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Estimating Aggregate Capital Stocks Using the Perpetual Inventory Method

– New Empirical Evidence for 103 Countries –

MICHAEL BERLEMANN
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Zusammenfassung/ Abstract

The lack of internationally comparable capital stock data has been a major obstacle to empirical studies of the contribution of the capital stock to economic growth. In this paper, we provide estimations of aggregate capital stocks for 103 countries in 2010. Depending on data availability the time series of the sample countries start in between 1960 and 1991. The estimation is based on World Bank investment data and applies a unified approach of applying the Perpetual Inventory Method. The data can easily be extended for more recent years as soon as new data is available.

JEL-Klassifikation / JEL-Classification: O47

Schlagworte / Keywords: aggregate capital stock, investments, perpetual inventory method

1 Introduction

In theoretical models of economic growth the physical capital stock, consisting of e.g. machinery, buildings and computers, is one of the major input factors of the production function. In order to study the contribution of the existing capital stock to aggregate output, data on the capital stock is necessary. However, since the capital stock of a country is not easily observable, data on the development of the capital stock has been unavailable for most countries for a considerable time.

Nowadays, at least many industrial countries spend substantial effort on measuring their capital stocks.[3] However, although international standards of measuring capital stocks slightly evolve, the applied methods differ from case to case quite substantially.[4] As a consequence internationally comparable datasets are yet widely unavailable. While the OECD maintains a database of international capital stock data for 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 careful usage of the data for international comparisons.[5]

The lack of internationally comparable capital stock data has been a major obstacle to empirical studies of the contribution of the capital stock to economic growth. In the absence of reliable capital stock data the scientific literature has often employed different proxies for capital accumulation.[6] As a prominent example BARRO (1991), and much of the related literature thereafter, employed gross investment rates as a proxy for physical capital accumulation. While - in the absence of reliable measures of the capital stock - the use of these proxies is an acceptable alternative, the construction of capital stock data is surely the superior method. However, due to the fact that constructing capital stock data is a time-consuming task, most of the related literature has yet relied on the proxy approach.

Against the background of the considerable efforts to construct capital stock data it is not too surprising that only a few attempts have yet been made in the literature to generate

[3] A documentation of the system of capital stock measurement in the United States is reviewed in BUREAU OF ECONOMIC ANALYSIS (2003), the Canadian method in STATISTICS CANADA (2001). For a description of the methods of measuring the German capital stock, see SCHMALWASSER and SCHIDLOWSKI (2006).
[4] SCHREYER ET AL. (2011), p. 2.
[5] SCHREYER ET AL. (2011).
[6] BENHABIB and SPIEGEL (1994), p. 144.

larger capital stock datasets. Interestingly enough, these few attempts all rely on applying the Perpetual Inventory Method (PIM), a methodology which is also most often used in statistical offices.

An early example is GRILICHES (1980) who constructs capital stock data from US 3-digit manufacturing industry data provided by the Bureau of Labor Statistics for 1959 to 1977 in order to study the effects of R&D investments on output. In their study of the growth determinants of developing countries NEHRU and DHARESWHAR (1993) constructed capital stock data for 92 countries over the period of 1960 to 1990, thereby employing data from the WORLD BANK's Economic and Social Indicators Database. DOMENECH and DE LA FUENTE (2000) study the effect of different measures of human capital in growth regressions and therefore construct capital stock data for OECD countries for the period of 1950 to 1997. In order to do so they use different OECD and IMF statistics.

Two more recent papers focus directly on providing data for further analyses. KAMPS (2006) generated capital stock estimates for 22 OECD countries using investment data from the OECD Analytical Database. The resulting capital stock estimates (disaggregated for 3 different asset classes) range from 1960 to 2001 and can be downloaded from the internet page of the Kiel Institute for the World Economy.[7] DERBYSHIRE, GARDINER and WAIGHTS (2010) recently constructed regional capital stock estimates for the 27 EU countries on the NUTS II level. While the data come primarily from Eurostat, several different sources have been used.

This paper contributes to the literature by constructing new estimates of the aggregate capital stock for a large sample of countries. In order to do so, we propose a method which relies on the frequently used Perpetual Inventory Method. To avoid some of the disadvantages of earlier applications of the PIM we propose a unified approach which combines some elements of these applications. Using the WORLD BANK's World Development Indicators Database enables us to estimate the aggregate capital stocks of 103 countries for the period 1991 to 2010. Depending on data availability, the time series for many countries date back to as early as 1960, thereby providing a rich database for empirical analyses. The

[7] See: http://www.ifw-kiel.de/academy/data-bases/netcap_e/database-on-capital-stocks-in-oecd-countries/view?set_language=en.

employed methodology comes at the advantage that the dataset can easily be extended to more recent years as the data becomes available.

The paper is constructed as follows. Section 2 introduces the PIM. Section 3 gives an overview on earlier implementations of the PIM and discusses the relative advantages and disadvantages of these approaches. Based on this discussion section 4 proposes and explains a unified approach to construct aggregate capital stock estimates using the PIM. Section 5 describes the employed data sources and gives an overview on the development of the number of sample countries over the sample period. Section 6 presents and discusses the results. Section 7 concludes.

2 Perpetual Inventory Method

Almost all attempts of estimating capital stocks employ some variant of the Perpetual Inventory Method (PIM). Before studying these variants in more detail in the next section, we shall describe the basic approach underlying the PIM.

The basic idea of the PIM is to interpret an economy`s capital stock as an inventory. The stock of inventory increases with capital formation (investments). Once an investment enters the economy's inventory, it remains there forever and provides services to the inventory’s owner. The quantity of services, the investment provides, is at its maximum directly after the investment has been made and decreases in the course of time. The amount by which the capital stock falls per period is the depreciation rate. However, while the value of the investment decreases in the course of time, it never falls to zero. Thus, an investment principally has a perpetual use.

The net capital stock at the beginning of period *t*, $\mathrm{K_t}$, can be written as a function of the net capital stock at the beginning of the previous period *t-1*, $\mathrm{K_{t-1}}$, gross investment in the previous period, $\mathrm{I_{t-1}}$, and consumption of fixed capital, $\mathrm{D_{t-1}}$:

$$\mathrm{K_t = K_{t-1} + I_{t-1} - D_{t-1}}$$

Assuming geometric depreciation at a constant rate δ we can rewrite the capital stock as:

$$K_t = (1-\delta)K_{t-1} + I_{t-1}$$

Repeatedly substituting this equation for the capital stock at the beginning of period *t-1*, K_{t-1}, leads to:

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

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

Obviously, calculating the actual capital stock in an accurate manner requires to have a complete time series of past investments. For many countries time series of investment data are available for at least a certain number of years. However, these time series typically cover only the (very) recent part of the capital stock history. Given the available time series of investments is incomplete, we nevertheless can calculate the current capital stock K_t accurately whenever the initial capital stock at the beginning of the investment time series, $\overline{K}$, is known:

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

Thus, in order to be able to apply the PIM to calculate the current capital stock, we need (i) a time series of investment data, (ii) information on the initial capital stock at the time when the investment time series starts and (iii) information on the rate of depreciation of the existing capital stock.

3 Implementations of the Perpetual Inventory Method

Over the years, various researchers have used the PIM to construct capital stock data. While the basic technique is quite similar and follows the idea outlined in the previous section, the specific implementation of the PIM differs to some extent. Methodological differences especially exist with respect to the method to estimate the initial capital stock. In this section we give an overview on the most important approaches employed in the literature. After discussing the advantages and drawbacks of these approaches we employ World Bank investment data to study how much the results differ when applying the various approaches. We thereby focus on the three different approaches used most frequently in the literature.

3.1 Steady State Approach

A first approach of estimating the initial capital stock is based on HARBERGER (1978). This approach employs neoclassical growth theory and relies on the assumption that the economy under consideration is at its steady state. As a consequence of this assumption, output grows at the same rate as the capital stock, i.e.:

$$g_{GDP} = g_K = \frac{K_t - K_{t-1}}{K_{t-1}} = \frac{I_t}{K_{t-1}} - \delta .$$

Solving this equation for the stock of capital in period t-1 leads to:

$$K_{t-1} = \frac{I_t}{g_{GDP} + \delta}$$

Thus, if in fact an economy is in its equilibrium, information on the current level of investments, the depreciation rate and the growth rate of output are sufficient to calculate the capital stock in the preceding period.

An obvious problem of this ''Steady State Approach'' is that the estimate of the initial capital stock depends crucially on the investments and the growth rate of output in a single year. While this is unproblematic if the economy under consideration is in fact in equilibrium, a short-term investment shock in the first period of the available time-series of investments would lead to a strongly biased initial capital stock estimate.

Aware of this problem, HARBERGER (1978) uses three-year averages instead of a single year to generate more stable and reliable capital stock estimates. In a later application of the Steady State Approach, NEHRU and DHARESHWAR (1993) proposed an alternative procedure. In order to generate a reliable initial value of the investment time series they regress the time series of log investments on time and then use the fitted value for the first period to calculate the initial capital stock.

3.2 Disequilibrium Approach

A second approach of estimating the initial capital stock goes back to GRILICHES (1980) and was used and further refined by DOMENECH and DE LA FUENTE (2000). Similar as the Steady State Approach, the reasoning of this method bases on the neoclassical growth model. As outlined earlier, the capital stock can be written as

$$K_{t-1} = \frac{I_t}{g_{GDP} + \delta} = \frac{I_t}{g_K + \delta}.$$

DOMENECH and DE LA FUENTE (2000) argue that the growth rate of the capital stock can be approximated by the growth rate of investments, i.e.

$$K_{t-1} \approx \frac{I_t}{g_I + \delta}.$$

However, different from the approaches in the tradition of HARBERGER (1978), DOMENECH and DE LA FUENTE (2000) argue that an economy typically is outside its long-term equilibrium. From their point of view it is more reasonable to assume that economies are most of the time on their adjustment path towards equilibrium. Throughout this adjustment process investment and capital accumulation tend to follow a systematic pattern. DOMENECH and DE LA FUENTE (2000) therefore propose to use data for longer time-periods to estimate the initial capital stock. More precisely they use a Hodrick-Prescott-Filter[8] to smooth the time-series of investment data. Since the HP-Filter is known to display anomalities at

[8] HODRICK and PRESCOTT (1997).

endpoints they drop the first 5 annual observations of the smoothed investment time-series. As proxy for the growth rate of investments they then use the average of the first ten observations.

3.3 Synthetic Time Series Approach

A third procedure of estimating the initial capital stock goes back to JACOB, SHARMA and GRABOWSKY (1997) and was further refined by KAMPS (2006). The idea behind this approach is to construct an artificial, historical time series of investments. This time series, together with an assumption on capital depreciation rates is then used to calculate the initial capital stock.

The applied procedure starts out from the first observation of investments which is available (I_t). For reasons of simplicity, KAMPS (2006) assumes a constant annual growth rate of investments of 4 percent (w_I =0.04), which coincides with the average growth rate of investments in the United States from 1960 to 2001. Applying this assumption, the level of investments in an arbitrarily chosen base year t_0 can then be calculated as:

$$I_0 = \frac{I_t}{e^{w_I \cdot (t-t_0)}}$$

Using this formula, an artificial time-series of investments can be constructed.[9] This time series is then used to calculate the initial capital stock for period t-1.[10] However, in order to be able to do so, an assumption on the prevailing rate of capital depreciation has to be made. KAMPS (2006), basing his assumptions on data of the U.S. BUREAU OF ECONOMIC ANALYSIS, employs time-varying depreciation profiles, thereby distinguishing between three different subgroups of investments (private residential, private non-residential, public). For the synthetic time series, covering the period from 1860 to 1960, KAMPS (2006) assumes a constant depreciation rate of 4.25 percent for nonresidential assets, 1.5 percent for

[9] KAMPS (2006) does not adjust the resulting time series for catastrophic losses from e.g. natural disasters or wars. He argues that countries experiencing catastrophic losses typically recovered quickly, thereby returning to the long-term trend.

[10] Obviously, this procedure neglects the capital stock which was accumulated before the chosen base period. However, provided the base period is chosen early enough, the capital stock in the base period can be neglected since capital depreciation led to an almost complete erosion of this initial capital stock.

residential assets and 2.5 percent for government assets. For the subsequent years 1961 to 2001 he assumes the rate for private nonresidential assets to increase gradually from 4.25 percent to 8.5 percent, for government assets from 2.5 to 4.0 percent, thereby applying the formula

$$\delta_t^j = \delta_{min}^j \left(\left(\frac{\delta_{max}^j}{\delta_{min}^j} \right)^{\frac{1}{41}} \right)^{t-2001+41}$$

The depreciation rate for private residential assets is held constant at 1.5 percent. Figure 1 shows the earlier described capital depreciation scheme applied by KAMPS (2006).

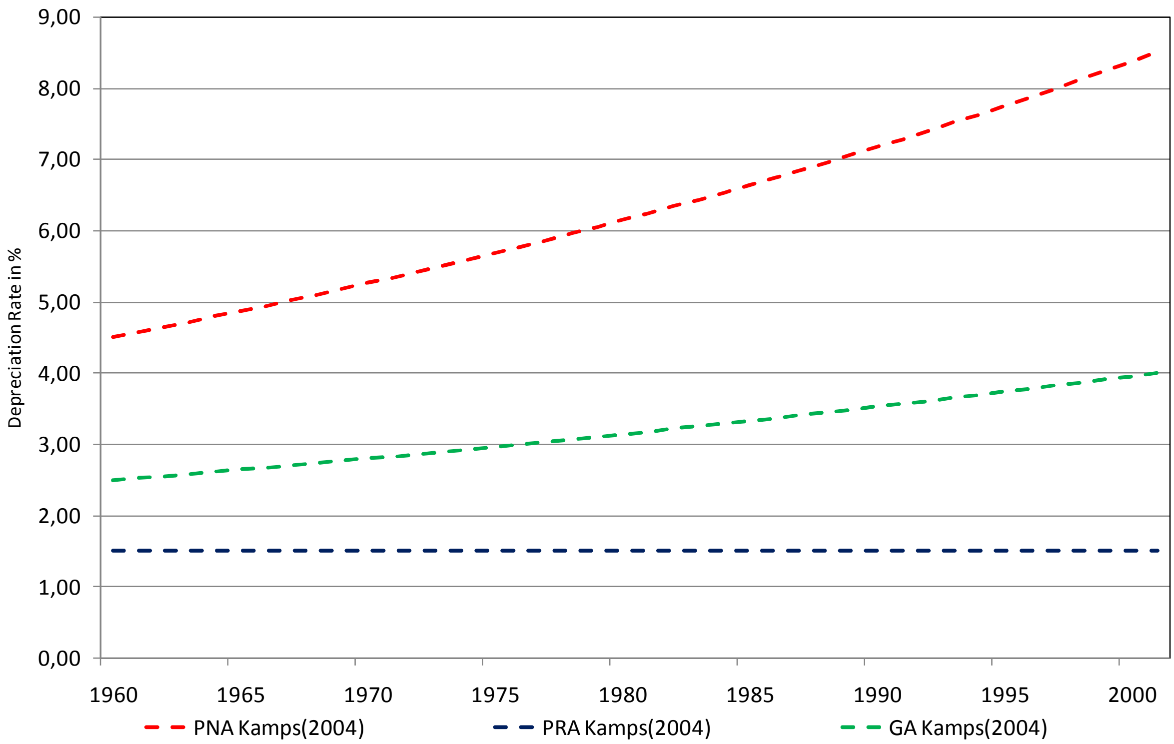

Figure 1: Depreciation Rates of Gross Fixed Asset Categories 1960-2001 according to KAMPS (2006)

3.4 Comparison of the Approaches

All three described approaches of estimating the initial capital stock have been used in the literature. However, they all have their specific drawbacks .The Steady State Approach might lead to rather implausible results whenever the (average) growth rate of a country turns out to be negative in the period(s) which are used to calculate the initial capital stock. Whenever the absolute value of the growth rate is considerably larger than the rate of depreciation, the term $g_{GDP+\delta}$ becomes strongly negative. As a consequence, the estimate of the initial capital stock also becomes negative, which is implausible. Whenever the growth rate of GDP is negative and its absolute value is (almost) equal to the rate of capital depreciation, i.e. $g_{GDP} + \delta \approx 0$, the estimated capital stock becomes either implausibly large or highly negative, i.e.

$$\lim_{g_{GDP}+\delta_t \to 0} \frac{I_t}{g_{GDP} + \delta} = +/-\infty$$

Both results are again highly implausible.

When using the Disequilibrium Approach some filter is necessary to extract information on the likely adjustment path of investments. However, conventional filters like the Hodrick Prescott Filter typically deliver inefficient results at the start and endpoints of a sample.[11] Thus, when fitting the investments series, the first observations are typically dropped,[12] thereby leading to a loss of information.

In the Synthetic Time Series Approach the initial capital stock depends critically on the first and thus a single observation of the investment time series. Whenever this observations turns out to be an outlier, the initial capital stock can be severely over- or underestimated.

4 A Unified Approach

As almost all approaches of estimating capital stock data we make use of the perpetual inventory method in the following. However, in order to prevent the disadvantages of the various methods of estimating the initial capital stock we combine them in a unified methodology. We outline this methodology in the following.

In general, our unified approach follows the procedure proposed by DOMENECH and DE LA FUENTE (2000). We thus follow the idea to calculate the initial capital stock K_{t0} from the

[11] See e.g. MISE, KIM and NEWBOLD (2005).

[12] As an example DOMENECH and DE LA FUENTE (2000) drop the first 5 datapoints.

investments I_{t1}, the long-term growth rate of Investments g_I and the rate of capital depreciation δ:

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

However, we deviate from the procedure of DOMENECH and DE LA FUENTE (2000) in three respects.

First, we do not use a filter to estimate the initial investment value. In order not to lose any investment information we instead follow the idea of NEHRU and DHARESHWAR (1993) to calculate 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 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.

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

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_0.

Second, we deviate from DOMENECH and DE LA FUENTE (2000) in the way of calculating the growth rate of investments g_I. Instead of using the mean of the investment time series (or subsamples of the series) we employ the estimated parameter of β_i from the regression as measure of trend investment growth.

Third, we do not use a constant rate of depreciation in our approach, neither for the calculation of the initial capital stock nor for the further construction of the time series of capital stocks using the PIM. Instead we follow the idea of KAMPS (2006) to use time-varying depreciation schemes, which seem to be the more plausible variant.

Since the capital depreciation schemes proposed by KAMPS (2006) end in 2000 it is impossible to simply apply them to our data directly. The time series would have to be extended in a plausible way. However, since there is no obvious way of prolonging the time-series we opt for a slightly different approach. KAMPS (2006) bases his assumptions on capital depreciation schemes on US data, provided by the U.S. Bureau of Economic Analysis. We follow this procedure and also base our assumptions on the same database, although the now larger number of observations. However, instead of defining a synthetic mathematical function which delivers a similar pattern as the observed values we estimate the depreciation rates for the period of 1950 to 2011 in three separate linear OLS regressions. 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, 1950-2011

	Private Non-Residential Fixed Assets	Private Residential Fixed Assets	Government Fixed Assets
Constant	-66.6852*** (3.0571)	-3.9470*** (0.5286)	23.6991*** (4.0462)
Depreciation Rate	0.0370*** (0.002)	0.0003*** (0.0003)	-0.0102*** (0.0020)
Adj. R^2	0.90	0.63	0.28
F-Statistic	575.79***	105.37***	25.01***

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

In figure 2 we show the actual time series of depreciation rates, the estimated depreciation rates as they result from the fitted values of the regression and the referring assumptions used by KAMPS (2006) for every fixed asset class. While for the depreciation rate of private residential fixed assets (PRA) the results are quite similar to the assumptions of KAMPS (2006), our findings for government fixed assets (GA) and private non-residential fixed assets (PNA) somewhat differ. Obviously, the occurring differences can not only be completely explained by the differing sample periods.

According to our findings, the depreciation rate of private non-residential fixed assets increases from roughly 5.5% in 1950 to 7.8% in 2011. Thus, while we also find a rigorous increase in the depreciation rate of private non-residential fixed assets, this growth rate is somewhat lower as assumed in KAMPS (2006), who assumes the depreciation rate to increase from 4.5% to 8.5% in between 1960 and 2001. While KAMPS (2006) assumes a constant depreciation rate of 1.5% for private residential fixed assets, we find the depreciation rate to increase slightly from 1.4% to 1.6%. However, the difference is negligible. The most obvious difference occurs for government fixed assets. While KAMPS (2006) assumes an increase of the depreciation rate from 2.5% to 4% over his sample period, we find the depreciation rate of government assets to decrease from 3.8% in 1950 to 3.2% in 2011. As our estimation bases on more and more actual data, we in the following apply the fitted values as prevailing depreciation rates. In the absence of comparable data from other countries we follow KAMPS (2006) in assuming that these depreciation rates apply to all countries in the sample.

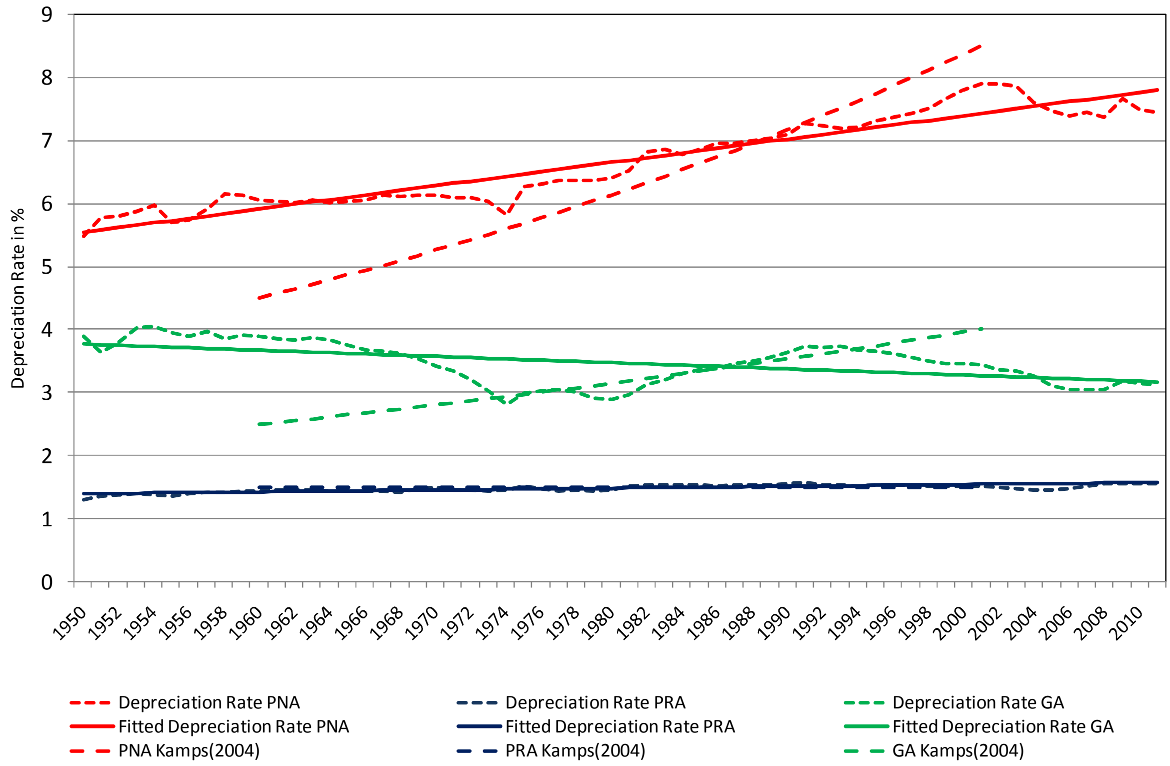

Figure 2: Various Depreciation Rates of Gross Fixed Asset Categories 1950-2010

Before the derived capital depreciation rates can be used in our empirical approach they have to be aggregated in a suitable manner. 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.[13] The resulting depreciation rate, which is shown in figure 3, is then applied to all sample countries.

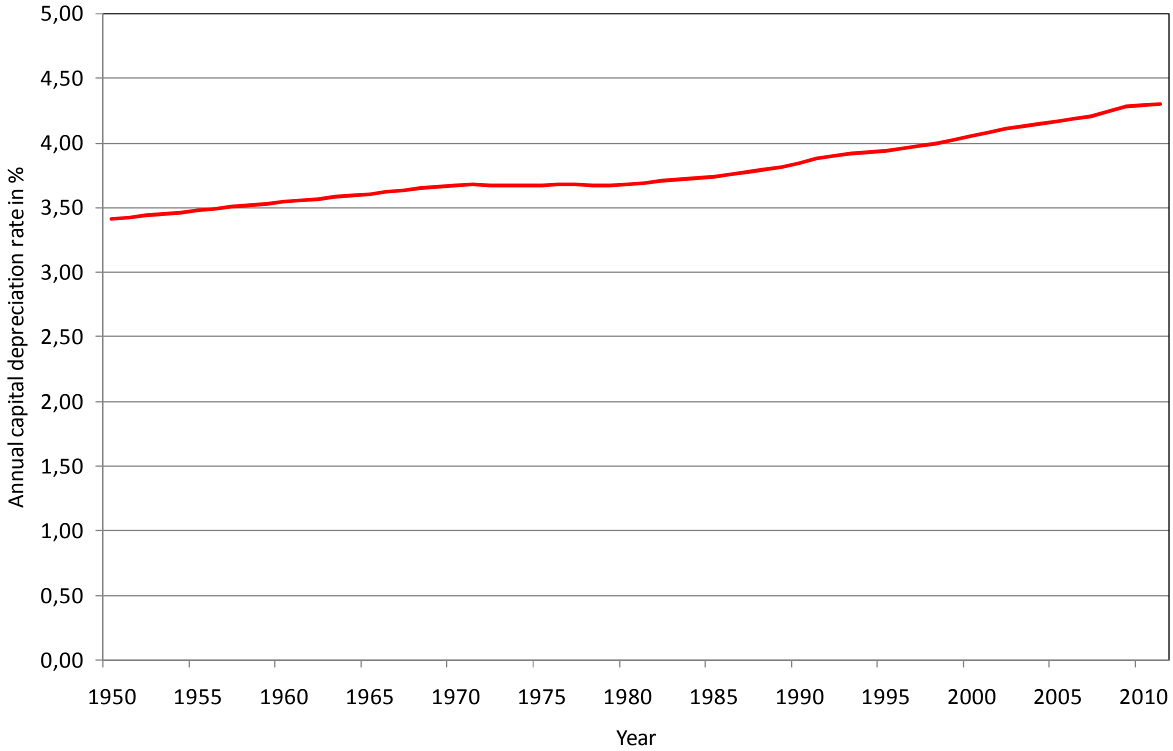

Figure 3: Assumed Aggregate Depreciation Rate of Gross Fixed Assets, 1950-2010

5 Sample Countries and Data

Our aim is to construct time series for capital stock data for a large sample of countries. Instead of using OECD data, which allow to differentiate between three classes of capital investment but are only available for 22 OECD countries, we rely on the aggregate investment data provided by the WORLD BANK in the World Development Indicators (WDI) database. We extracted the gross fixed capital formation data with code NE.GDI.FTOT.KD on 03/20/2012 from the database. The data 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

[13] Since our time series of depreciation rate has to date back to earlier years than 1970 and thus to years for which nor disaggregate data are available, we decided to use the data of 1970 for these years. For all years after 1970 the actual weighting factors are used.

commercial and industrial buildings. According to the 1993 SNA, net acquisitions of valuables are also considered as capital formation. Data are in constant 2000 U.S. dollars.[14]

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. Figure 4 illustrates aggregate data availability. For 30 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 (8 countries), 1970 (16 countries), 1980 (7 countries) and 1990 (14 countries). The 14 countries added in 1990 are primarily East European transformation countries. Since 1991 the number of countries for which data is available amounts constantly to 103. A table with more detailed information can be found in the appendix.

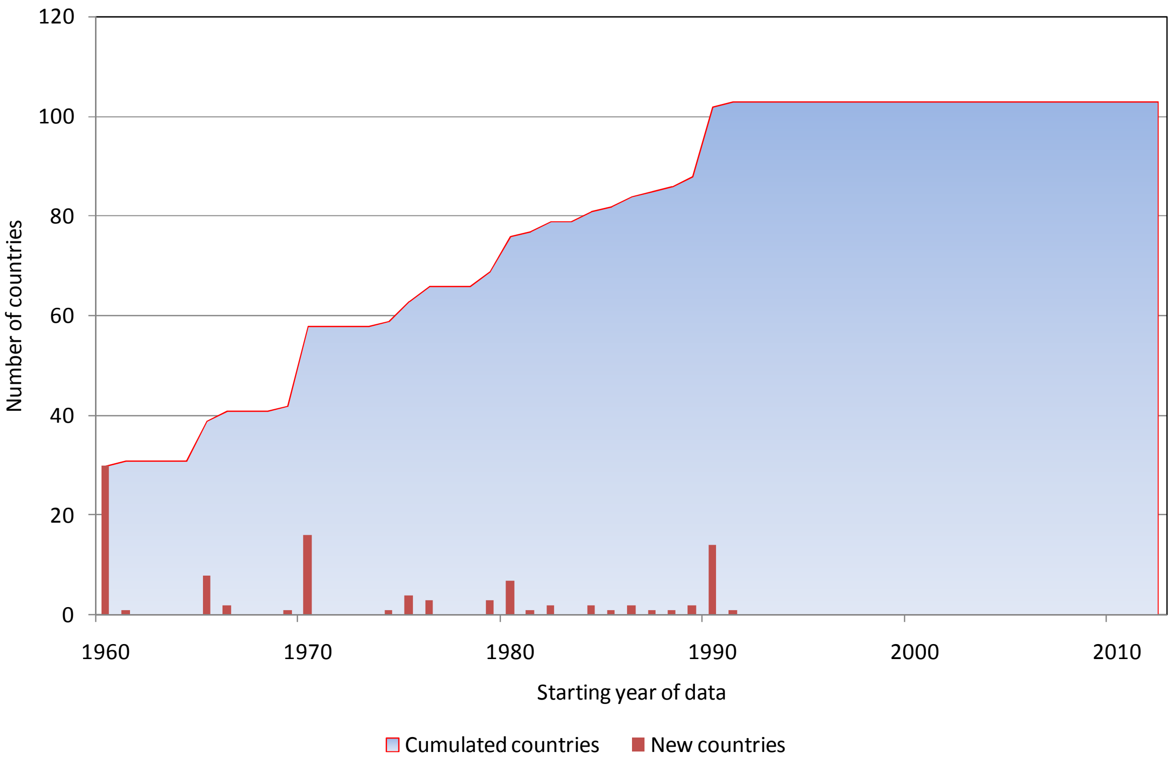

Figure 4: Number of Sample Countries over Time

The country sample consists of countries with quite different levels of development. According to the WORLD BANK classification four types of countries are distinguished: low,

[14] For a description of the data see the website of the WORLD BANK at : HTTP://DATABANK.WORLDBANK.ORG/DDP/VIEWSOURCENOTES?REQUEST_TYPE=802&DIMENSION_AXIS=

lower middle, upper middle and high income countries.[15] As figure 5 reveals, the country sample consists of countries of all four classes, although because of data availability reasons especially the low income countries are somewhat under- and especially the high income countries overrepresented.

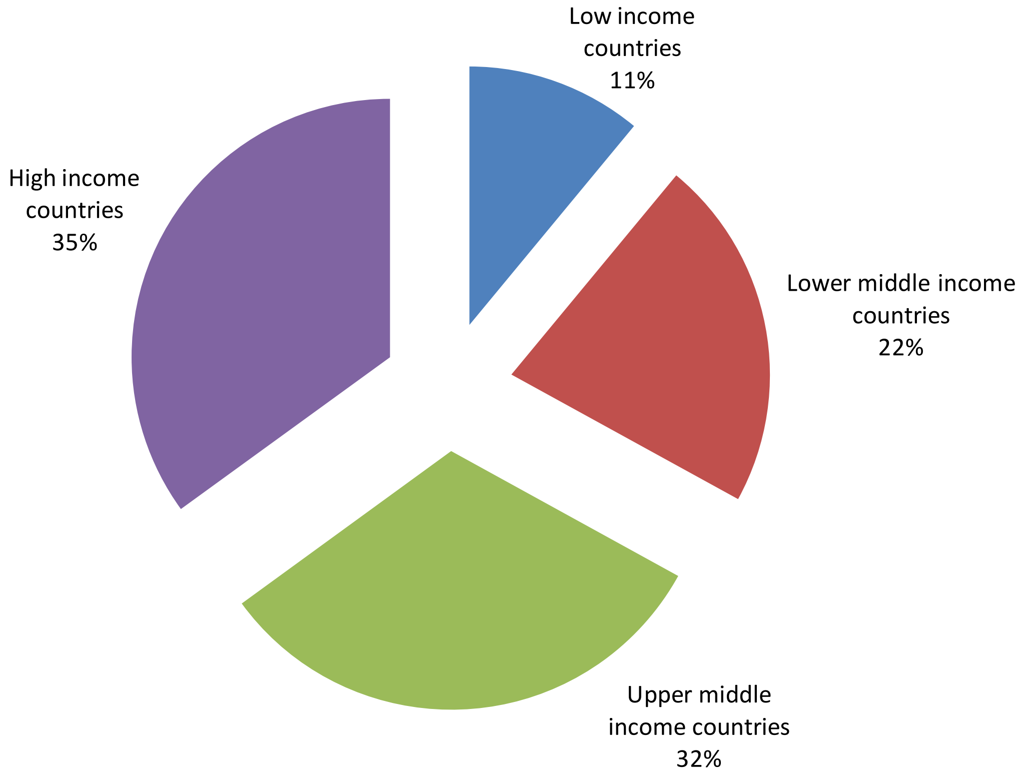

Figure 5: Country sample by World Bank classification

6 Results

In the following we give an overview on the most important and interesting results of our aggregate capital stock estimations. 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). We also study the development of dispersion of these measures over time. Some of the presented graphs

[15] We classify the countries by income groups: Economies are divided according to 2011 GNI per capita, calculated using the World Bank Atlas method. The groups are: low income (USD 1025 or less); lower middle income (USD 1026 - USD 4035); upper middle income (USD 4036 - USD 12475); and high income (USD 12476 or more). The WORLD BANK classification can be found on http://data.worldbank.org/about/country-classifications.

necessarily concentrate on subgroups of all sample countries. However, more detailed results are summarized in the appendix.

6.1 Aggregate capital stocks

In figure 6 we show a map visualizing the estimated aggregate stocks for 2010. Somewhat unsurprisingly, the countries with the most inhabitants tend 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 2010. In fact, only three countries with less than 20 million inhabitants are among the 20 countries with the largest capital stocks: the Netherlands, Switzerland and Belgium. The United States and Japan turn out to have by far the highest capital stocks. While China makes it to the third place of the ranking, its capital stock is only slightly higher than one quarter of the capital stock of the United States. Germany follows closely behind China. On the fourth, fifth and sixth place we find France, the United Kingdom and Italy with only slightly differing capital stocks. The next group of countries with similar aggregate capital stocks consists of Spain, Canada, South Korea, Brazil, India, Russia, Mexico and Australia. The final group is headed by the Netherlands and includes Switzerland, Argentina, Turkey and Belgium.

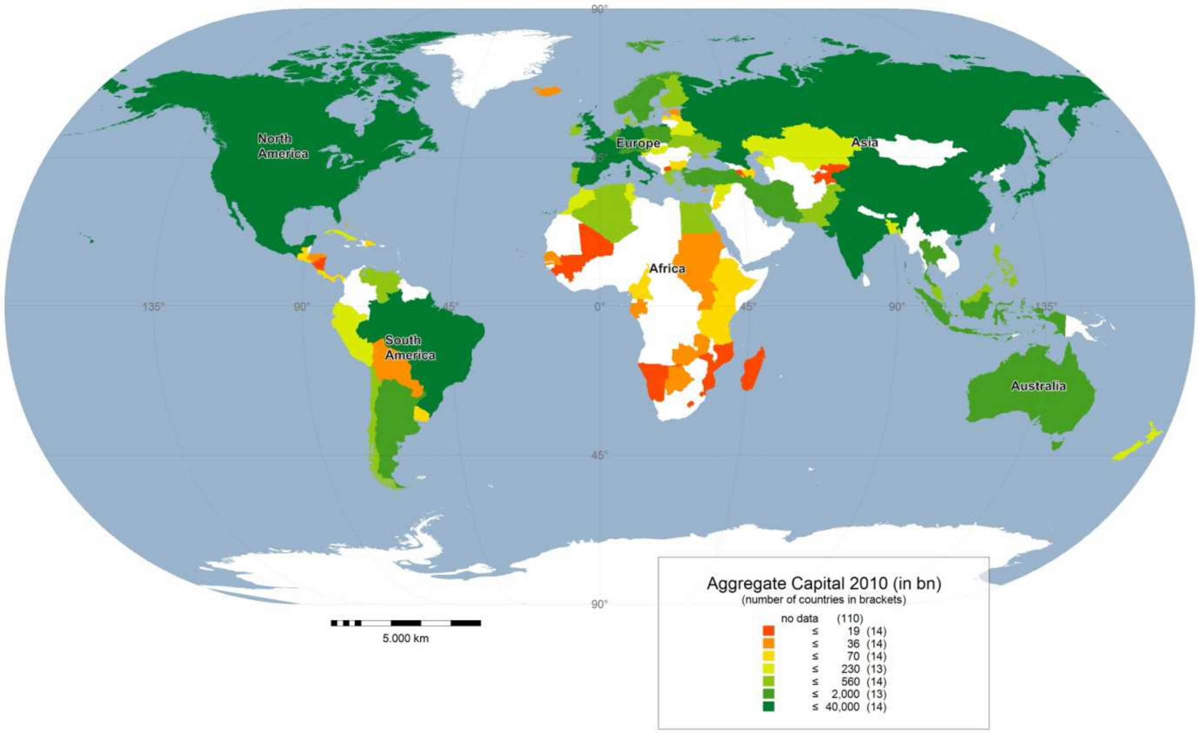

Figure 6: Estimated aggregate capital stocks 2010, 103 countries

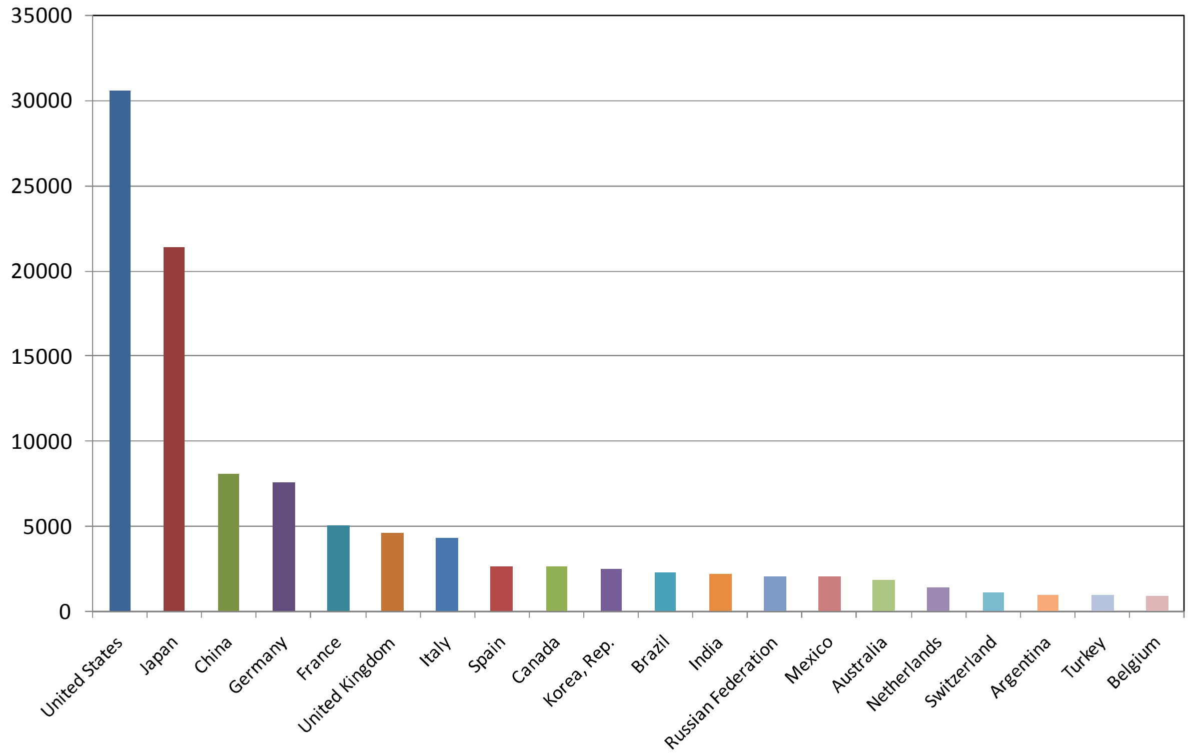

Figure 7: Sample countries with highest estimated aggregate capital stock 2010

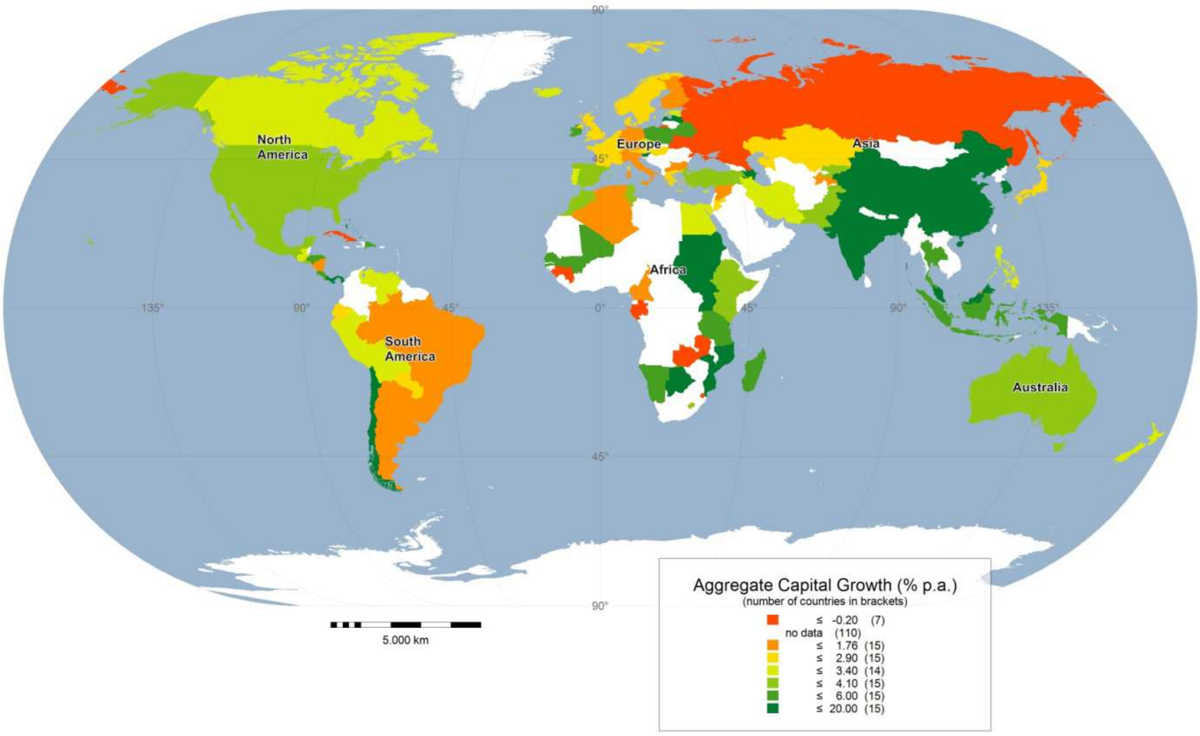

Figure 8: Growth of estimated aggregate capital stocks 1991-2010, 103 countries

In Figure 8 we show a world map reporting the annual growth rates of the aggregate capital stock in the sample countries in between 1991 and 2010.[16] It is easy to see that capital growth varies significantly between our sample countries. In seven sample countries, the capital stock decreased throughout the last two decades. Among these countries are a few African countries such as Guinea (-1.48%), Zambia (-1.24%), Swaziland (-0.48%) and Gabon (-0.46%) but also Cuba (-1.55%). Russia's aggregate capital stock also decreased over the last two decades by almost one percent per year. The worst development of the aggregate capital stock of all sample countries occurred in the Ukraine (-1.94%).

Figure 9 reports the 20 sample countries with the highest aggregate capital stocks growth rates in the last two decades. Azerbaijan (19,0%) realized the highest annual growth rate of the capital stock throughout the period of 1991-2010. With an annual growth rate of 11,0% China follows on the second place. The other 18 countries realized annual growth rates of the aggregate capital stock in between 8.2% and 5.8%. This group of countries

[16] We chose the period of 1991 to 2010 because for this period data for all 103 countries in our sample are available.

includes 6 African countries (Sudan, Uganda, Mozambique, Botswana, Madagascar and Tanzania), besides Azerbaijan 3 additional transition countries (Slovenia, Latvia and Poland) and besides China 5 additional East-Asian countries (Republic of Korea, India, Bangladesh, Macao and Malaysia). The remaining countries come from Middle and South-America: The Bahamas, Chile, the Dominican Republic and Panama.

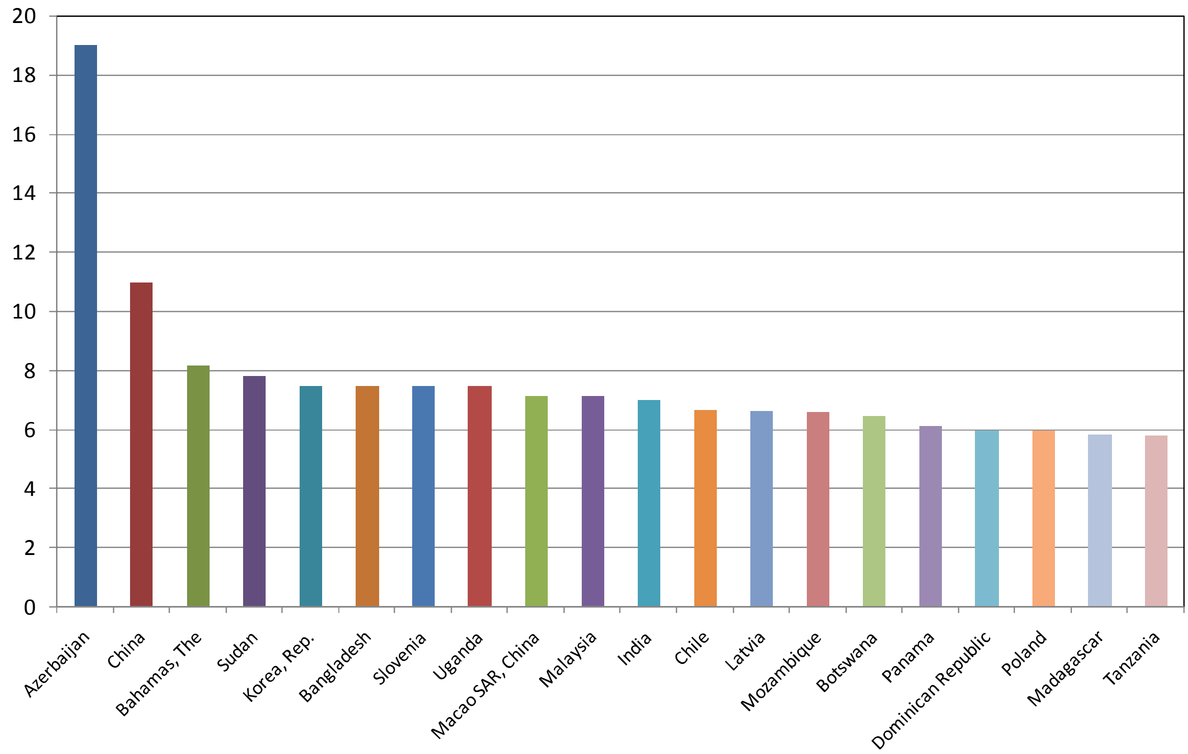

Figure 9: Sample countries with highest estimated growth rate of capital stock 1991-2010

Figure 10 shows the development of the aggregate capital stock for the 10 countries with the highest capital stock in 2010 over the sample period. For a long time Japan's capital stock was only slightly lower than the one of the United States. In the late 1990s Japan almost closed the remaining gap. However, since then Japan's capital stock development somewhat flattened, while the capital stock of the United States continued to increase considerably. For almost the whole sample period, Germany held the third position in the absolute capital stock. However, in the course of time the gap to the United States and Japan grew larger and larger. According to our estimations China overtook Germany recently in terms of the absolute capital stock in 2009 and now holds the third place. In general, China's capital stock experienced a remarkable development. While in 1970 only the Korean Republic had a lower capital stock than China (among the 2010 top ten countries), since then

China overtook all other countries except Japan and the United States. The only additional change in positions occurred in 2004 when the United Kingdom's capital stock grew larger than the one of Italy.

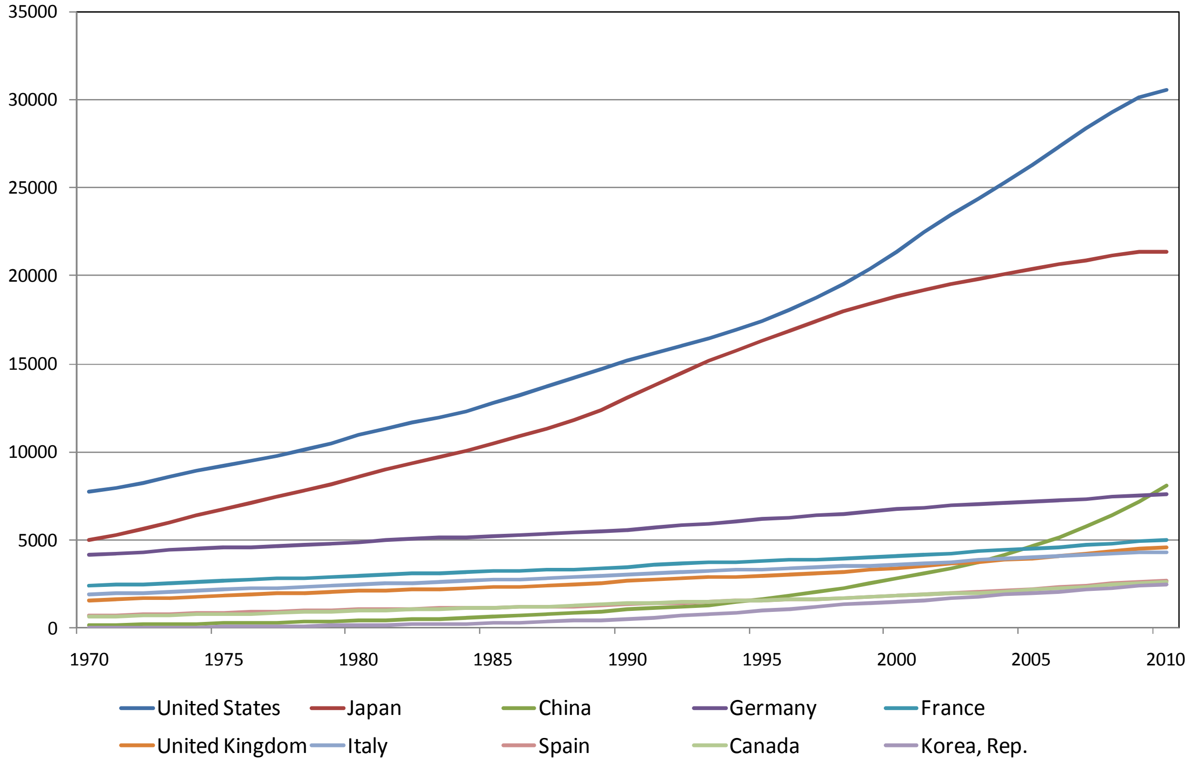

Figure 10: Gross fixed assets 1970-2010, 10 countries with largest aggregate capital stocks in 2010 (in USD of 2000)

Over the period of 1991-2010 the average aggregate capital stock of the 103 sample countries almost doubled from 676 bn. USD in 1991 to 1194 bn. USD in 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 rose strongly from 2188 bn. USD in 1991 to 3882 bn. USD in 2010.

6.2 Capital Intensity

While absolute aggregate capital stock data are often useful for empirical analyses one might argue that the capital stock available per worker, i.e. capital intensity, is - at least from some perspectives - the more interesting variable. High capital intensities indicate that the amount of physical capital available per worker in the production process is also high.

In figure 11 we show a world map reporting capital intensities for the year 2010. It is easily visible that the ranking for this indicator is quite different from those reported in section 6.1. 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, Ireland, Austria, Luxemburg and even the Bahamas appear among the 20 countries with the highest capital intensities.

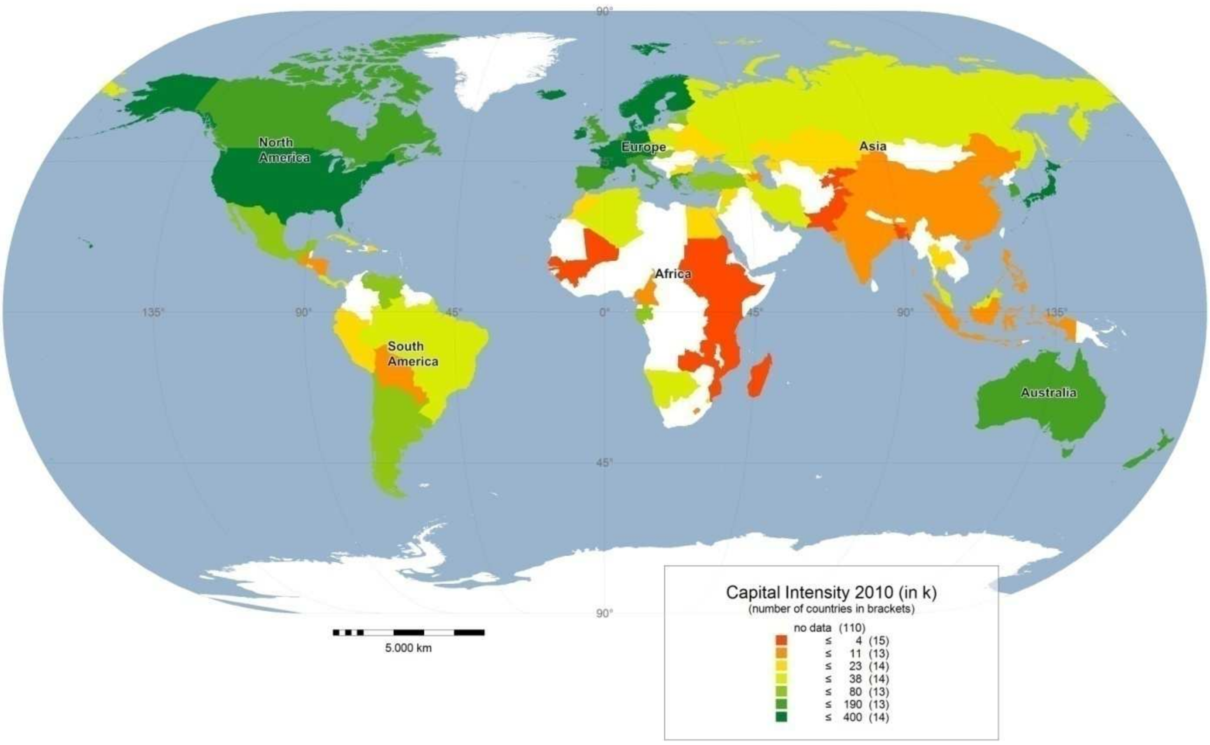

Figure 11: Gross fixed assets per worker 2010 (in USD of 2000)

As figure 12 reveals, Japan turns out to be the country with the highest capital intensity, however, with only a small advantage before Luxemburg. Even Switzerland and Norway exhibit considerably higher capital intensity than the United States. Almost on the same level as the United States we find countries like Belgium, Hong Kong SAR, Denmark, Iceland, Austria, Ireland, Finland, Germany, France and Italy. Lagging slightly behind that large group, the top 20 are completed by the Netherlands, Australia, the United Kingdom and the Bahamas.

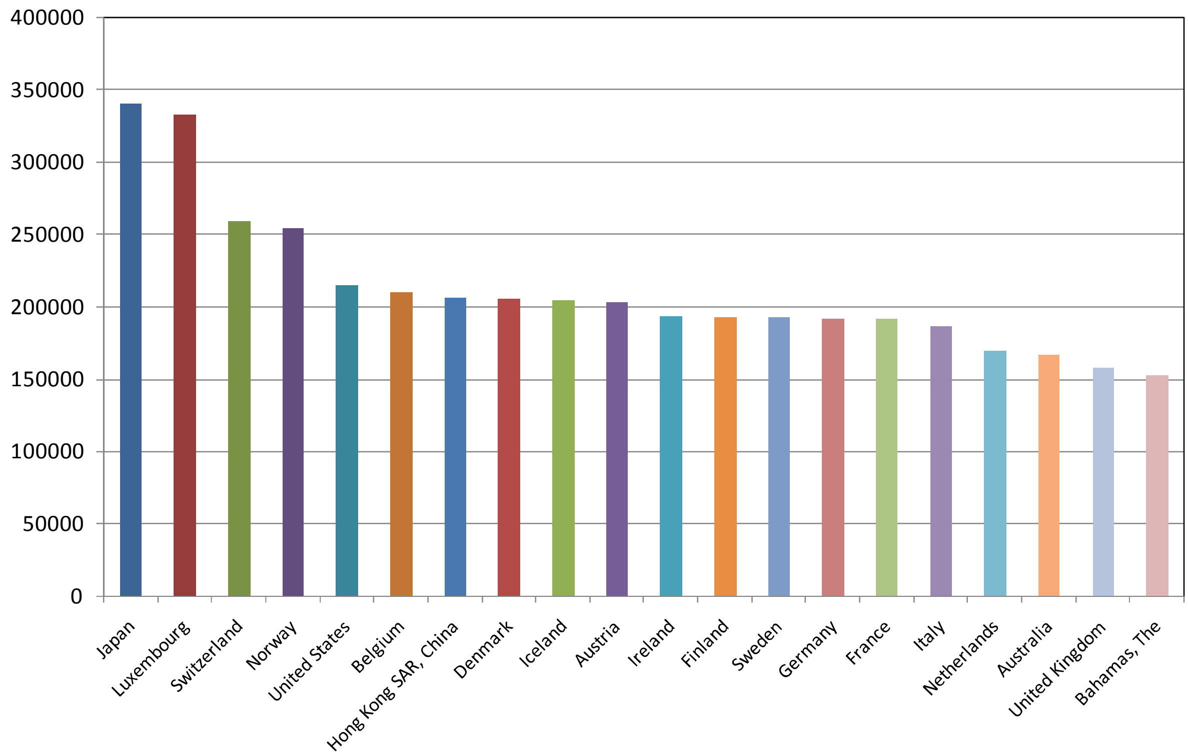

Figure 12: Countries with highest capital intensities in 2010 (in USD of 2000)

Over the period from 1991 to 2010, average capital intensity in our sample countries rose from 50461 to 67606. However, again there dispersion within the sample also increased. While the standard deviation of capital intensities in 1991 was 61844 it rose to 81634 in 2010. Thus, we observe no convergence of capital intensities in the sample countries.

6.3 Capital Coefficients

It is also an interesting question, how much capital a country needs to generate the current output. In order to study this question, we calculate capital coefficients for all countries in our country sample. The capital coefficient is simply the amount of capital divided by the gross domestic product. The capital coefficient informs how much capital is needed to generate one unit of output. Figure 13 shows a world map with capital coefficients. Figure 14 delivers an overview on the 20 countries with the highest capital coefficients.

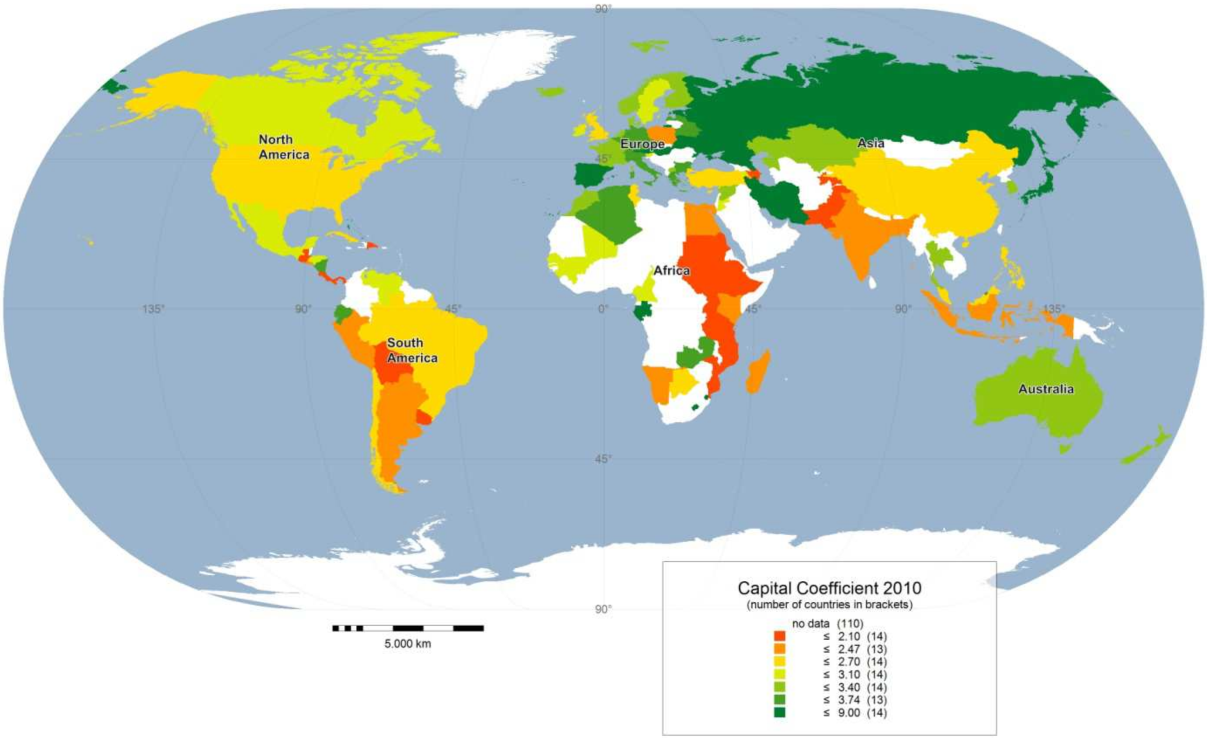

Figure 13: Capital coefficients 2010 (in USD of 2000)

The country with the by far highest capital coefficient is the Ukraine (8.07), followed by Gabon (5.68), Lesotho (5.01), Russia (4.99), Swaziland (4.71), Estonia (4.37), Japan (4.20) and Brunei/Darussalam (4.02). The following group of countries consists of the Bahamas, Portugal, Iran, Hungary, Spain, Austria, Italy, Switzerland, the Czech Republic, Germany, Ecuador and Bulgaria with quite homogenous capital coefficients in between 3.92 and 3.57. The countries with the lowest capital coefficients are Tajikistan (1.72), the Dominican Republic (1.65), Macao (1.46) and Sudan (1.22).

Interestingly enough, the mean capital coefficient of our sample countries remained quite stable in between 1991 and 2010. It fell only slightly from 3.17 in 1991 to 3.00 in 2010. Moreover, the capital coefficients show a strong tendency to converge, as the standard deviation decreased from 1.75 to 0.93 throughout the last two decades.

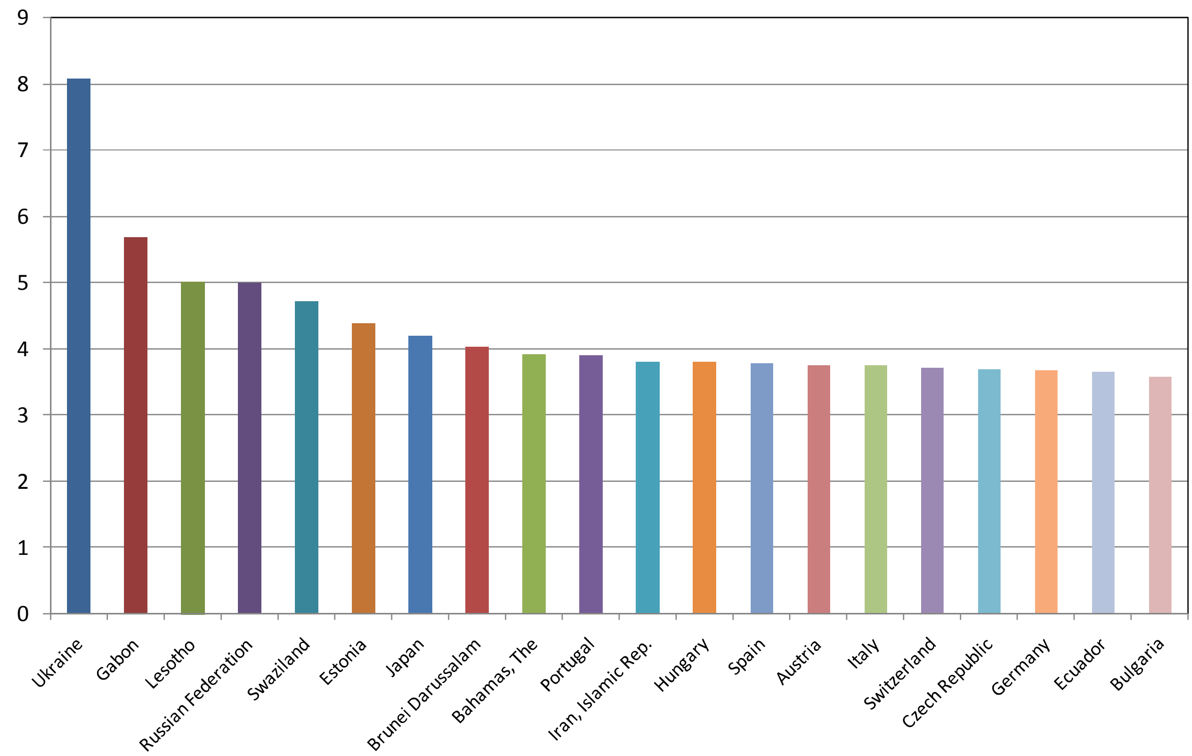

Figure 14: Countries with highest capital coefficients in 2010 (in USD of 2000

7 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. In order to avoid this problem, various authors have constructed capital stock data using some variant of the Perpetual Inventory Method in the past. However, doing so is quite time-consuming and it is obviously inefficient that researchers derive capital stock estimates with the same methods and data simultaneously. Moreover, differences in the implementation are likely leading to a variety in the derived empirical results which is undesirable.

This paper tries to stimulate empirical research on the role of capital in the process of economic growth by providing a large dataset of aggregate capital stock estimations for 103 countries around the globe. The underlying data come from the World Bank's World Development Indicators database. The applied methodology bases on the well-established Perpetual Inventory Method. In our application of the method we use a combination of the approaches used in the previous literature in order to avoid most of the problems of these approaches.

The resulting dataset is large enough to allow for pure cross section analyses as well as for panel studies. At least for the subsample of 58 countries, for which investment data are available at least since 1970, the data can even be used to conduct time-series analyses. However, since for many countries (non-comparable) official aggregate capital stock data is available, one might prefer the official data for the latter purpose.

The database can be easily downloaded from our internet page. Our approach allows to extend the existing time series of capital stock estimations in a quite simple and consistent way. Since the investment time series in the World Development Indicators database is updated regularly, we will extend the dataset in certain intervals to secure availability of actual data.

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Appendix

Table A-1: Start and end of capital stock time series by country

Country	Start	End
Algeria	1968	2010
Argentina	1960	2010
Armenia	1989	2010
Australia	1964	2010
Austria	1969	2010
Azerbaijan	1989	2010
Bahamas, The	1988	2010
Bangladesh	1979	2010
Belarus	1989	2010
Belgium	1969	2010
Bolivia	1969	2010
Botswana	1973	2010
Brazil	1969	2010
Brunei Darussalam	1988	2010
Bulgaria	1979	2010
Cameroon	1974	2010
Canada	1960	2010
Cape Verde	1985	2010
Chile	1960	2010
China	1964	2010
Costa Rica	1960	2010
Cuba	1969	2010
Cyprus	1974	2010
Czech Republic	1989	2010
Denmark	1965	2010
Dominican Republic	1960	2010
Ecuador	1964	2010
Egypt, Arab Rep.	1964	2010
El Salvador	1960	2010
Estonia	1987	2010
Ethiopia	1980	2010
Finland	1960	2010
France	1969	2010
Gabon	1979	2010
Germany	1969	2010
Greece	1960	2010
Guatemala	1960	2010
Guinea	1985	2010
Honduras	1960	2010

Hong Kong SAR, China	1964	2010
Hungary	1960	2010
Iceland	1960	2010
India	1960	2010
Indonesia	1978	2010
Iran, Islamic Rep.	1964	2010
Ireland	1969	2010
Italy	1960	2010
Japan	1960	2010
Jordan	1975	2010
Kazakhstan	1989	2010
Kenya	1978	2010
Korea, Rep.	1960	2010
Kyrgyz Republic	1989	2010
Latvia	1989	2010
Lesotho	1969	2010
Luxembourg	1960	2010
Macao SAR, China	1981	2010
Macedonia, FYR	1989	2010
Madagascar	1983	2010
Malaysia	1960	2010
Mali	1978	2010
Malta	1969	2010
Mauritius	1975	2010
Mexico	1960	2010
Moldova	1990	2010
Morocco	1965	2010
Mozambique	1979	2010
Namibia	1979	2010
Netherlands	1969	2010
New Zealand	1969	2010
Nicaragua	1960	2010
Norway	1960	2010
Pakistan	1960	2010
Panama	1979	2010
Paraguay	1964	2010
Peru	1960	2010
Philippines	1960	2010
Poland	1989	2010
Portugal	1969	2010
Romania	1989	2010
Russian Federation	1989	2010
Senegal	1964	2010
Seychelles	1983	2010
Singapore	1974	2010

Slovenia	1989	2010
Spain	1969	2010
Sudan	1975	2010
Swaziland	1979	2010
Sweden	1960	2010
Switzerland	1960	2010
Syrian Arab Republic	1974	2010
Tajikistan	1984	2010
Tanzania	1989	2010
Thailand	1960	2010
Tunisia	1960	2010
Turkey	1986	2010
Uganda	1981	2010
Ukraine	1989	2010
United Kingdom	1969	2010
United States	1960	2010
Uruguay	1960	2010
Venezuela, RB	1960	2010
Zambia	1969	2010

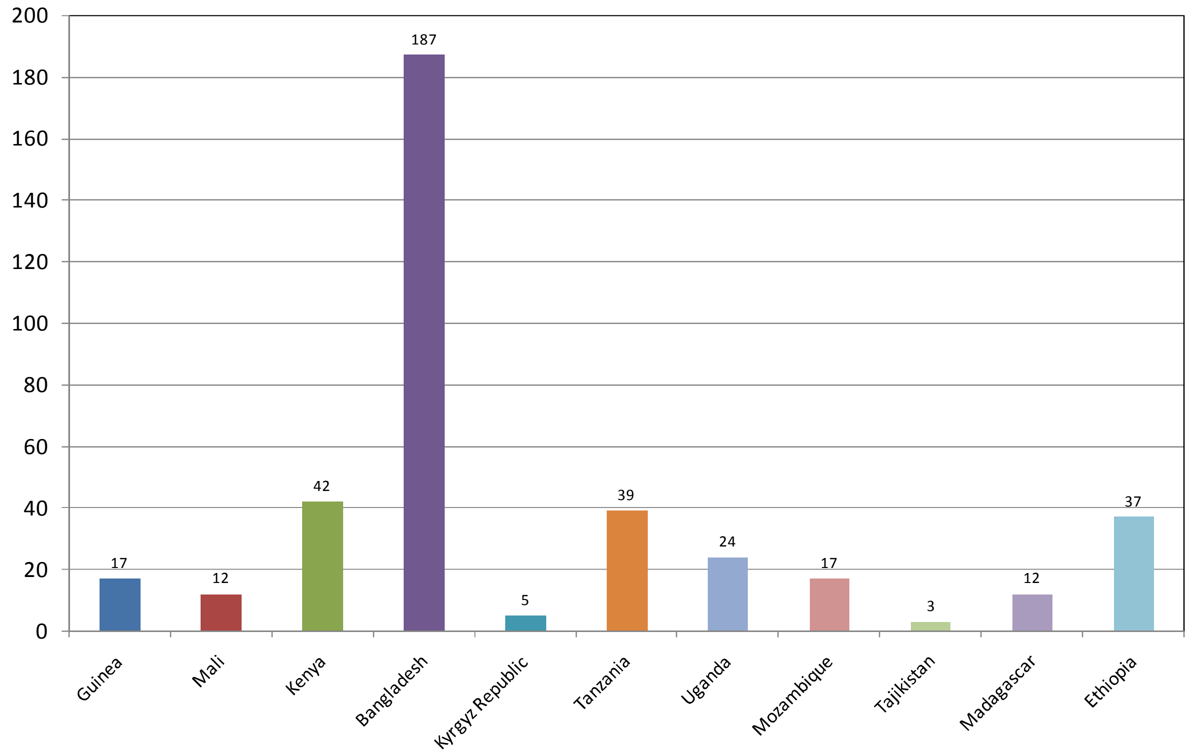

Figure A-1: Aggregate capital stocks in low income countries (in bn. USD of 2000)

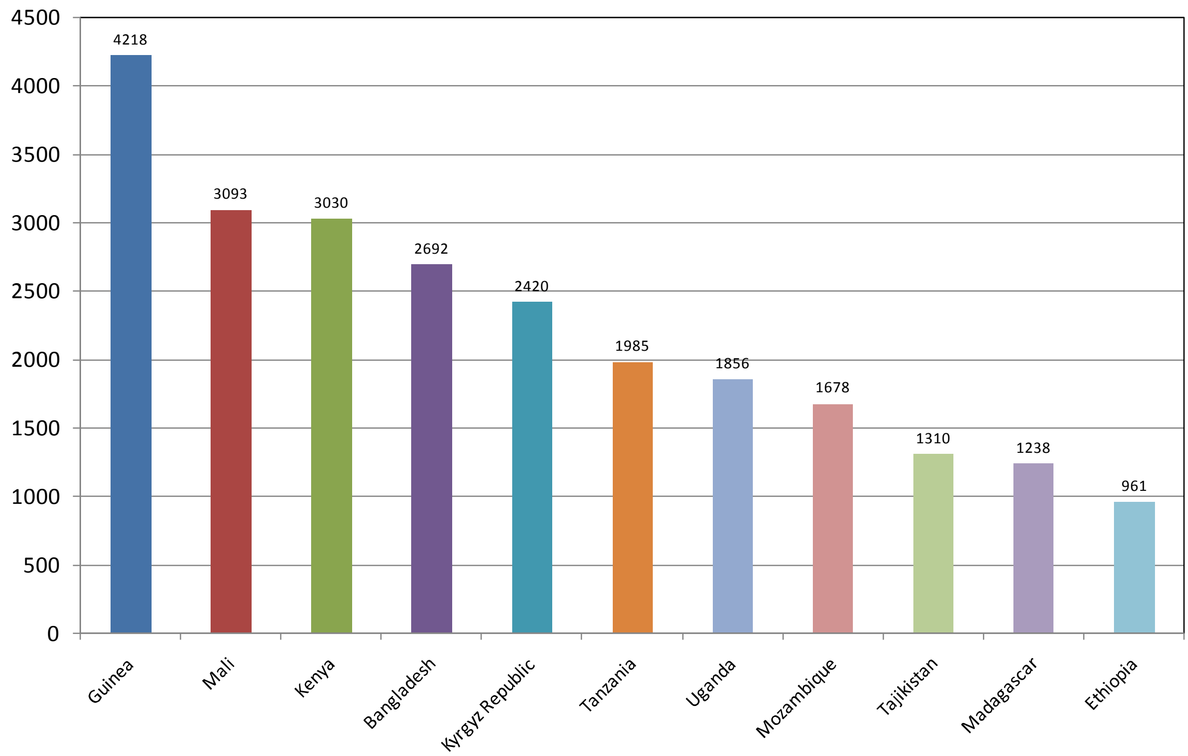

Figure A-2: Capital intensities in low income countries (in USD of 2000)

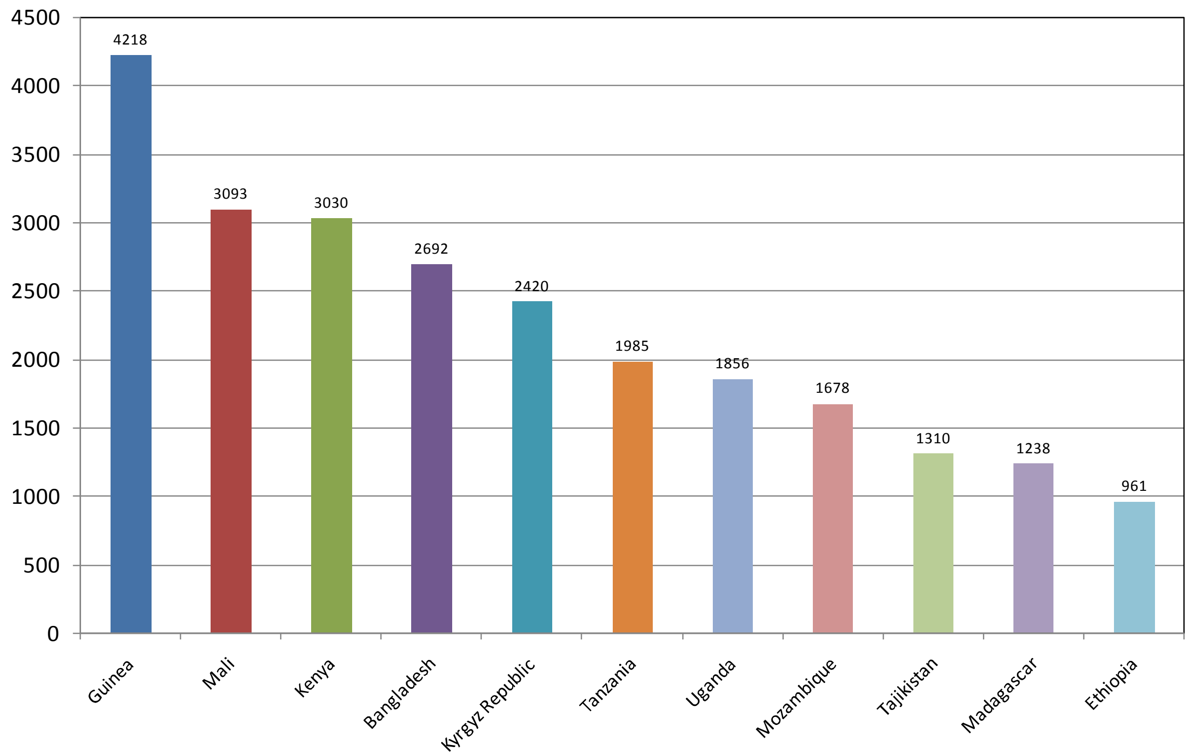

Figure A-3: Capital coefficients in low income countries (based on USD of 2000)

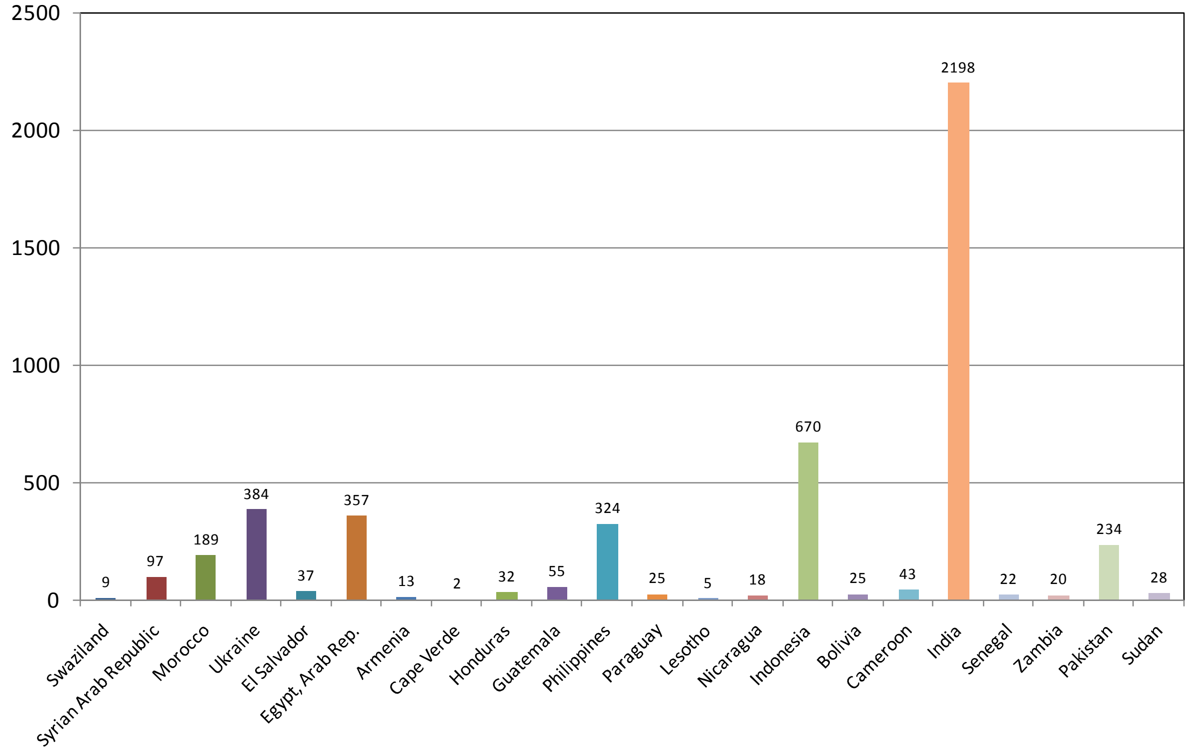

Figure A-4: Aggregate capital stocks in lower middle income countries (in bn. USD of 2000)

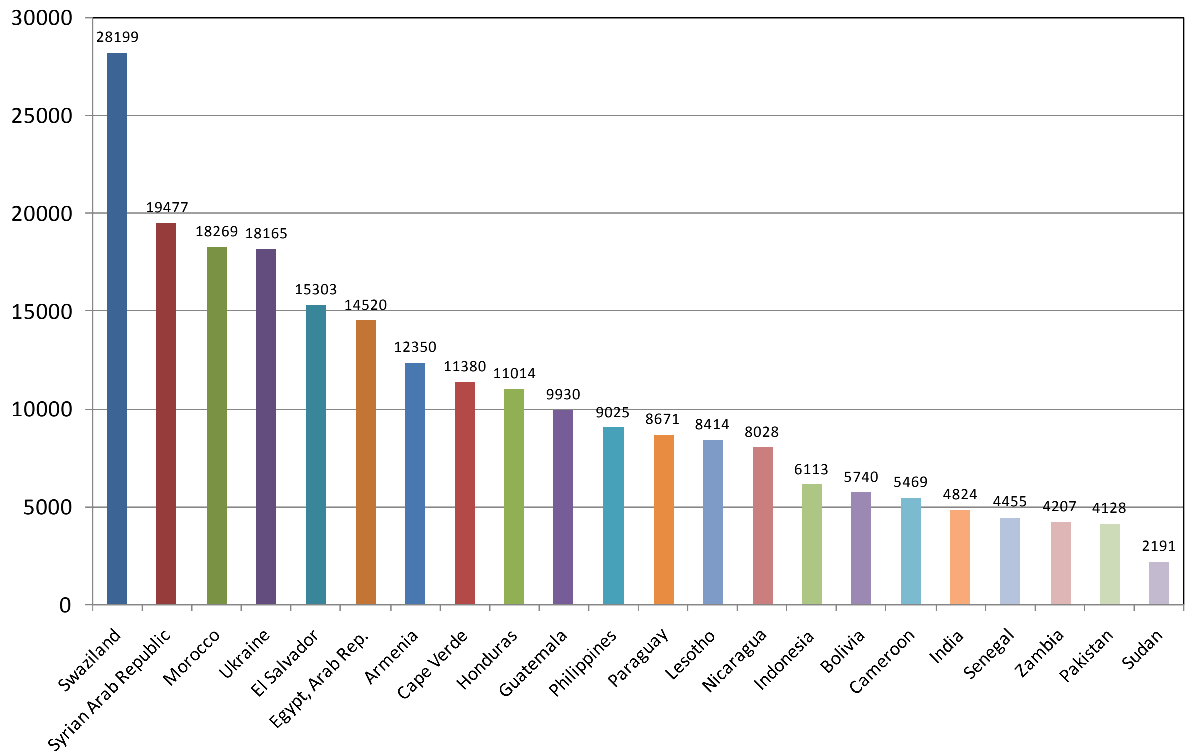

Figure A-5: Capital intensities in lower middle income countries (in USD of 2000)

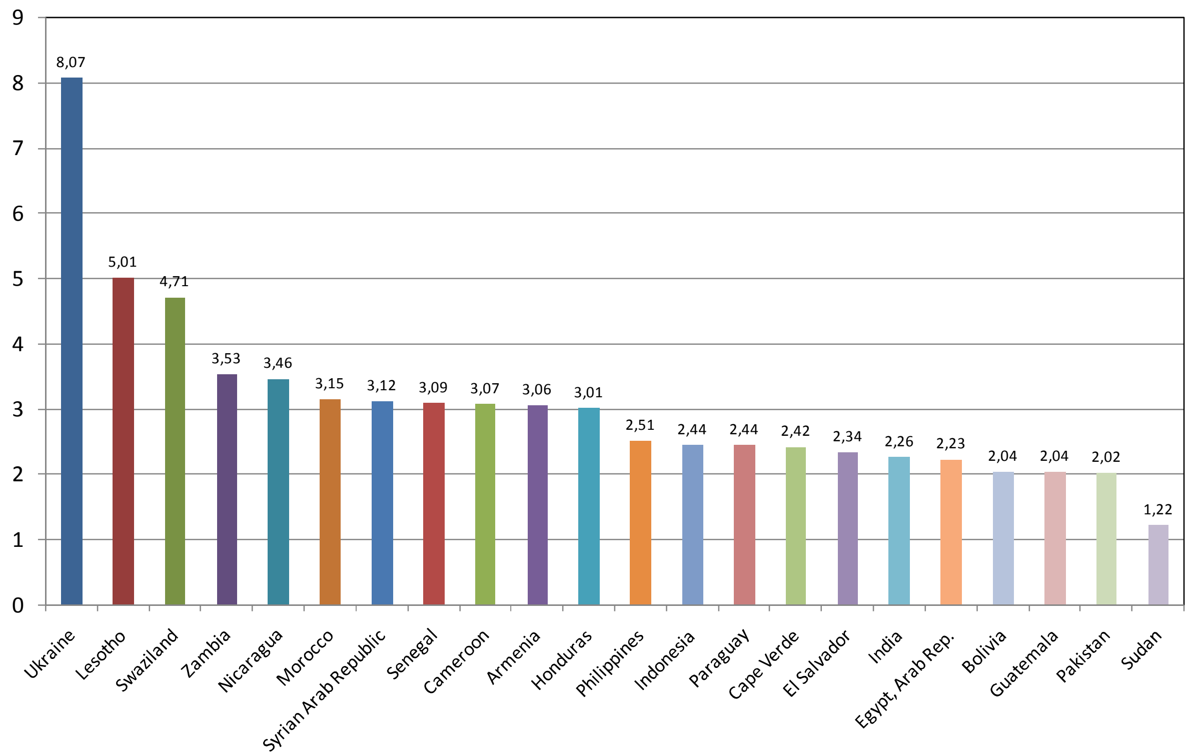

Figure A-6: Capital coefficients in lower middle income countries (based on USD of 2000)

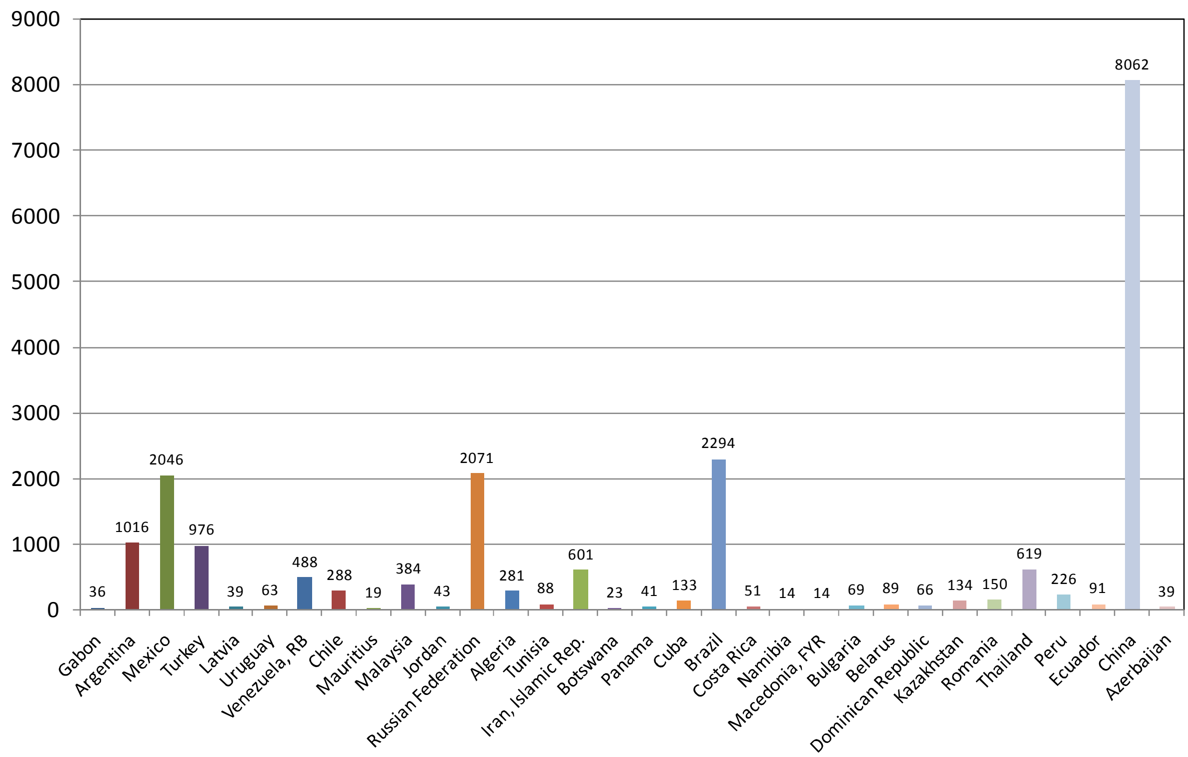

Figure A-7: Aggregate capital stocks in upper middle income countries (in bn. USD of 2000)

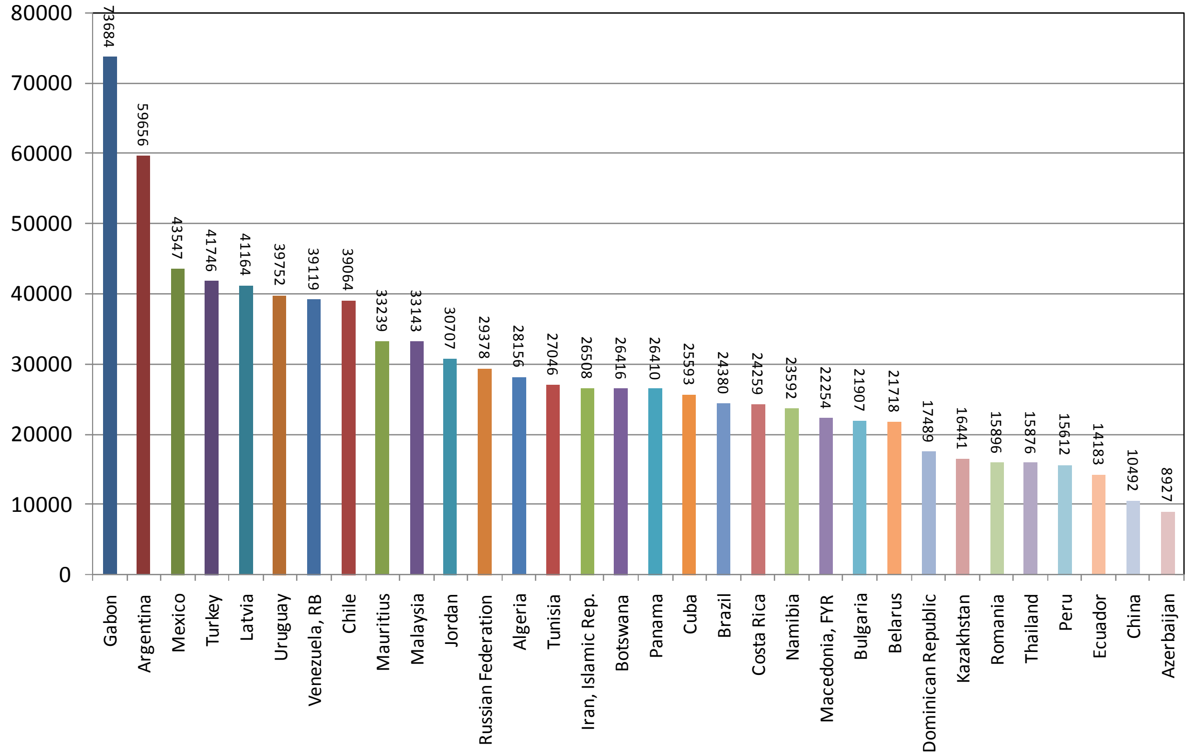

Figure A-8: Capital intensities in upper middle income countries (in USD of 2000)

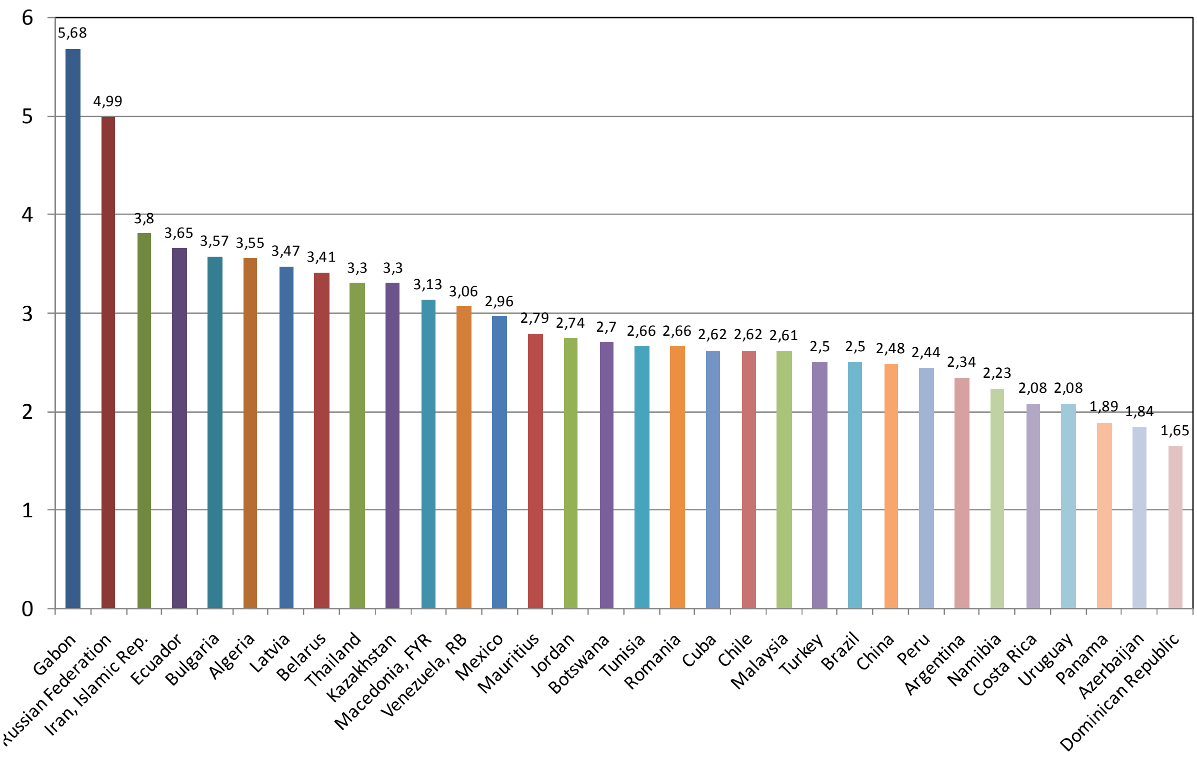

Figure A-9: Capital coefficients in upper middle income countries (based on USD of 2000)

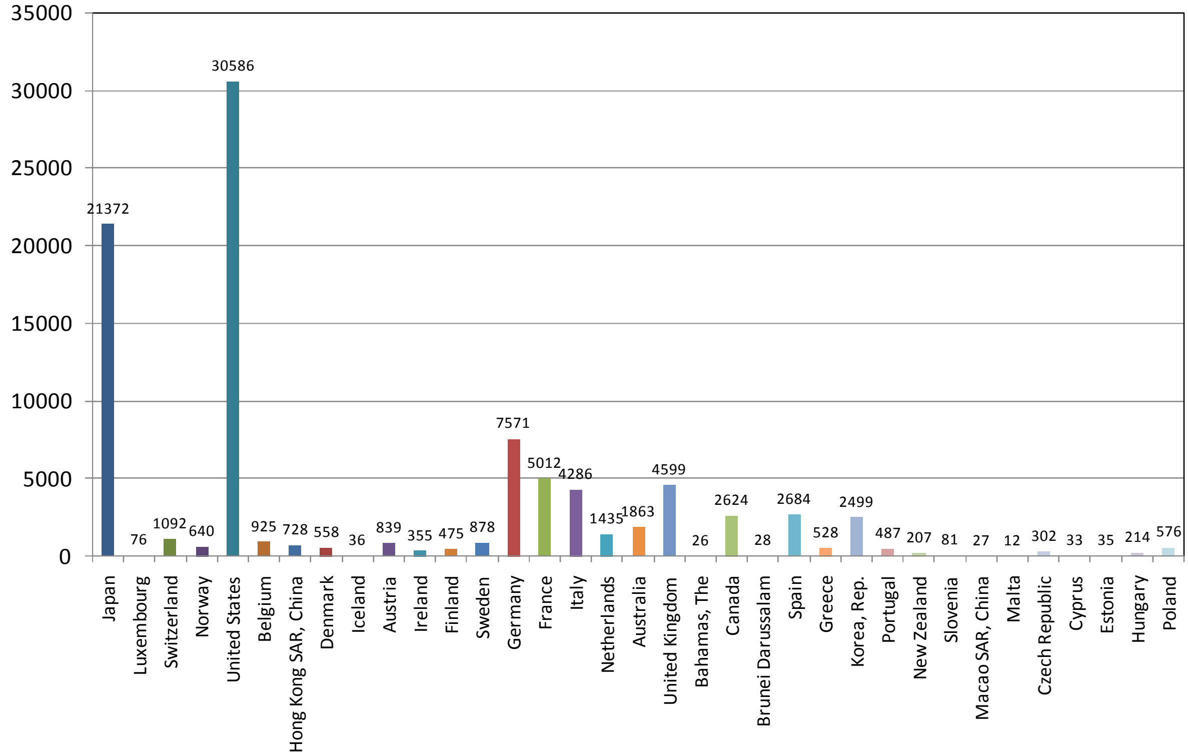

Figure A-10: Aggregate capital stocks in high income countries (in bn. USD of 2000)

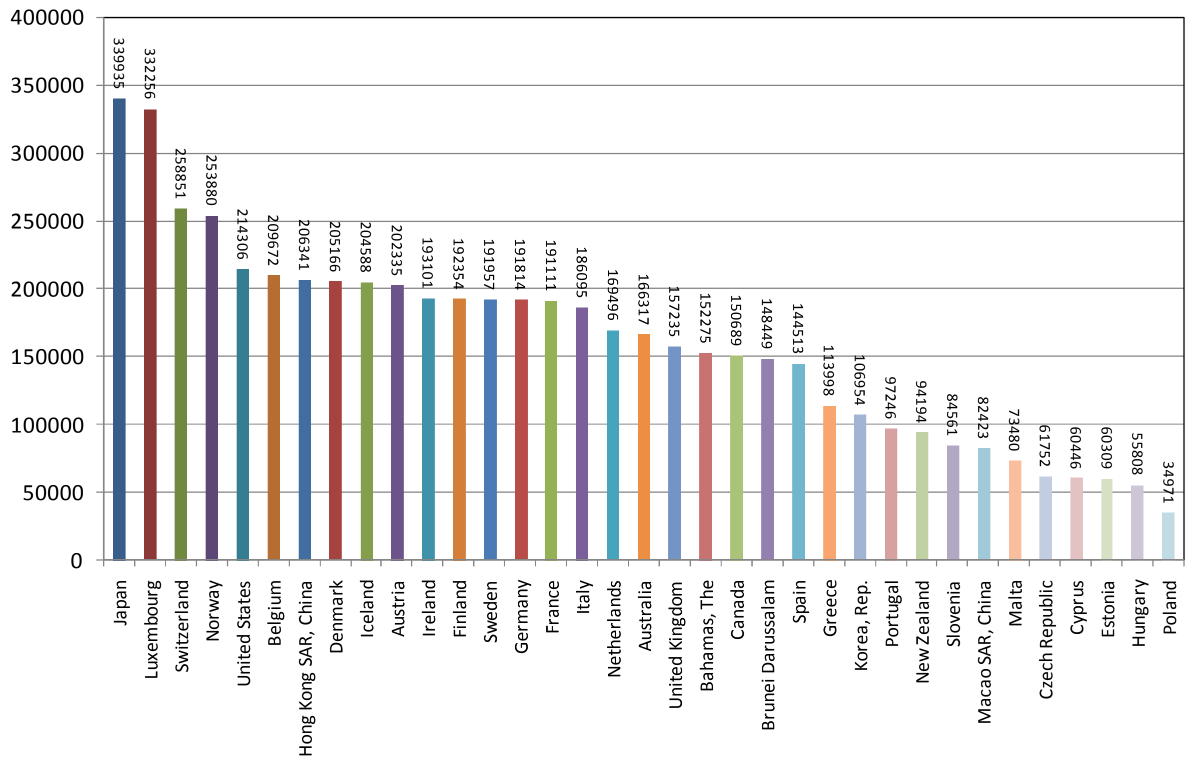

Figure A-11: Capital intensities in high income countries (in USD of 2000)

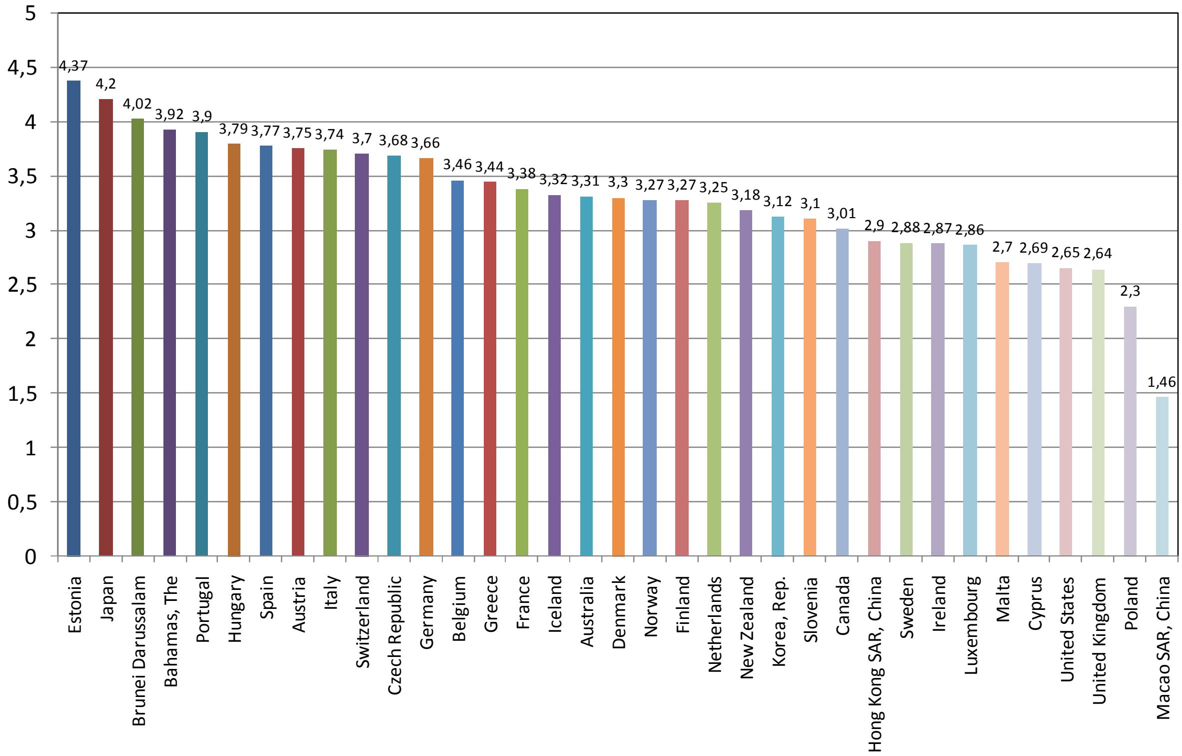

Figure A-12: Capital coefficients in high income countries (based on USD of 2000)

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