	Costa Rica	Lesotho
Indonesia	Swaziland	Colombia	Uganda
Uruguay	Cote d'Ivoire	Peru	
Singapore	Lesotho		
Costa Rica	Bangladesh		
Malaysia	Tanzania		
Mauritius	Zambia		

Source: PWT8.1. Barro & Lee, 2013. World Bank, 2016

Table A7: Countries: Development accounting exercise

132 countries

Albania	Gabon	Mongolia	Taiwan
Argentina	United Kingdom	Mozambique	Tanzania
Armenia	Ghana	Mauritania	Uganda
Australia	Gambia	Mauritius	Ukraine
Austria	Greece	Malawi	Uruguay
Burundi	Guatemala	Malaysia	United States
Belgium	Hong Kong	Namibia	Venezuela
Benin	Honduras	Niger	Vietnam
Bangladesh	Croatia	Netherlands	Yemen
Bulgaria	Hungary	Norway	South Africa
Bahrain	Indonesia	Nepal	Zambia
Belize	India	New Zealand	Zimbabwe
Bolivia	Ireland	Pakistan	
Brazil	Iran	Panama	
Barbados	Iraq	Peru	
Brunei Darussalam	Iceland	Philippines	
Botswana	Israel	Poland	
Central African Republic	Italy	Portugal	
Canada	Jamaica	Paraguay	
Switzerland	Jordan	Qatar	
Chile	Japan	Romania	
China	Kazakhstan	Russian Federation	
Cote d'Ivoire	Kenya	Rwanda	
Cameroon	Kyrgyzstan	Saudi Arabia	
Democratic Republic: Congo	Cambodia	Sudan	
Congo	Republic of Korea	Senegal	
Colombia	Kuwait	Singapore	
Costa Rica	Lao	Sierra Leone	
Cyprus	Liberia	El Salvador	
Czech Republic	Sri Lanka	Slovakia	
Germany	Lesotho	Slovenia	
Denmark	Lithuania	Sweden	
Dominican Republic	Luxembourg	Swaziland	
Ecuador	Latvia	Syrian Arab Republic	
Egypt	China: Macao SAR	Togo	
Spain	Morocco	Thailand	
Estonia	Maldives	Tajikistan	
Finland	Mexico	Trinidad and Tobago	
Fiji	Mali	Tunisia	
France	Malta	Turkey	

Source: PWT8.1. Barro & Lee, 2013.

Table A8: Caselli countries: 94 countries total

88+6 countries

Argentina	Fiji	Mexico	Taiwan
Australia	Finland	Mozambique	Thailand
Austria	France	Nepal	Togo
Bangladesh	Gambia	Netherlands	Trinidad & Tobago
Barbados	Ghana	New Zealand	Tunisia
Belgium	Greece	Niger	Turkey
Benin	Guatemala	Norway	Uganda
Bolivia	Honduras	Pakistan	United Kingdom
Botswana	Hong Kong	Panama	United States
Brazil	Iceland	Paraguay	Uruguay
Cameroon	India	Peru	Venezuela
Canada	Indonesia	Philippines	Zambia
Central African Republic	Iran	Portugal	Zimbabwe
Chile	Ireland	Republic of Korea	Algeria
China	Israel	Romania	Ethiopia
Colombia	Italy	Rwanda	Guyana
Congo	Jamaica	Senegal	Haiti
Costa Rica	Japan	Sierra Leone	Nicaragua
Cyprus	Jordan	Singapore	Papua New Guinea
Democratic Republic of the Congo	Kenya	South Africa	
Denmark	Lesotho	Spain	
Dominican Republic	Malawi	Sri Lanka	
Ecuador	Malaysia	Sweden	
Egypt	Mali	Switzerland	
El Salvador	Mauritius	Syrian Arab Republic	

Source: PWT6.1. Barro & Lee, 2001.

Table A9: Regional groupings: New data, 1995

Advanced Economies		East Asia and the Pacific	Europe and Central Asia	Latin America and the Caribbean	Middle East and North Africa	South Asia	Sub-Saharan Africa	
Australia	Luxembourg	Brunei Darussalam	Albania	Argentina	Bahrain	Bangladesh	Benin	Mauritania
Austria	Netherlands	Cambodia	Armenia	Barbados	Cyprus	India	Botswana	Mauritius
Belgium	New Zealand	China	Bulgaria	Belize	Egypt	Iran	Maldives	Burundi
Canada	Norway	Hong Kong	Croatia	Bolivia	Iraq	Nepal	Cameroon	Namibia
Denmark	Portugal	Macao	Czech Republic	Brazil	Israel	Pakistan	Central African Rep.	Niger
Finland	Spain	Fiji	Estonia	Chile	Jordan	Sri Lanka	Congo	Rwanda
France	Sweden	Indonesia	Hungary	Colombia	Kuwait		Cote d'Ivoire	Senegal
Germany	Switzerland	Lao P.D.R.	Kazakhstan	Costa Rica	Malta		Congo	Sierra Leone
Greece	Turkey	Malaysia	Kyrgyzstan	Dominican Republic	Morocco		Gabon	South Africa
Iceland	United Kingdom	Mongolia	Latvia	Ecuador	Qatar		Gambia	Sudan
Ireland	United States	Philippines	Lithuania	El Salvador	Saudi Arabia		Ghana	Swaziland
Italy		Republic of Korea	Poland	Guatemala	Syrian Arab Rep.		Togo	Kenya
Japan		Singapore	Romania	Honduras	Tunisia		Lesotho	Uganda
		Taiwan	Russia	Jamaica	Yemen		Liberia	Tanzania
		Thailand	Slovakia	Mexico			Malawi	Zambia
		Vietnam	Tajikistan	Panama			Mali	Zimbabwe
			Ukraine	Paraguay				Mozambique
				Peru				
				Trinidad and Tobago				
				Uruguay				
				Venezuela				

Table A10: Regional groupings: Caselli data, 1996

Advanced Economies	East Asia and the Pacific	Europe and Central Asia	Latin America and the Caribbean	Middle East and North Africa	South Asia	Sub-Saharan Africa
Australia	China	Romania	Argentina	Algeria	Bangladesh	Benin
Austria	Fiji		Barbados	Cyprus	India	Botswana
Belgium	Hong Kong		Bolivia	Egypt	Nepal	Cameroon
Canada	Indonesia		Brazil	Iran	Pakistan	Central African Rep.
Denmark	Malaysia		Chile	Israel	Sri Lanka	Congo
Finland	Papua New Guinea		Colombia	Jordan		D.R. of the Congo
France	Philippines		Costa Rica	Syrian Arab Rep.		Ethiopia
Greece	Republic of Korea		Dominican Rep.	Tunisia		Gambia
Iceland	Singapore		Ecuador			Ghana
Ireland	Taiwan		El Salvador			Kenya
Italy	Thailand		Guatemala			Lesotho
Japan			Guyana			Malawi
Netherlands			Haiti			Mali
New Zealand			Honduras			Mauritius
Norway			Jamaica			Mozambique
Portugal			Mexico			Niger
Spain			Nicaragua			Rwanda
Sweden			Panama			Senegal
Switzerland			Paraguay			Sierra Leone
Turkey			Peru			South Africa
United Kingdom			Trinidad and Tobago			Togo
United States			Uruguay			Uganda
			Venezuela			Zambia
						Zimbabwe

10.2 Explanation: Variables in the analysis

Table B1: Explanation of variables in the Baumol replication

Variable	Explanation
$Growth_{i,x-y}$	Growth rate calculated using log differences for GDP per capita between year y and x, for country i
$ratio_{i,1870}$	Ratio calculated using equation (1) with Australia being the richest country in 1870
$ratio_{i,2008}$	Ratio calculated using equation (1) with USA being the richest country in 1870
$lnGDP_{i,x}$	Logarithm of real GDP per capita in year x

Table B2: Explanation of variables in the De Long replication

Variable	Explanation
$Growth_{i,x-y}$	Growth rate calculated using log differences between GDP per capita for country i given year y and x
$lnGDP_{i,x}$	Logarithm of real GDP per capita for country i in year x, calculated by Equation (5), (6) and (7)
ρ	Ratio of the error variances; assumed to be 0, 0.5, 1, 2 or 1000

Table B3: Explanation of variables in the Pritchett replication

Variable	Explanation
$Growth_{i,x-y}$	Growth rate calculated using log differences for GDP per capita between year y and x, for country i
$ratio_{i,1870}$	Ratio calculated using Equation (1) with USA being the richest country in 1870. GDP per capita for country i in 1870 is calculated by Equation (8)
$ratio_{i,2008}$	Ratio calculated using Equation (1) with USA being the richest country in 1870
Boundary	Assumed lower bound; either 250, 200 or 150

Table B4: Explanation of variables in the Barro replication

Variable	Explanation
$Growth_{i,1970-2010}$	1970-2010 growth calculated using a standard macroeconomic approach for country i
$lnGDP70_i$	Logarithm of real GDP per capita in 1970 for country i
$PRIM70_i$	The ratio of primary-school enrolment in 1970 for country i
$SEC70_i$	The ratio of secondary-school enrolment in 1970 for country i
$STTEAPRI_i$	Student-teacher ratio for primary schools in 1970 in country i
$STTEASEC_i$	Student-teacher ratio for secondary schools in 1970 in country i

10.3 Baumol replication: Additional calculations

Table C1: Maddison 2013: 16 Baumol countries

	1870		2008	
Country	Real GDP/capita	Ratio	Real GDP/capita	ratio
Australia	3273	1.0	25218	1.2
Austria	1863	1.8	24565	1.3
Belgium	2692	1.2	23701	1.3
Canada	1695	1.9	25262	1.2
Denmark	2003	1.6	24789	1.3
Finland	1140	2.9	24694	1.3
France	1876	1.7	22057	1.4
Germany	1839	1.8	20801	1.5
Italy	1542	2.1	19460	1.6
Japan	737	4.4	22175	1.4
Netherlands	2755	1.2	25112	1.2
Norway	1360	2.4	28464	1.1
Sweden	1345	2.4	25181	1.2
Switzerland	2876	1.1	25293	1.2
UK	3190	1.0	24602	1.3
USA	2445	1.3	31251	1.0

1990 International dollars

Table C2: 1870: Top 5 rich and poor

Richest 5			Poorest 5		
Country	Real GDP/capita	Ratio	Country	Real GDP/capita	Ratio
Australia	3273	1.0	North Korea	337	9.7
UK	3190	1.0	South Korea	337	9.7
New Zealand	3040	1.1	Nepal	397	8.2
Switzerland	2876	1.1	Ecuador	411	8.0
Netherlands	2755	1.2	Ghana	439	7.5

1990 International dollars

Table C3: 2008: Top 5 rich and poor

Richest 5			Poorest 5		
Country	Real GDP/capita	Ratio	Country	Real GDP/capita	Ratio
USA	31251	1.0	Congo-Kinshasa	249	125.5
Hong Kong	29810	1.0	Burundi	479	65.2
Norway	28464	1.1	Niger	521	60.0
Singapore	26638	1.2	Central African Republic	536	58.3
Switzerland	25293	1.2	Comoro Islands	549	56.9

1990 International dollars

Table C4: Maddison 2013 data: Lowest reported GDP/capita

Country	Year	Real GDP/capita
Congo	2001	203
Guinea-Bissau	1950	289
Guinea	1950	303
Malawi	1950	324
North Korea	1820	335
South Korea	1820	335

1990 International dollars

10.4 Residual plots

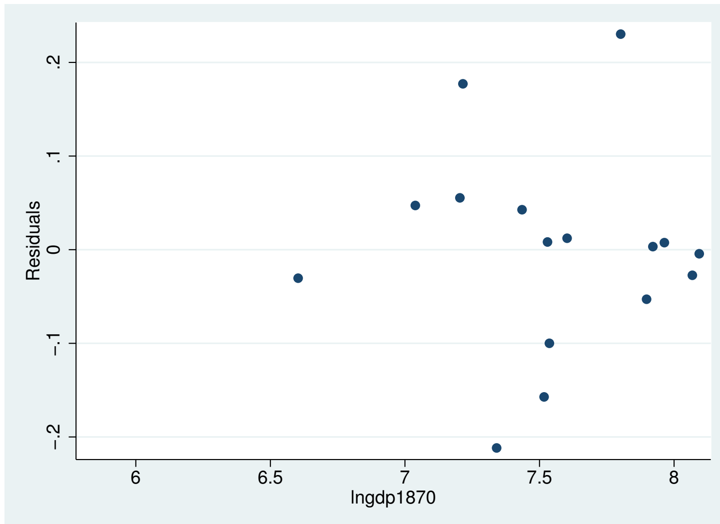

Figure 2: 16-country sample: 1870-2008 growth regression

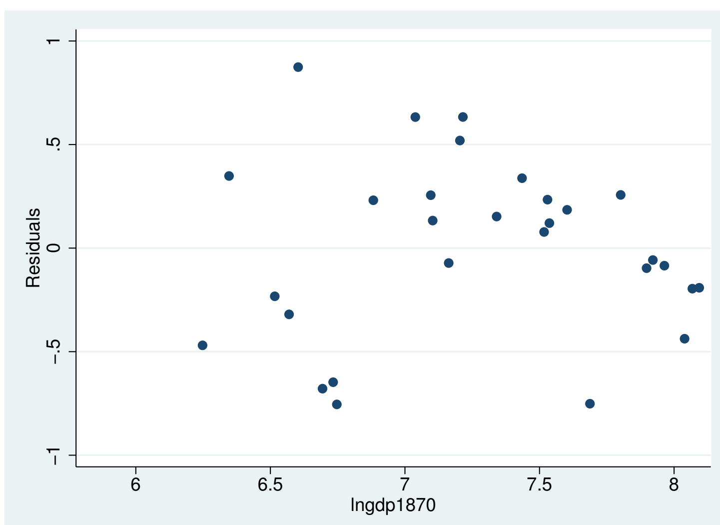

Figure 3: Full sample: 1870-2008 growth regression

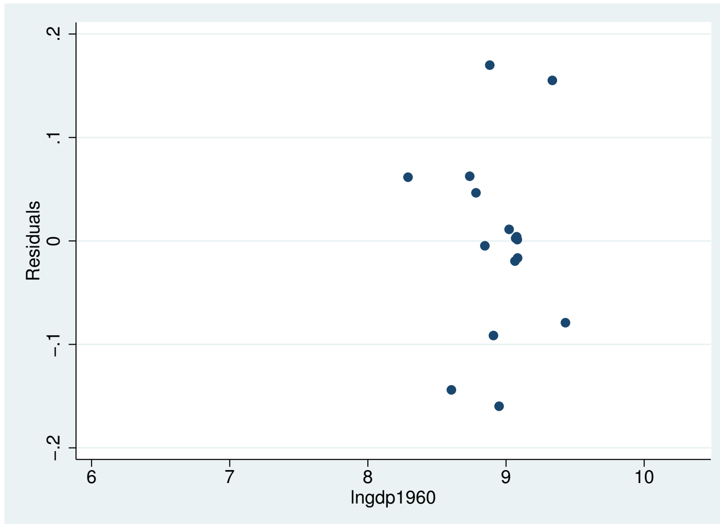

Figure 4: 16-country sample: 1960-2008 growth regression

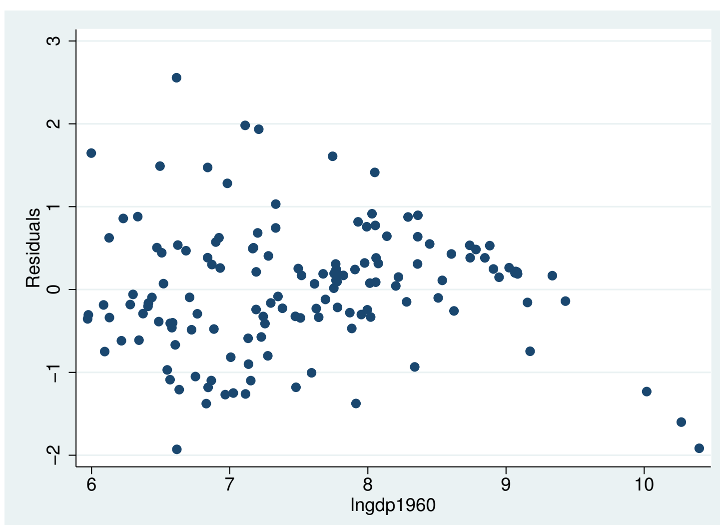

Figure 5: Full sample: 1960-2008 growth regression