Michael Berlemann* and Jan-Erik Wesselhöft

Aggregate Capital Stock Estimations for 122 Countries: An Update

https://doi.org/10.1515/roe-2017-0004

Abstract: Using newly available investment data from the World Bank's World Development Indicators database we provide an update and an extension of the aggregate capital stock estimations provided in (BERLEMANN, M. and J.-E. WESSELHÖFT (2014): Estimating Aggregate Capital Stocks Using the Perpetual Inventory Method: A Survey of Previous Implementations and New Empirical Evidence for 103 Countries, *Review of Economics* 65(1), 1–34). The new database contains comparable unbalanced panel data for 122 countries and the period of 1960 to 2016.

Keywords: aggregate capital stock, investments, Perpetual Inventory Method
JEL Codes: O47

1 Introduction

For a long period of time, the absence of internationally comparable capital stock data has been a major obstacle to empirical studies of the contribution of the capital stock to economic growth and related studies. While the OECD maintains a database of international capital stock data of its member countries, the data is a mixture of data collected from the national statistical offices and own estimations of the OECD. The OECD therefore recommends to be very careful in using the data for international comparisons.[1] Since the 8.0 version of the Penn World Tables capital stock data is also available from this source, however, in an attempt to construct a database covering a large range of countries and long periods of time, data from very different

1 SCHREYER et al. (2011).

***Corresponding author: Michael Berlemann,** Faculty of Economics & Social Sciences, Helmut-Schmidt-University Hamburg, Holstenhofweg 85, 22008 Hamburg, Germany; and CESifo Munich and ifo Institute of Economic Research Munich, Munich, Germany,
E-mail: Michael.Berlemann@hsu-hh.de
Jan-Erik Wesselhöft, Carl-Friedrich-Gauß Faculty, Institute of Economics,
Technical University Brunswick, Spielmannstraße 9, 38106 Brunswick, Germany,
E-mail: j.wesselhoeft@tu-braunschweig.de

sources which were constructed with differing methods were merged.[2] While this approach has its obvious merits, the high number of applied country-specific corrections and assumptions is not unproblematic for cross-country studies.

An alternative to using the two mentioned databases is to use investment data to construct capital stock data with the Perpetual Inventory Method. While doing so helps to overcome the problem of incomparability, constructing capital stock data is quite time-consuming. Moreover, the existing studies[3] differ to quite some extent, especially in the way the initial capital stock is estimated.[4] Against this background Berlemann and Wesselhöft (2014) proposed a unified approach of applying the Perpetual Inventory Method. Based on this approach and employing investment data from the World Bank's World Development Indicators database, the authors construct an unbalanced panel dataset of aggregate capital stock data for 103 countries over the period of 1970 to 2010 and made it publicly available. As the database has been employed quite frequently[5] and thus proved to be useful we decided to update the data. While we stick to the methodological approach developed in Berlemann and Wesselhöft (2014) we make some further extensions. First, we extend the dataset back to 1960 where possible. Doing so leads to considerably longer time series for the referring countries which might be useful for many applications. Second, we updated the investment time series from the World Banks's World Development Indicators database. Doing so allows us to extend the data to 2016. Third, as the newest investment data is available for more countries we added numerous countries to the dataset. The new panel data now covers as many as 122 countries.

This article describes the update and summarizes the main features of the new dataset. Section 2 outlines the unified approach of constructing aggregate capital stock estimates using the Perpetual Inventory Method proposed in Berlemann and Wesselhöft (2014). Section 3 describes the employed data sources and gives an overview on the development of the number of sample countries over the sample period. Section 4 presents and discusses the basic results. Section 5 concludes.

2 For a documentation see Inklaar and Timmer (2013).

3 See e.g. Griliches (1980), Nehru and Dhareswhar (1993), De la Fuente and Domenech (2000), Kamps (2006) and Derbyshire, Gardiner and Waights (2013).

4 For a survey of the related literature, see Berlemann and Wesselhöft (2014).

5 See e.g. Prettner (2016), Ashraf, Herzer and Nunnenkamp (2016), Thorbecke (2015) or Pang, Deng and Hu (2015).

2 “Unified” estimation approach

Almost all capital stock estimations make use of the Perpetual Inventory Method.[6] The Perpetual Inventory Method interprets an economy`s capital stock as an inventory which is feed by new investments while written-off capital leaves the inventory. In order to be able to apply the idea of the Perpetual Inventory Method strictly we would need information on the whole history of past investments (I). However, time series of investments typically cover only the (very) recent part of the capital stock history. Whenever the available time series of investments is incomplete (as almost always in practice), we nevertheless can calculate the current capital stock K_t accurately whenever the initial capital stock at the beginning of the investment time series, $\bar{K}$, and the depreciation rate δ are known. We then can calculate the capital stock at time t as

$$K_t = (1-\delta)^{t-1}\bar{K} + \sum_{i=0}^{t-1} (1-\delta)^i I_{t-(i+1)}$$

Thus, the capital stock in period t is a weighted sum of the initial capital stock and the known history of capital investments. The weights result from the geometric depreciation function.

In order to be able to apply this method three sorts of information are necessary. First, it is necessary to have a time series of investment data. Second, information on applicable depreciation rates has to be available. Finally, we are in need of data on the initial capital stock at the time when the investment time series starts. While information on investments and depreciation rates can be obtained from various sources (we discuss the employed sources in the third subsection) there is obviously no database on initial capital stocks. To solve this problem we calculate the initial capital stock K_{tO} from the investments I_{t1}, the long-term growth rate of Investments g_I and the rate of capital depreciation δ:

$$K_{to} \approx \frac{I_{t1}}{g_I + \delta}$$

In order to avoid that the calculations depend on a single observation of investments, which might be an outlier, we derive the initial investment value I_{t1} from a regression approach. We therefore use the whole time series of investments, ranging from time t_2 to T. In order to do so, we regress the time series of

6 For a more detailed description of the Perpetual Inventory Method see BERLEMANN and WESSELHÖFT (2014).

log investments $ln(I_{i,t})$ for any country i on time t. Thus, we estimate the equation

$$\ln I_{i,t} = \alpha_i + \beta_i \cdot t + \varepsilon_{i,t}$$

using the OLS method. In a next step we calculate the fitted value for period t_1, thereby using the estimated parameters α_i and β_i, i.e.

$$\ln\widehat{(I_{t1})} = \alpha_i + \beta_i \cdot t_1.$$

After transforming the fitted value using the exponential function we end up with a time series of investments ranging from t_1 to T. We then use the first (and thus the fitted) value of this time series to calculate the initial capital stock in period t_O. Moreover, we use the estimated parameter β_i as estimator for the long-run growth rate of investments g_I.

Rather than assuming a constant rate of depreciation, as it is often done in the related literature (for reasons of convenience) we use time-varying depreciation schemes, which seem to be the more plausible variant. As Kamps (2006) we base our assumptions on capital depreciation schemes on US data, provided by the U.S. Bureau of Economic Analysis (see Figure 1). Instead of defining a synthetic mathematical function which delivers a similar pattern as the observed values, we estimate the depreciation rates for the

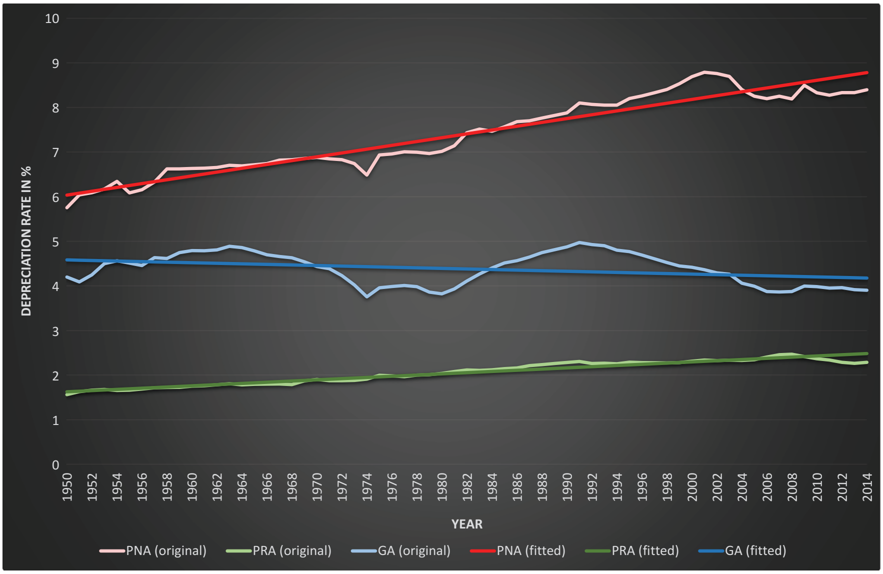

Figure 1: Depreciation rates of gross fixed asset categories 1950–2014.

period of 1950 to 2014 in three separate linear OLS regressions (private non-residential, private residential and government fixed assets). The estimation results are summarized in Table 1.

Table 1: Estimation results depreciation rates of private non-residential, private residential and government fixed assets, United States, 1950–2014.

	Private non-residential fixed assets	Private residential fixed assets	Government fixed assets
Constant	−77.6376*** (3.2015)	−24.4737*** (0.8411)	17.0076*** (4.4565)
Time	0.0429*** (0.0016)	0.0134*** (0.0004)	−0.0064*** (0.0020)
Adj. R^2	0.92	0.94	0.10
F-Statistic	705.76***	994.95***	8.03***

"***": significant on the 99% confidence level, "**": significant on the 95% confidence level, "*": significant on the 90% confidence level; values in brackets are standard errors

According to our findings, the depreciation rate of private non-residential fixed assets (PNA) increases from roughly 6.0% in 1950 to 8.8% in 2014. For private residential fixed assets, we find the depreciation rate to increase moderately from 1.6% to 2.5%. For government fixed assets (GA) we find a negative trend of the depreciation rate. The depreciation rate falls from 4.6% in 1950 to 4.2% in 2014. As we have no comparable data for the other sample countries we follow Kamps (2006) in assuming that these depreciation rates apply to all countries in the sample.[7]

In order to construct an adequate aggregate depreciation rate we calculate a weighted average of the three depreciation rates of private residential, private non-residential and government fixed assets. As weighting factor we use the average mix of all 22 OECD countries in the OECD Economic Outlook database.[8] The resulting depreciation rate, which is shown in Figure 2, is then applied to all sample countries.

7 The lack of comparable data for the other sample countries is also the primary reason why we rely on the fitted rather than the original values of the depreciation rates. Using the fitted values at least removes U.S. specific variance in the depreciation rates as they might result from business cycle fluctuations.

8 Since our time series of depreciation rate has to date back to earlier years than 1970 and thus to years for which no disaggregated data is available, we decided to use the data of 1970 for these years. For all years after 1970 the actual weighting factors are used.

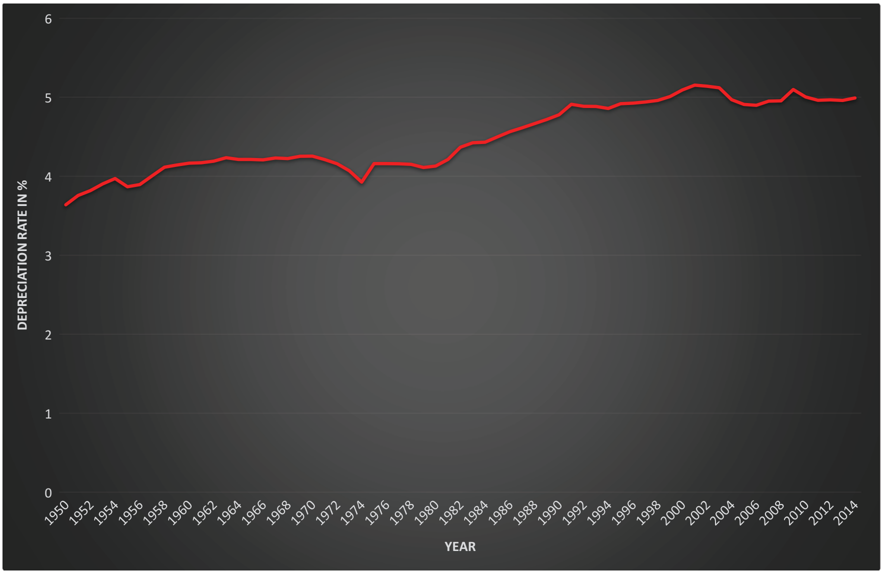

Figure 2: Assumed aggregate depreciation rate of gross fixed assets, 1950–2014.

3 Sample countries and data

In order to construct time series of capital stock data for a large sample of countries without having to rely country-specific and thus likely incomparable data sources, we rely on aggregate investment data provided by the World Bank in the World Development Indicators (WDI) database.[9] The investment data[10] includes land improvements (fences, ditches, drains, and so on), plant, machinery, and equipment purchases; the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings and commercial and industrial buildings. According to the 1993 SNA, net acquisitions of valuables are also considered as capital formation. Data are in constant 2010 USD.[11]

9 We used gross fixed capital formation data with the code: NE.GDI.FTOT.KD on 11/20/2016 from the WDI database.

10 For a description of the data see the website of the World Bank: http://databank.worldbank.org/ddp/viewSourceNotes.

11 Note that our last release of capital stock data are reported in constant 2000 USD, see Berlemann and Wesselhöft (2014).

While the WDI database of the World Bank contains aggregate investment data on a large number of countries, the starting dates of the data differ heavily from country to country. We only included countries in our dataset, for which at least 20 observations of investment data were available and we thus can construct reasonably long time series of capital stock data. Nevertheless, the resulting dataset is highly unbalanced. Figure 3 illustrates aggregate data availability. For 32 countries, the investment time series start out as early as in 1960. Major increases in the number of countries, for which data is available are 1965 (6 countries), 1970 (13 countries), 1980 (10 countries), 1990 (14 countries) and 1995 (5 countries). The 14 countries added in 1990 are primarily East European transformation countries. Since 1996 the number of countries, for which data is available, amounts constantly to 122. A table with more detailed information can be found in the Appendix.

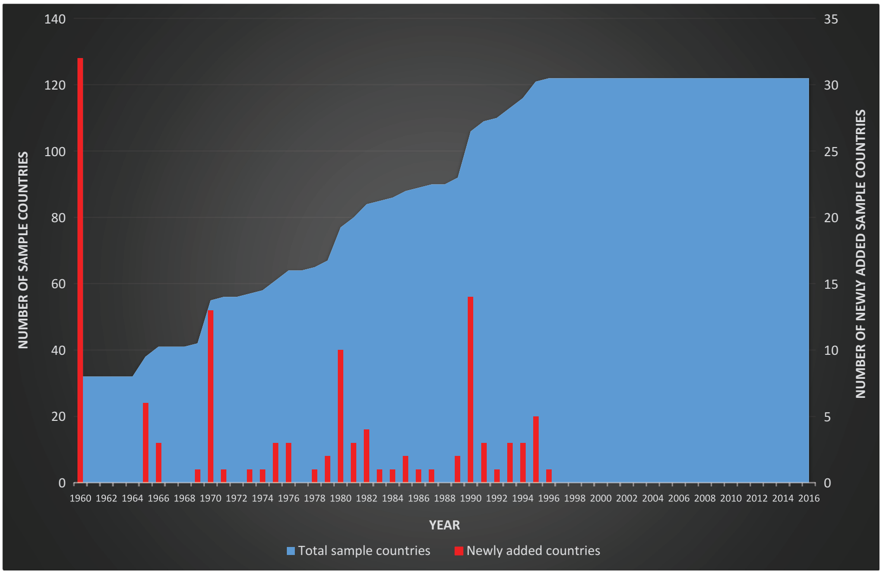

Figure 3: Number of sample countries over time in capital stock database.

The country sample consists of countries on quite different levels of development. According to the World Bank classification four types of countries are distinguished: low, lower middle, upper middle and high income countries.[12] As Figure 4 reveals, most countries for which data is available come from the high

12 We use the World Bank Classification by income groups of 2017. The classification can be found on http://data.worldbank.org/about/country-classifications.

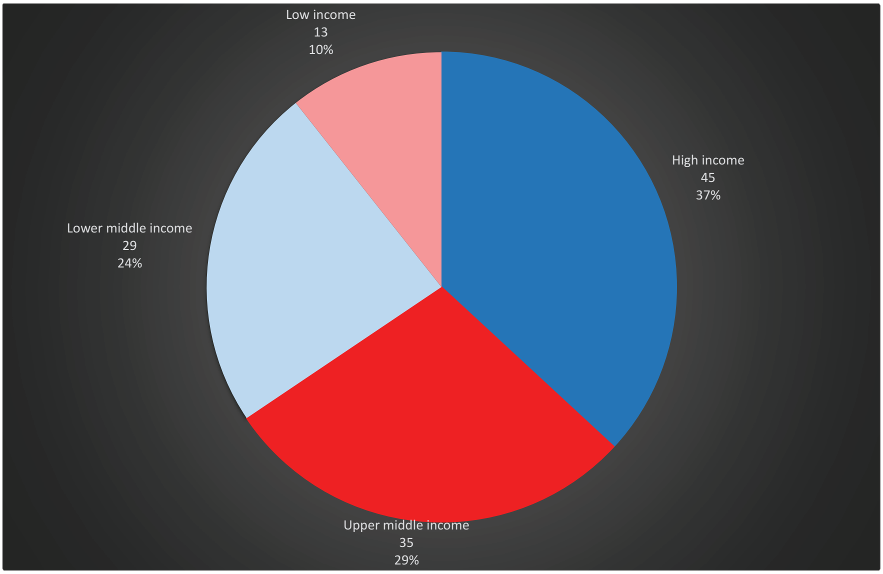

Figure 4: Country sample by World Bank classification.

income group (45 countries, 37%) while the low income countries represent only 10% of the whole sample (13 countries). However, as it is shown in Figure 5, the share of the four country groups in all countries is very similar in our dataset as compared to the full WDI dataset of countries (which includes 218 countries).

4 Capital stock estimation results under the unified approach

In the following we give an overview on the most important results of our aggregate capital stock estimations.[13] Due to space restrictions we concentrate on reporting the estimation results for the absolute aggregate capital stocks, capital intensities (capital per worker), and capital coefficients (capital per unit of GDP).

In Figure 6 we show a map visualizing the estimated aggregate stocks for 2016. Somewhat unsurprisingly, the countries with the largest populations tend

13 The complete dataset can be downloaded from the authors' internet page. For further requests contact the corresponding author.

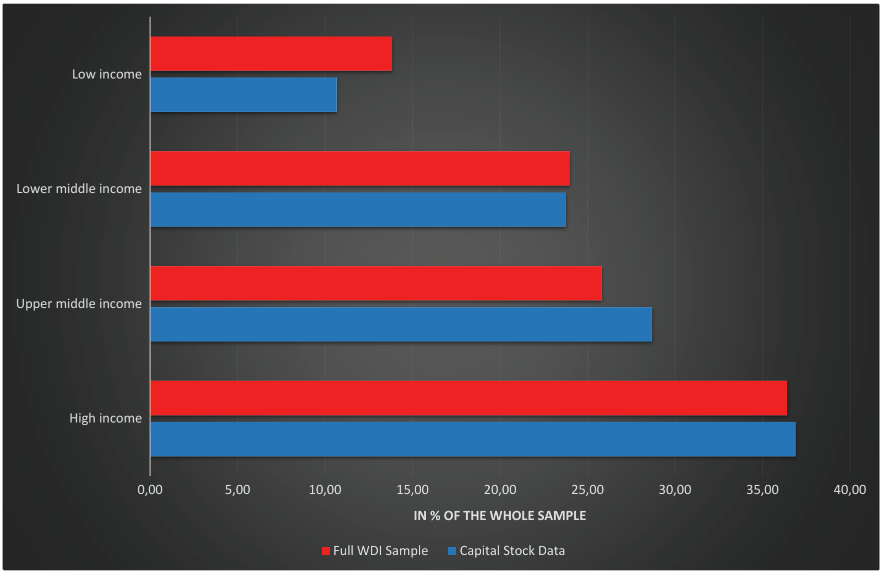

Figure 5: Countries in WDI Dataset versus Capital Stock Dataset.

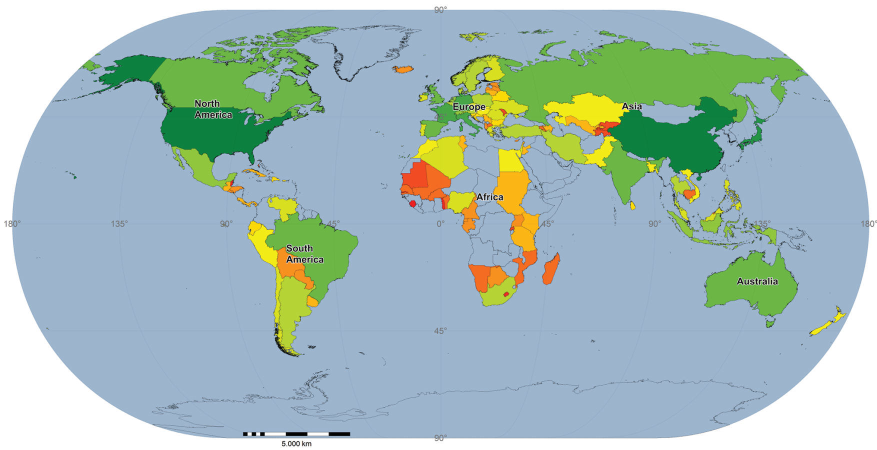

Figure 6: Estimated aggregate capital stocks 2016, 122 countries (in bn. USD of 2010).

to have also the highest capital stocks, at least whenever they are at least upper middle income countries. In Figure 7 we show the 20 countries with the highest aggregate capital stocks in 2016. In fact, only two countries with less than 20 million inhabitants are among the 20 countries with the largest capital stocks:

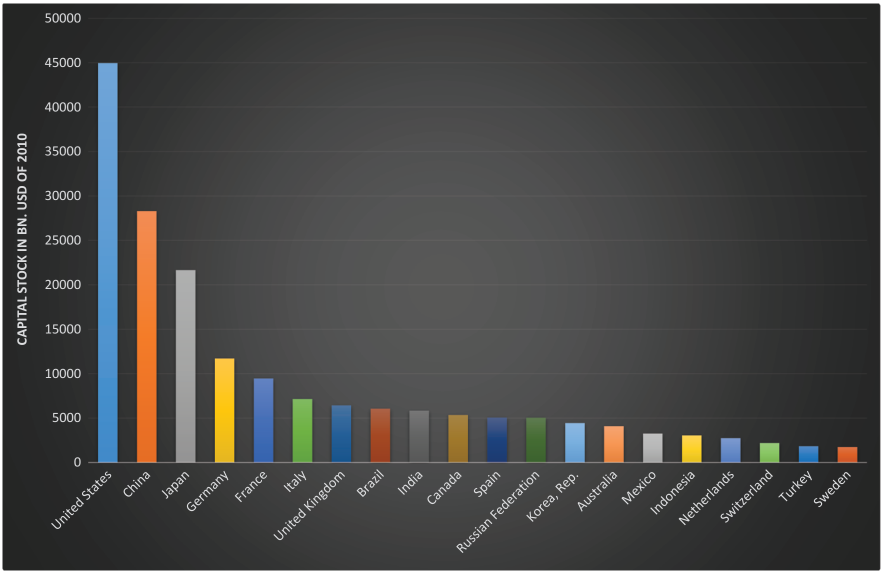

Figure 7: Sample countries with highest estimated aggregate capital stock 2016 (in bn. USD of 2010).

the Netherlands and Switzerland. The United States have by far the largest capital stock, followed by China, and Japan. Germany leads the following group of European countries, followed by France, Italy and the United Kingdom. Brazil, India and Canada complete the top ten countries with the largest absolute capital stocks.

Figure 8 shows the development of the aggregate capital stock for the 10 countries with the highest capital stock in 2016 over the period of 1978 to 2016. Over the entire period, the United States had the highest capital stock of all sample countries. Until the late 1990s, Japan's capital stock developed at a similar pace as its U.S. counterpart. However, since then the difference between the U.S. and Japan grew considerably larger. The same holds true for almost all other sample countries with the exception of China and India. China exhibits a strongly upward development since 1978. In 2008, China's capital stock exceeded Germany's capital stock for the first time. As of 2014, China also overtook Japan and is now owner of the second largest capital stock, with the capital stock still growing at a larger pace than its U.S. counterpart. A continuation of this development would lead to a further convergence over the next years. Besides China, India also shows a strong upward trend. Starting out from a similarly low capital stock as China, India's capital stock exceeded the one of

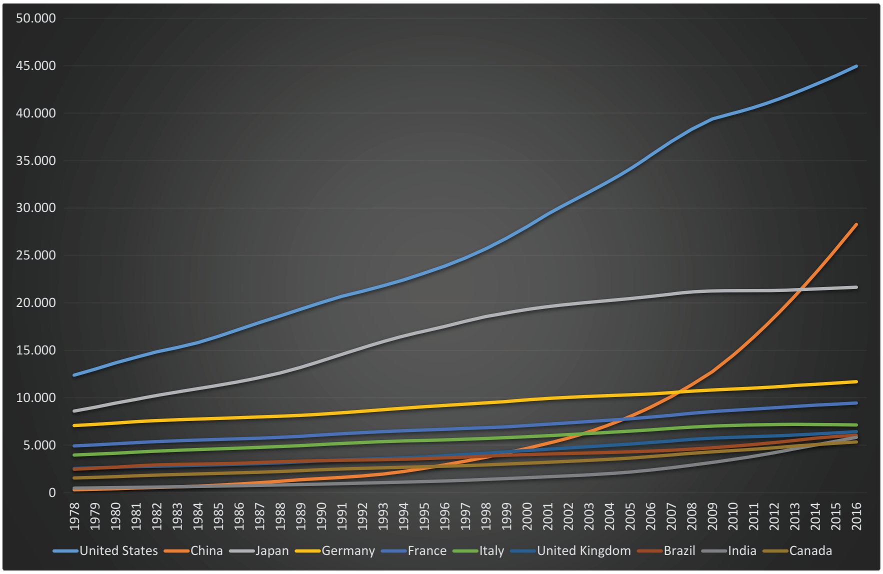

Figure 8: Gross fixed assets 1978–2016, 10 countries with largest aggregate capital stocks in 2016 (in bn. USD of 2010).

Canada for the first time in 2014. In absolute terms, India had the 9th largest capital stock in 2016.

Over the period of 1996 to 2016 the average aggregate capital stock of the 122 sample countries almost doubled from 113.207 bn. USD in 1991 to 212.452 bn. USD in 2016 (USD of 2010). However, this increase in the mean level was not accompanied by a convergence of the capital stocks. Over the same horizon, the standard deviation of the aggregate capital stocks also almost doubled.

While absolute aggregate capital stock data are often useful for empirical analyses the capital stock available per worker,[14] i.e. capital intensity, is often the more interesting variable. High capital intensities indicate that the amount of physical capital[15] available per worker in the production process is also high.

14 In order to calculate capital intensity we use the total labor force from the World Development Indicators Database of the World Bank.

15 While we have capital stocks for all years until 2016, population and employee data were only available for 2015 and 2014, respectively. We therefore report capital intensity for the year 2014.

In Figure 9 we show a world map reporting capital intensities for the year 2014. It is easily visible that the ranking for this indicator is quite different from those reported in the previous section. Especially China, but also India and to some lower extent also Brazil and Russia do not perform very well in terms of capital intensity. On the other hand comparatively small but highly developed countries like the Scandinavian countries, Belgium, Ireland, Austria and Luxemburg appear among the 20 countries with the highest capital intensities.

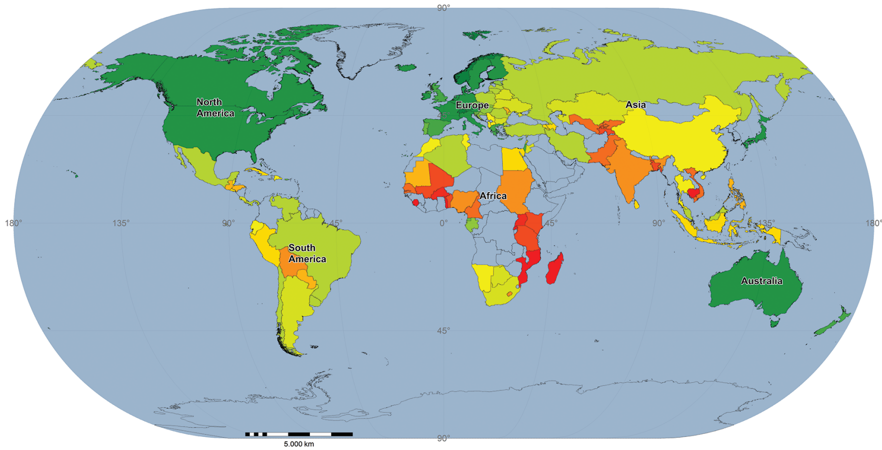

Figure 9: Gross fixed assets per worker 2014 (in USD of 2010).

As Figure 10 reveals, Norway and Japan turn out to have the highest capital intensities in our sample, ranging closely to 500,000 USD per worker, closely followed by Switzerland. The next group of countries has capital of slightly more than 300,000 USD per worker and is led by Japan, followed by Denmark, Belgium, Austria, Sweden, Finland, France and Australia. Germany, the United States and Canada range only on 15th, 16th and 17th place, the United Kingdom does not even range among the first 20 countries.

It is also an interesting question, how much capital a country needs to generate the current output. This question can be answered by studying capital coefficients, i.e. the amount of available capital divided by the gross domestic product.[16] Figure 11 shows a world map with capital coefficients.

16 In order to calculate capital coefficients we use GDP per capita and total population from the World Development Indicators Database of the World Bank.

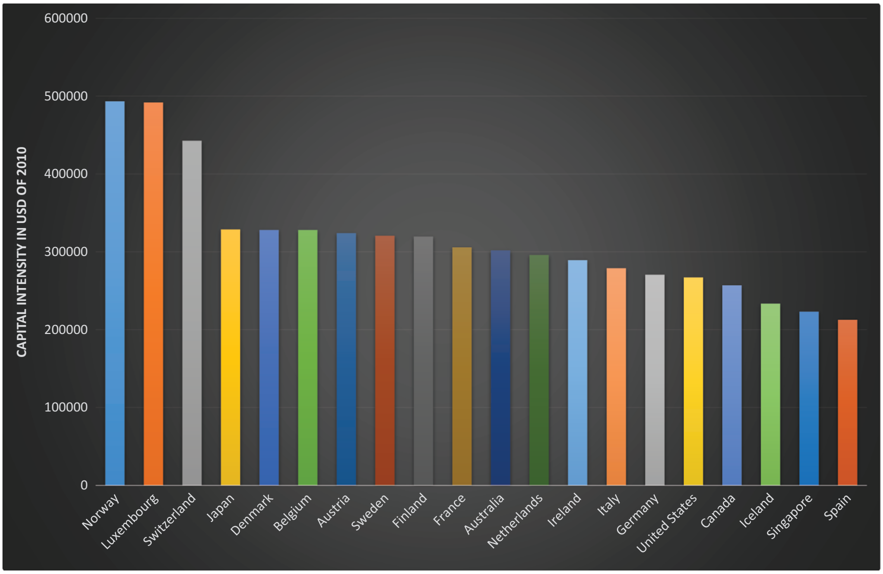

Figure 10: Countries with highest capital intensities in 2014 (in USD of 2010).

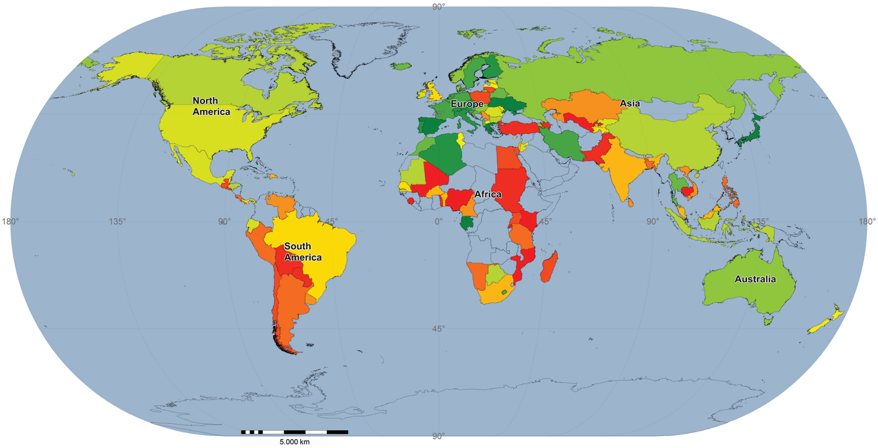

Figure 11: Capital coefficients 2014 (based on USD of 2010).

When comparing capital coefficients between countries on strongly differing levels of development, the results are not too informative as the economies structures and thus also their need of capital differ enormously. In Figure 12

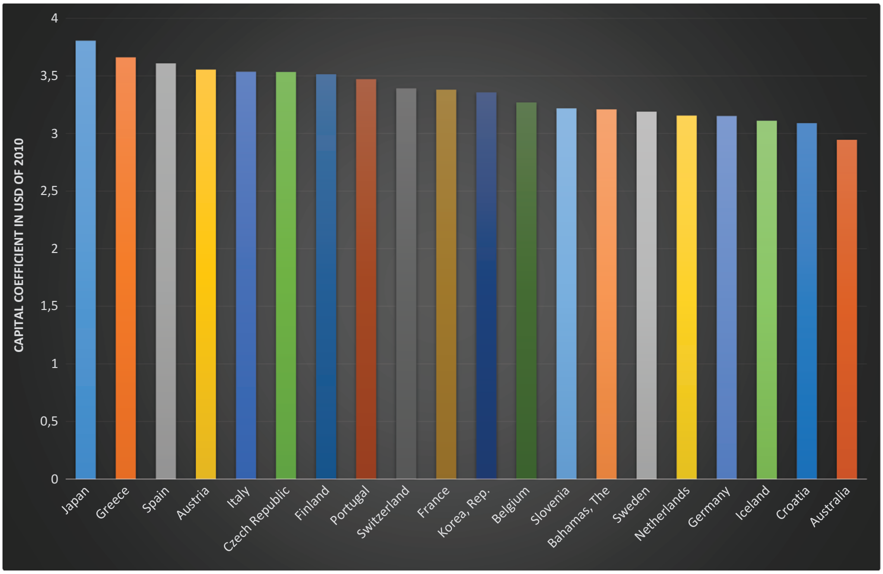

Figure 12: High income countries with highest capital coefficients in 2014 (based on USD of 2010).

we therefore concentrate on a comparison of capital coefficients in high income countries.

The country with the highest capital input per unit of GDP is Japan, where 3.8 units of capital are utilized to produce one unit of output. Capital coefficients of more than 3.5 are also prevailing in Greece, Spain, Austria, Italy, the Czech Republic and Finland. Other large industrial countries such as Germany (3.2) and Australia (2.9) turn out to exhibit somewhat lower capital coefficients. Even lower capital coefficients can be observed for China (2.8), the United States (2.7) and the United Kingdom (2.4).

5 Summary and conclusions

The lack of internationally comparable capital stock data has been a major obstacle to empirical multi-country research on the role of physical capital in the process of economic growth. The feedback on our approach to overcome this problem by delivering consistent estimates of aggregate capital stocks using the Perpetual Inventory Method (see Berlemann and Wesselhöft

2014) motivated us to deliver an update of the dataset, which now covers the time period of 1960 to 2016 for 122 countries (unbalanced). As in the previous version, the dataset can be downloaded from the authors' internet page freely.

Appendix

Table A1: Sample countries (122).

Country	First year of data	WDI classification
Albania	1996	Upper middle income
Algeria	1969	Upper middle income
Antigua and Barbuda	1981	High income
Argentina	1960	Upper middle income
Armenia	1990	Lower middle income
Australia	1960	High income
Austria	1970	High income
Azerbaijan	1990	Upper middle income
Bahamas, The	1989	High income
Bangladesh	1980	Lower middle income
Belarus	1990	Upper middle income
Belgium	1970	High income
Belize	1981	Upper middle income
Benin	1982	Low income
Bolivia	1960	Lower middle income
Botswana	1974	Upper middle income
Brazil	1970	Upper middle income
Brunei Darussalam	1989	High income
Bulgaria	1980	Upper middle income
Burkina Faso	1983	Low income
Cambodia	1993	Lower middle income
Cameroon	1975	Lower middle income
Canada	1960	High income
Chile	1960	High income
China	1978	Upper middle income
Congo, Dem. Rep.	1993	Low income
Congo, Rep.	1985	Lower middle income
Costa Rica	1960	Upper middle income
Croatia	1995	High income
Cuba	1970	Upper middle income
Cyprus	1975	High income
Czech Republic	1990	High income
Denmark	1966	High income

(*continued*)

Table A1: (*continued*)

Country	First year of data	WDI classification
Dominican Republic	1960	Upper middle income
Ecuador	1965	Upper middle income
Egypt, Arab Rep.	1982	Lower middle income
El Salvador	1965	Lower middle income
Equatorial Guinea	1980	Upper middle income
Estonia	1993	High income
Finland	1960	High income
France	1970	High income
Gabon	1980	Upper middle income
Gambia, The	1966	Low income
Germany	1970	High income
Greece	1960	High income
Guatemala	1960	Lower middle income
Honduras	1960	Lower middle income
Hong Kong SAR, China	1973	High income
Hungary	1991	High income
Iceland	1960	High income
India	1960	Lower middle income
Indonesia	1979	Lower middle income
Iran, Islamic Rep.	1960	Upper middle income
Ireland	1970	High income
Israel	1995	High income
Italy	1960	High income
Japan	1960	High income
Jordan	1976	Upper middle income
Kazakhstan	1990	Upper middle income
Kenya	1979	Lower middle income
Korea, Rep.	1960	High income
Kyrgyz Republic	1990	Lower middle income
Latvia	1995	High income
Lebanon	1994	Upper middle income
Lesotho	1970	Lower middle income
Lithuania	1995	High income
Luxembourg	1960	High income
Macao SAR, China	1982	High income
Macedonia, FYR	1990	Upper middle income
Madagascar	1984	Low income
Malaysia	1960	Upper middle income
Mali	1985	Low income
Mauritania	1965	Lower middle income
Mauritius	1976	Upper middle income
Mexico	1960	Upper middle income

(*continued*)

Table A1: (*continued*)

Country	First year of data	WDI classification
Moldova	1991	Lower middle income
Morocco	1966	Lower middle income
Mozambique	1980	Low income
Namibia	1980	Upper middle income
Netherlands	1970	High income
New Zealand	1970	High income
Nigeria	1981	Lower middle income
Norway	1960	High income
Pakistan	1960	Lower middle income
Panama	1980	Upper middle income
Paraguay	1991	Upper middle income
Peru	1960	Upper middle income
Philippines	1960	Lower middle income
Poland	1990	High income
Portugal	1970	High income
Puerto Rico	1971	High income
Romania	1990	Upper middle income
Russian Federation	1990	Upper middle income
Rwanda	1965	Low income
Senegal	1965	Low income
Serbia	1995	Upper middle income
Sierra Leone	1980	Low income
Singapore	1975	High income
Slovak Republic	1992	High income
Slovenia	1990	High income
South Africa	1960	Upper middle income
Spain	1970	High income
Sri Lanka	1960	Lower middle income
Sudan	1976	Lower middle income
Sweden	1960	High income
Switzerland	1960	High income
Tajikistan	1986	Lower middle income
Tanzania	1990	Low income
Thailand	1960	Upper middle income
Togo	1980	Low income
Trinidad and Tobago	1980	High income
Tunisia	1965	Lower middle income
Turkey	1987	Upper middle income
Uganda	1982	Low income
Ukraine	1990	Lower middle income
United Kingdom	1970	High income

(*continued*)

Table A1: (*continued*)

Country	First year of data	WDI classification
United States	1960	High income
Uruguay	1960	High income
Uzbekistan	1990	Lower middle income
Venezuela, RB	1960	Upper middle income
Vietnam	1994	Lower middle income
West Bank and Gaza	1994	Lower middle income

References

Ashraf, A., D. Herzer and P. Nunnenkamp (2016): The Effects of Greenfield FDI and Cross-border M & As on Total Factor Productivity, World Economy 39(11), 1728–1755.

Berlemann, M. and J.-E. Wesselhöft (2014): Estimating Aggregate Capital Stocks Using the Perpetual Inventory Method: A Survey of Previous Implementations and New Empirical Evidence for 103 Countries, Review of Economics 65(1), 1–34.

Derbyshire, J., Gardiner, B. and S. Waights (2013): Estimating the capital stock for the NUTS2 regions of the EU27. Applied Economics 45 (9), 1133–1149.

de la Fuente, A. and R. Domenech (2000): Human Capital in Growth Regressions: How Much Difference Does Data Quality Make? Economics Department Working Paper, 262, OECD, Paris.

Griliches, Z. (1980): R&D and the Productivity Slowdown. NBER Working Paper Series, 434, Cambridge/Mass.

Inklaar, R. and M. P. Timmer (2013): Capital, labor and TFP in PWT8.0, Working Paper, July.

Kamps, C. (2006): New Estimates of Government Net Capital Stocks for 22 OECD Countries 1960–2001. IMF Staff Paper 53 (1), 120–150.

Nehru, V. and A. Dhareshwar (1993): A new database on physical capital stock: Sources, methodology and results. Revista de Analisis Economico 8(1), 37–59.

Pang, R.-Z., Deng, Z.-Q. and J.-L. Hu (2015): Clean energy use and total-factor efficiencies: An international comparison, Renewable and Sustainable Energy Reviews 52(C), 1158–1171.

Prettner, C. (2016): Nonlinearities and Parameter Instability in the Finance-Growth Nexus, Department of Economics Working Paper No. 224, Wirtschaftsuniversität Wien.

Schreyer, P., Arnaud, B., Dupont, J. and S.-H. Koh (2011): Measuring Multi-Factor Productivity by Industry: Methodology and First Results from the OECD Productivity Database, OECD.

Thorbecke, W. (2015): China–US trade: A global outlier, Journal of Asian Economics 40(C), 47–58.