Logistic growth of the global economy and competitiveness of nations

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Abstract

In the first part of the paper we are dealing with the possibility of predicting long-term development on the basis of logistic/exponential curves. We have selected three characteristics of global development, namely the change of population size in the world, the volume of world output (measured by the value of global GDP) and global welfare (GDP per capita). The important feature of the proposed approach is that we propose to examine the impact of different identification criterion on the obtained predictions. It turns out that the assumed criterion of parameters' identification could essentially influence the obtained predictions.

In the second part of the paper, the extension of the logistic curve into the substitution-diffusion model is proposed. This allows us to evaluate the future share of national/regional economies in the global GDP and to estimate the competitiveness of these economies. It turns out that the competitiveness of nations/regions is far from being constant. A proposal of building the competitiveness ranking of nations/regions is presented. In the final section a possible scenario of development of the five countries/regions (namely the USA, the E12, Japan, China, India) is presented.

Keywords: logistic growth; logistic curve; s-curve; logistic substitution; globalization; global growth; competitiveness index;

The main goal of this paper is to present alternative predictions of global demographic and economic development using a trend analysis based on well-known logistic/exponential curves and to propose a method of prediction of the structure of economic growth (in terms of shares of different nations/regions in the global GDP) based on the evolutionary model of the substitution-diffusion model. A new concept of competitiveness of national and regional economies is presented. This approach allows us to generate ranking of the states according to diminishing competitiveness and to estimate tendencies of the evolution of national competitiveness .

Using trend analysis is a kind of classical approach, but frequently this approach is made in a routinized, let us say, 'mechanical' way, namely: on the basis of historical data the estimation (fitting to the real data; parameters' identification) of the logistic/exponential functions are made (usually applying standardised statistical packages) and the following extrapolations (predictions) of future values is done. We would like to point out that this kind of extrapolation ought to be done in a more cautious way. One of the questions stated in the paper, and to our knowledge, not discussed in the relevant literature is: to what extent the extrapolations (predictions) depend on the assumed criterion of the parameters' identification?

A growth with saturation (with upper limit) is frequently observed in real processes. From an economic point of view this is a natural phenomenon: limited resources (limited growth

factors) are the usual condition of socio-economic development. Therefore so called logistic curves (*S*-shaped, sigmoid curves) are very frequently used to describe the evolution of those processes. Logistic curves have been successfully used in such fields as demographics, biology, economics, engineering, and many others. The application of the logistic curve, e.g. to describe the evolution of population (in biology and demographics) or the diffusion of new technologies and products, as well as, in general, economic growth, is very illustrative and appealing (mainly due to nice graphic representation). The popularity of the logistic curve in the description of the variety of real phenomena dates from the middle of the 20th century, and the relevant literature is enormous.[1]

It is worth mentioning two researchers who have laid the ground for the steadily growing popularity of logistic curve application in numerous areas, namely Cesare Marchetti and Theodore Modis. A large number of their publications related to logistic growth is available to download from their websites: http://cesaremarchetti.org/index.html and http://www.growth-dynamics.com/, respectively.

For decades, *Technological Forecasting and Social Change* has been a good and friendly platform to present recent advancement in research on logistic growth. It is not possible to list all the relevant papers published in *TF&SCh* in recent decades, but some of them published in the last few years have spurred on this author to write this paper, among them are [1-5], and especially [6].

The logistic curve is often used to describe and to predict the development of social and economic processes. In a natural way, it is suitable to describe the development of the so-called 'Limited world'.

If we denote by *y* a measure of development (e.g. population size or national income) then the logistic growth (often called sigmoid, *S*-type growth, a growth with saturation) can be described by the differential equation (1), in the case of discrete measures such as population, or by the corresponding differential equation (2), in the case of continuous measurements, such as national income:

$$y_{t+1} = y_t + round\left(r\, y_t \left(1 - \frac{y_t}{K}\right)\right) \tag{1}$$

$$\frac{dy}{dt} = r\, y \left(1 - \frac{y}{K}\right) \tag{2}$$

where:

K – saturation level (sometimes called the capacity of the environment),

r – maximum growth rate.

Properties (especially related to the fluctuation behaviour) of the discrete logistic curve are discussed by F. Phillips and N. Kim [7]. We will use the logistic equation in continuous form. This choice is motivated by the need to compare our results with the results obtained by other authors who use the logistic curve in the continuous form (e.g. [6]).

The solution of equation (2) is the logistic function:

$$y = \frac{K}{1 + ae^{-bt}} \tag{3}$$

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[1] probably for the first time the logistics curve (logistic equation) was used in 1838 by Pierre-François Verhulst to describe growth of human population (it was probably inspired by Thomas Malthus' *An Essay on the Principle of Population*). The equation was rediscovered in the 1920s by Raymond Pearl, Lowell Reed and Alfred J. Lotka (who in 1925 proposed to call it the *law of population growth*). Applications of the logistic equation to describe other processes beside population growth were spurred on by B. Ryan, N. Gross who published in 1943 the paper on "The diffusion of hybrid seed corn in two Iowa communities".

Selected bibliography for the Logistic Curve can be found at:
http://math.fullerton.edu/mathews/n2003/logisticcurve/LogisticEquationBib/Links/LogisticEquationBib_lnk_3.html

The logistic function has three parameters (K, a, b), which are associated with three parameters in the logistic equation (2) – environmental capacity (K), the maximum growth rate (r) and the initial value of the variable y (y_0).

To make the logistic function parameters more intuitive, this function is often presented in the following form (e.g. [8]):

$$y = \frac{K}{1 + e^{-\frac{\ln(81)}{\Delta t}(t - t_m)}} \tag{4}$$

Δt – is the time needed for y to increase from 10% to 90% of the maximum value of K (so called *characteristic duration*).

t_m – is the so called *midpoint*, i.e. the time t in which the value characteristics of the development y is equal to 50% of the saturation K.

When the size of the saturation of the environment tends to infinity, the logistic growth becomes exponential one (γ – the growth rate), i.e.

$$\lim_{K \to \infty} y = \lim_{K \to \infty} \frac{K}{1 + ae^{-bt}} = Ae^{\gamma t} \tag{5}$$

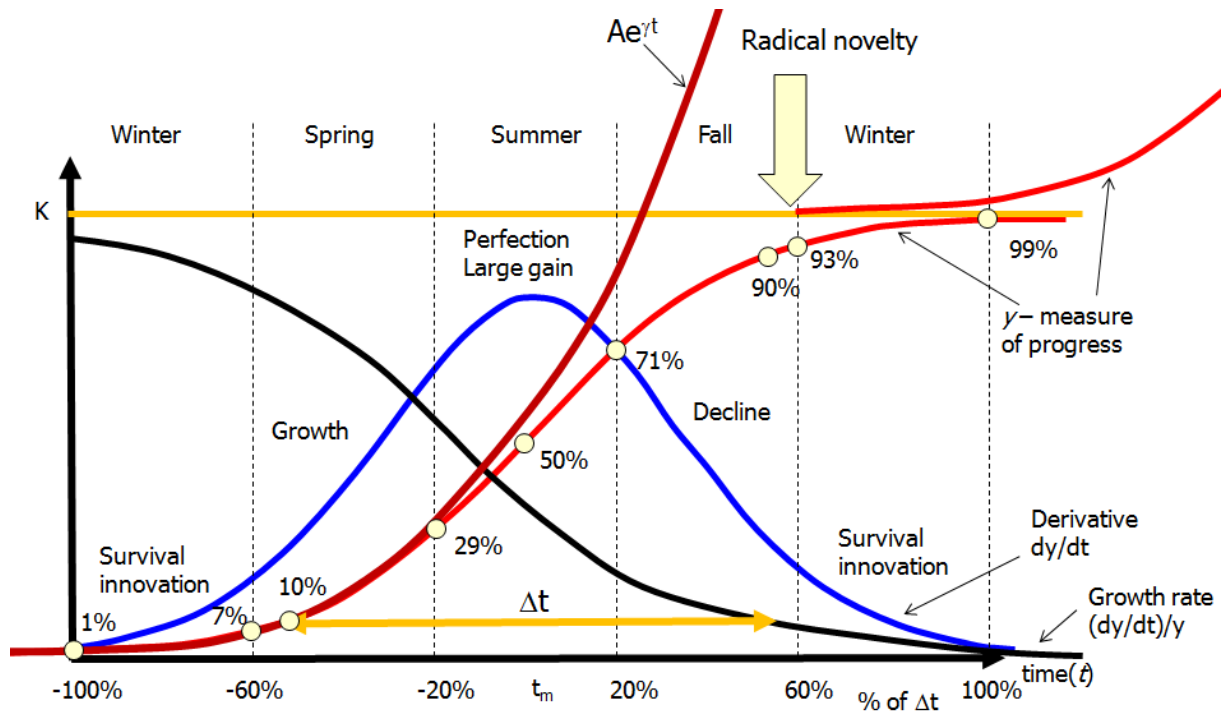Figure 1 illustrates the logistics growth in a qualitative way.

Figure 1. Qualitative characteristics of logistic growth

Theodore Modis [1] proposed the seasons' metaphor to describe in a friendlier manner the differences and special attributes of successive periods of growth, saturation, and decline in a logistic development. Boretos [6, p. 318] suggests a slight variation of the Modis metaphor and divides the period of growth of y from 1% to 99% of the value of K into five equal periods called *Winter, Spring, Summer, Autumn* and again *Winter*. Such a seasonal metaphor allows for distinguishing specific phases of development associated with the emergence of successive radical innovations. It suggests a relatively rapid growth associated with the spread of a radical innovation (in the *Spring*), the maturity of development (during the *Summer*), the

exhausting of potential for further growth based on a particular radical innovation (*Autumn*). The next *Winter* is related to the emergence of another radical innovation and entering the next phase of logistic growth with a higher capacity of the environment (*K*). Analysis of many processes of development suggests that during the slowdown of economic growth (*Autumn*) we can observe an increase of the intensity of the search for breakthrough innovation. Usually, as an effect of this intensive exploration, another radical innovation emerges (mostly in late *Autumn*/*Winter*) which enables further growth along a qualitatively different trajectory of development (along a different logistic curve). The full cycle (i.e. an increase in the value *y* from about 1% of the saturation *K* to about 99% of *K*) is equal to 2Δ*t*. The parameter Δ*t* informs us also about the length of the cycle. It is worth noting that the sum of periods of growth from 1% to 10% and from 90% to 99% is the same as the period of growth from 10% to 90% of the saturation *K*.

Our task seems to be typical, namely, having historical data describing the changes of the characteristics of development *y* in a period from t_0 to t_{max}, we ought to identify the values of the three parameters (K, Δ*t*, t_m) of the logistic function in such a way that this function fits the historical process in the best way. We have selected three characteristics of global development, namely the change of population size in the world, the volume of world output (measured by the value of global GDP) and the global GDP per capita. The historical data of these three characteristics are available on *The Conference Board Total Economy Database* website.[2] The data was downloaded on 19th November 2009. The available data covered the period from 1950 to 2008 in the case of world population, and from 1950 to 2006 in the case of global GDP and GDP per capita.[3]

We have adopted the two most widely used identification criteria, namely the mean square error (this criterion will be denoted by Q_1) and the relative mean square error (this criterion will be denoted by Q_2).[4] Thus by fitting the logistic curves to the historical data we will try to state the values of K, Δ*t*, and t_m to minimize one of the following criteria:

$$Q_1 = \sqrt{\frac{1}{t_{max} - t_0 + 1} \sum_{t=t_0}^{t_{max}} (y^r(t) - y^m(t))^2} \tag{6}$$

$$Q_2 = \sqrt{\frac{1}{t_{max} - t_0 + 1} \sum_{t=t_0}^{t_{max}} \left(\frac{y^r(t) - y^m(t)}{y^m(t)}\right)^2} \tag{7}$$

where:

t_0 and t_{max} – the initial and the final years of historical data used for identification of the logistic curve parameters, respectively.

$y^r(t)$ and $y^m(t)$ – the historical (real) data and the logistic curve (model) values at time *t*.

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[2] http://www.conference-board.org/data/economydatabase/

[3] The global GDP is expressed in constant purchasing power dollar terms in 1990, called Geary-Khamis PPPs. This methodology is widely accepted (including the World Bank and the International Monetary Fund), as was proposed in 1958 by Roy C. Geary and modified by Salem Hanna Khamis in the early 1970s.

[4] This choice is motivated by a desire to examine the impact of the selected identification criterion on the obtained predictions. The problem would require further, systematic research, as it is possible to choose other metrics (e.g. the absolute distance, the Manhattan metric). It would be interesting to investigate the influence not only of the relative and absolute criterions, but also the different metrics (not only the mean square metric).

There are no analytical methods for identifying the parameters of the nonlinear logistic function (as, for example, in the case of calculating linear regression models). Nor is there any method of the transformation of the logistic model into the linear model. Therefore, the only method of identification of the logistic function parameters is to use one of the known optimization methods. A very effective means of nonlinear optimization methods is based on genetic algorithms. In this work we used a computer program (*GeneticFinder*) developed by Mariusz Sobczak in 2008 (then a student of Wroclaw University of Technology). The program allows to define any parameterized function and to identify its parameters on the basis of historical data (given as a CSV file.) The results of optimization obtained using *GeneticFinder* seem trustworthy. This program has been tested in numerous test functions, moreover, the results of many test functions as well as selected results presented in this article were compared with the results obtained using *Wolfram Mathematica*.

In some cases the identification of the parameters of the logistic function is insensitive to the saturation value *K*, i.e. very often large fluctuations in the value of *K* result in minor changes of the value criterion for identification. Therefore, for many experiments of the identification of the logistic function parameters identification, the parameters of the exponential function are added (i.e. the logistic function when *K* tends to infinity, see equation (5)).

2. THE WORLD POPULATION GROWTH

Let us start with the identification of the parameters of the logistic function and the exponential function assuming that for the parameters' identification we use all the available data on global population growth, i.e. in the period 1950-2008. The parameter values that minimize both criteria and the values of the criteria are presented in Table 1. The corresponding approximating curves and historical data are presented in Figure 2. As we can see, for both criteria the identification error is much smaller for the logistic function (Figure 2, Table 1). Thus, it is appropriate to use the logistic function to forecast population growth. The prediction is presented in Figure 3, and as we can see in spite of the quite similar quality of approximation for both criterion (Q_1 and Q_2), the values of the identified parameters (Table 1) are significantly different. For example, the saturation level *K* in the case of the mean square relative error (Q_2) is over one billion larger than for the absolute mean square error (Q_1).

Table 1. The Word population growth.
The parameters values of the logistic and exponential curves. Historical data for identification: 1950-2008

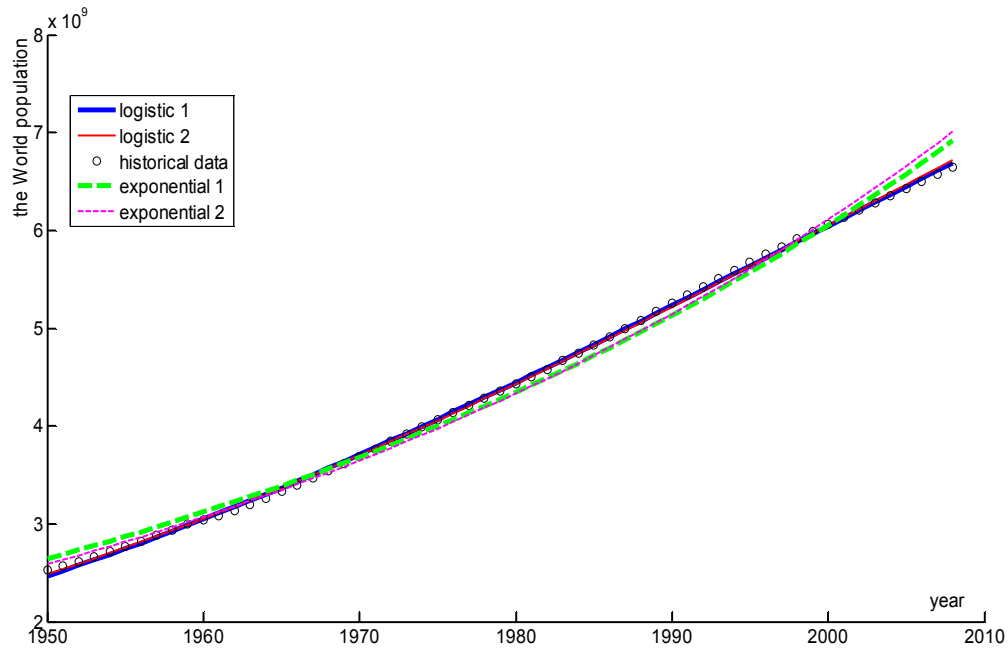| Curve/Criterion	K [$*10^9$]	Δt	t_m	Identification error
Logistic Q_1	11.856990	159.6778	1998.589	26903.66
Logistic Q_2	12.959189	168.4098	2005.108	0.00673835
	$A \rightarrow y$(1950) [$*10^9$]		γ	Identification error
Exponential Q_1	2.6426809		0.016581239	101118.6711
Exponential Q_2	2.5859190		0.017194096	0.02091690034

Figure 2. The world population in 1950-2008. Approximation of real data by logistic and exponential curves

Differences in these parameters cause significant differences in the estimated world population, especially when approaching the end of the 21st century. Although by 2040 the differences are relatively small, however in the second half of the twenty-first century they are clearly visible. According to these predictions, in the mid twenty-first century the global population will be approximately 9.5 billion but by the end of the twenty-first century the world population will be somewhere between 11.9 billion and 12.9 billion.

This and many other experiments (the results of some of them will be presented in this paper), suggest that the selection criterion for identification may have a significant impact on the forecasted development. Another question to which there is no unequivocal answer, is 'Which criterion is better?'.[5]

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[5] The problem of the proper selection of criterion for identifying from the viewpoint of the quality of forecasts will not be discussed in this work, but it is worth undertaking this and probably we will embark on that project in the future. In such a project it would necessary to increase the number of identification criteria, not limit it to only the two ones presented here.
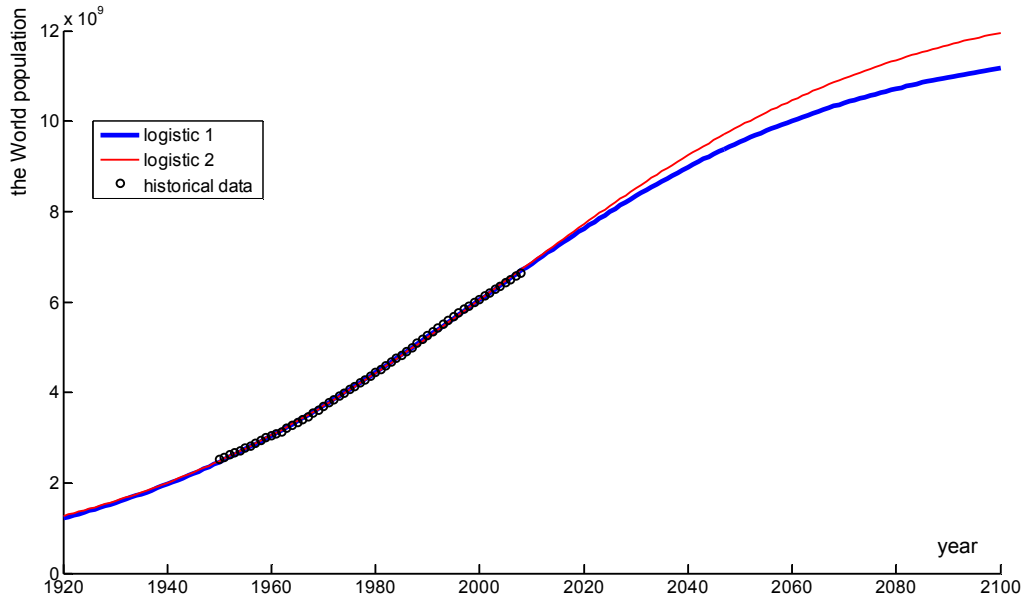
Figure 3. Forecast of the World population by the end of the 21st century (logistic function parameter identification based on historical data from the years 1950 to 2008)

3. GLOBAL ECONOMIC GROWTH

The available statistics on global GDP in the years 1950-2006 allow us to identify the parameters of logistic and exponential functions and to estimate the error of approximation. The results of these experiments are presented in Table 2 and Figure 4. As in the case of the approximation of global population growth, a better fit is obtained in the case of logistic functions. The fluctuations of GDP are much larger than the changes of the world population, which leads to much larger errors of estimation (approximation).

Table 2. Global GDP growth.
The parameters values of the logistic and exponential curves. Historical data for identification: 1950-2006

Curve/Criterion	K [*10^{13} US dol.]	Δt	t_m	Identification error
Logistic Q_1	15.903705	107.8116	2028.9320	817670.5046
Logistic Q_2	7.417883	86.85134	2000.2162	0.033703579
	$A \rightarrow y(1950)$ [*10^{13} US dol.]		γ	Identification error
Exponential Q_1	0.66738338		0.034468590	907728.54560
Exponential Q_2	0.59569569		0.037459243	0.063252585

Thus it is reasonable to select the logistic function to predict the world GDP growth in the twenty-first century. However, while the differences in growth projections of world population for both criteria might be considered as relatively small, it is not true in the case of the global GDP forecasts. The saturation level for the mean square criterion (Q_1) is over twice the saturation level for the relative mean square error (Q_2). Similar large differences in optimal values are for the two remaining parameters of the logistic function (see Table 2).

Large differences in the global GDP growth forecasts are clearly seen in Figure 5. As early as 2020 there is almost a 10% difference in the projections made by the two logistic functions:

$$y_1 = \frac{15.903705 \; 10^{13}}{1 + e^{-\frac{\ln(81)}{107.8116}(t - 2028.932)}} \; , \text{ for the mean square criterion } (Q_1),$$

$$y_2 = \frac{7.417883 \; 10^{13}}{1 + e^{-\frac{\ln(81)}{86.35134}(t - 2000.2162)}} \; , \text{ for the relative mean square error } (Q_2).$$

In the course of time the gap is widening, up to almost 100% at the end of the twenty-first century (Figure 5).
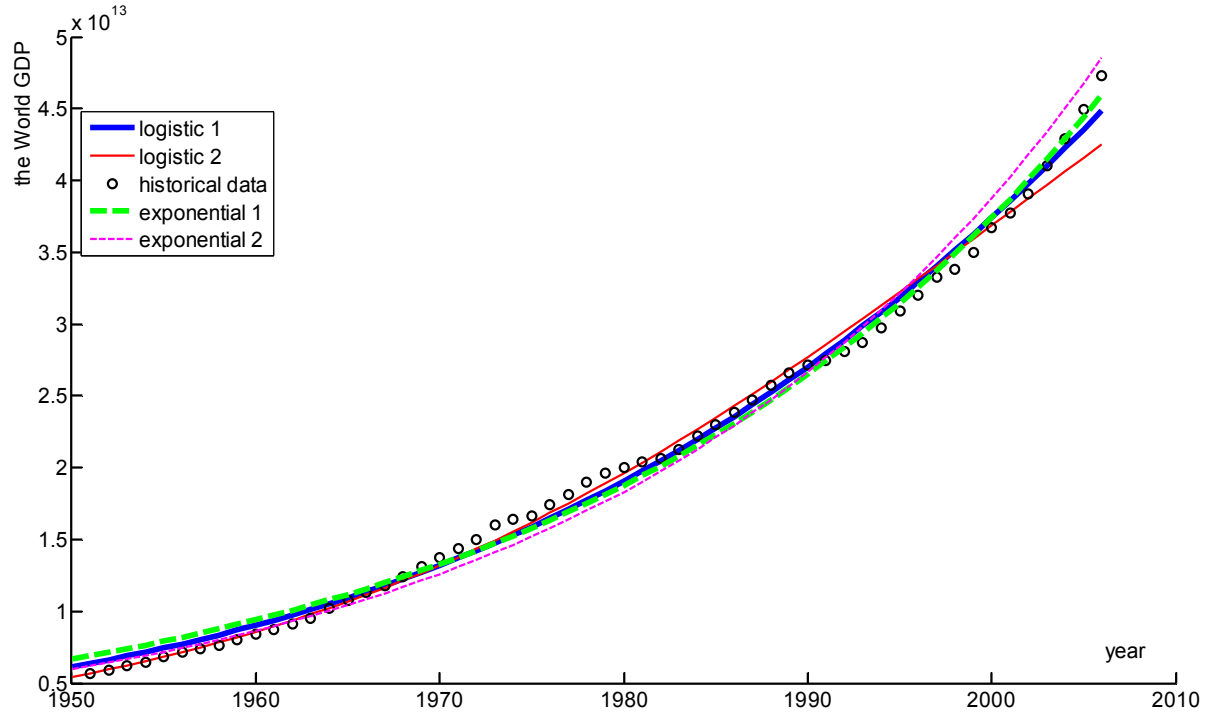

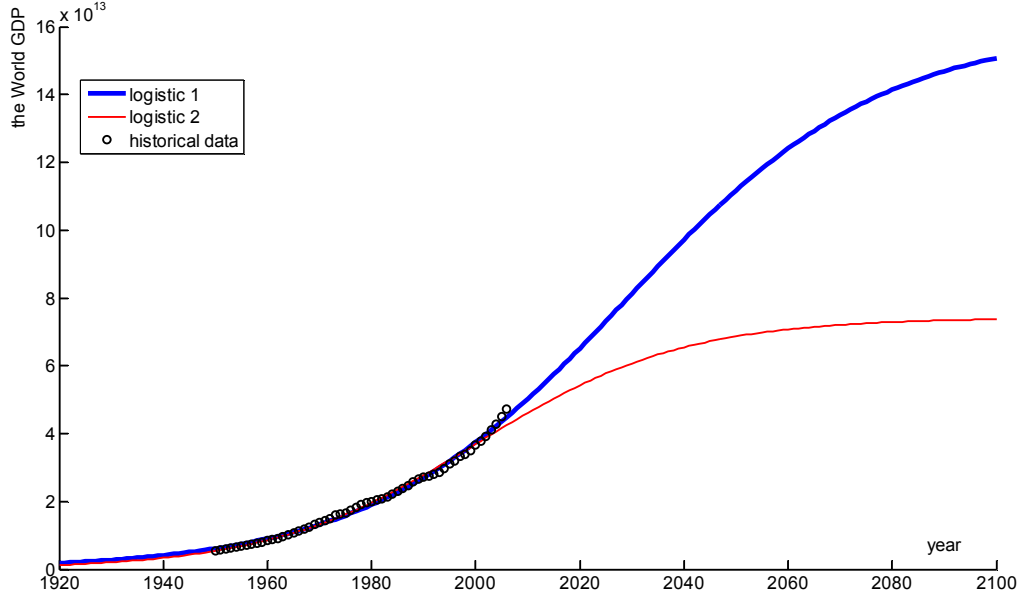Figure 4. Global GDP in 1950-2006. Approximation of real data by logistic and exponential curves

Figure 5. The global GDP forecast (logistic function parameter identification based on historical data from the years 1950 to 2006)

4. GDP *PER CAPITA*

The projection of GDP per capita can be done in two ways, either through the identification of parameters based on historical data on GDP *per capita,* or by the use of earlier forecasts of GDP growth and the global population growth (i.e. by dividing these values).

The first method is similar to that used in the previous two cases, compiled statistics for the period 1950-2006 allow us to identify the parameters of logistic and exponential functions using both criteria for identification (see Table 3 and Figure 6). Again, the logistic curve fits are clearly better than the exponential curve fits (see the errors of identification in Table 3). This is a strong argument for the use of logistic curves to make predictions. Once more we can observe large differences in the optimum values of parameters of logistic functions (Table 3). The saturation value for the mean square criterion is about 30% higher than in the case of the relative mean square error. The relevant logistic functions used to predict GDP per capita are the following:

$$y_1 = \frac{12387.948}{1+e^{-\frac{\ln(81)}{147.21609}(t-2000.5777)}} \text{, for the mean square criterion } (Q_1),$$

$$y_2 = \frac{8956.403}{1+e^{-\frac{\ln(81)}{118.85678}(t-1980.4684)}} \text{, for the relative mean square criterion } (Q_2).$$

Looking at the forecasts of GDP per capita (Figure 7), we notice large differences between these two projections. What is interesting is that there is a discrepancy between the identified trends and the trend observed in historical data in the last 10 years, i.e. in 1996-2006. Namely we can observe very fast real GDP growth per capita since the mid-1990s and the slowdown of growth in the last ten years in both the forecasted long-term trends. Naturally, this is caused by the significantly different nature of the change in the second half of the twentieth century (from 1950 to the mid-1990s.). This issue will be discussed later in this paper.

We get radically different predictions when we make them by dividing the values obtained from the forecasts of GDP growth (Figure 5) and the values of the forecast of the world

population (Figure 3). The results of this experiment are shown in Figure 8. Firstly, the value of GDP per capita calculated using the two forecasts based on the mean square error criterion (Q_1) is above the both extrapolative forecasts (Figure 7). Secondly, the calculation of GDP per capita by division of the global GDP by the global population obtained for the mean square relative error (Q_2) generate in the first decades of the forecast (up to around 2025) a small rise of GDP per capita and then, up to the end of the twenty-first century, a slow decline (the lower curve in Figure 8). To compare the results of these two approaches, all four forecasts are presented in Figure 9. It is seen that the extrapolative forecasts are between the two projections calculated by dividing the global GDP and the population of the world. It is also worth noting that all four trends fit quite well to the real data from the period 1950-2006, but long-term extrapolations give significantly different projections. It can be said that the future of global welfare is really uncertain and open to great variability.

Table 3. Global GDP growth.
The parameters values of the logistic and exponential curves. Historical data for identification: 1950-2006

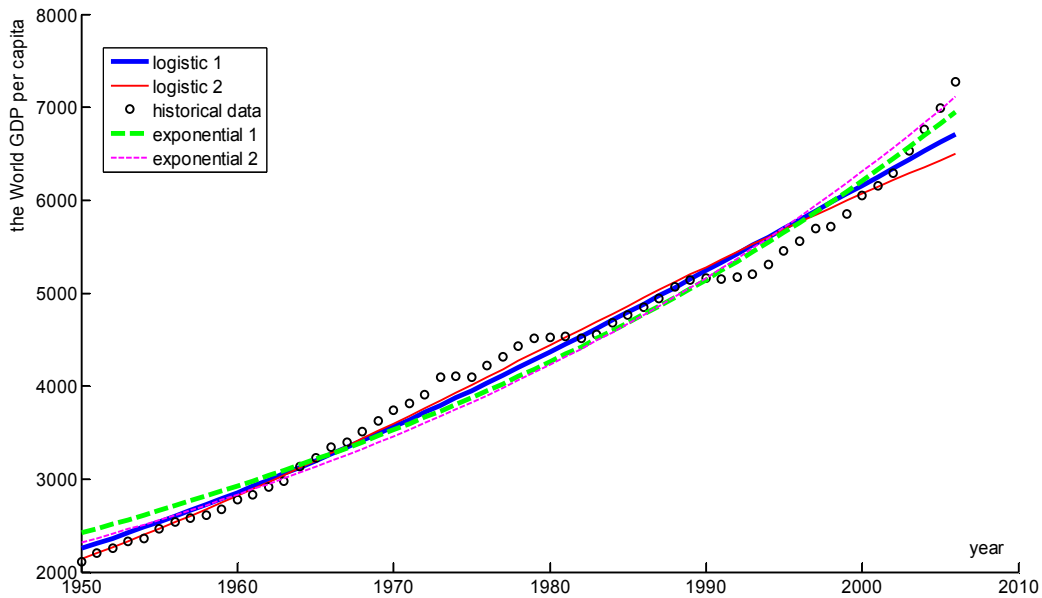| Curve/Criterion	K [US dol.]	Δt	t_m	Identification error
Logistic Q_1	12387.948	147.21609	2000.3777	552.593688
Logistic Q_2	8956.403	115.55678	1980.4634	0.033352293
	$A \rightarrow y$(1950) [US dol.]		γ	Identification error
Exponential Q_1	2422.1271		0.018829270	622.0300316
Exponential Q_2	2318.2722		0.020025927	0.051156468

Figure 6. Global GDP per capita in 1950-2006. Approximation of historical data by logistic and exponential curves
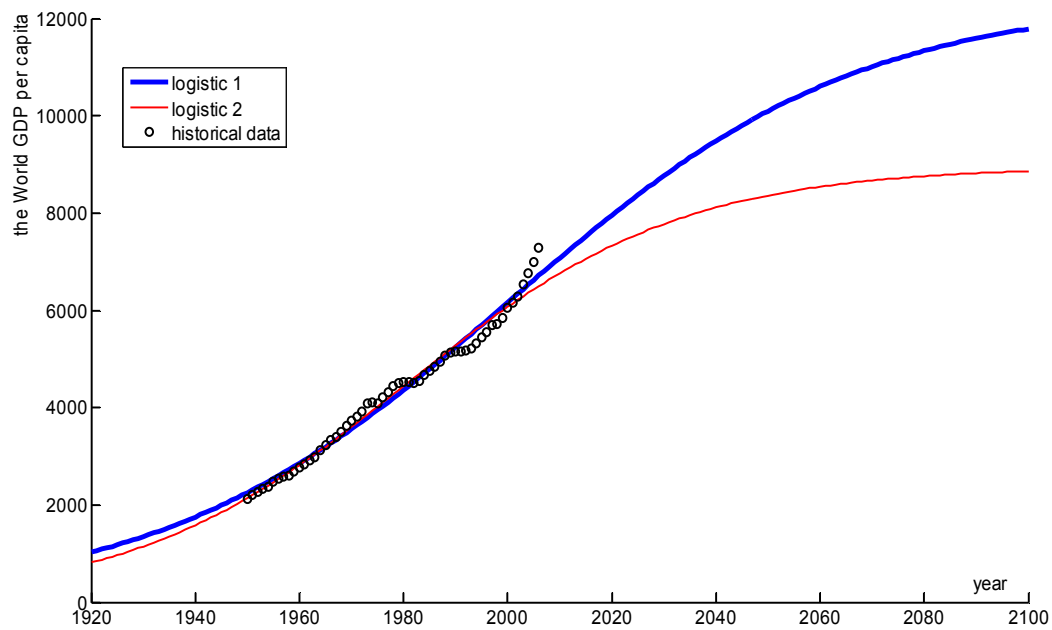
Figure 7. Forecast of global GDP per capita growth by the end of the 21st century (logistic function parameter identification based on historical data from the years 1950 to 2006)
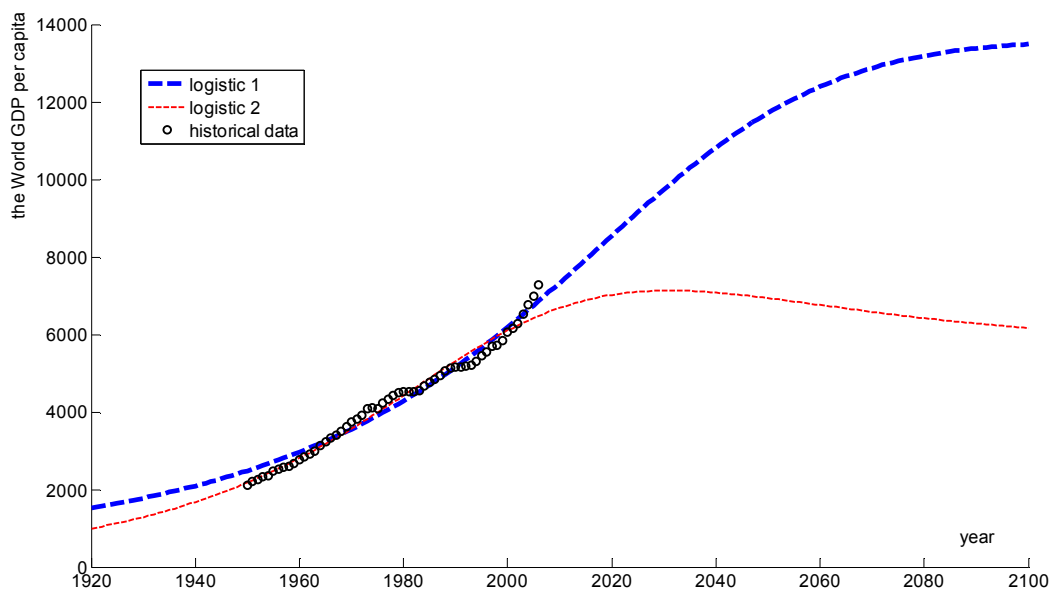

Figure 8. The forecasts of global GDP per capita growth by the end of the 21st century calculated from the partial projections of global GDP growth and the increase in the world population
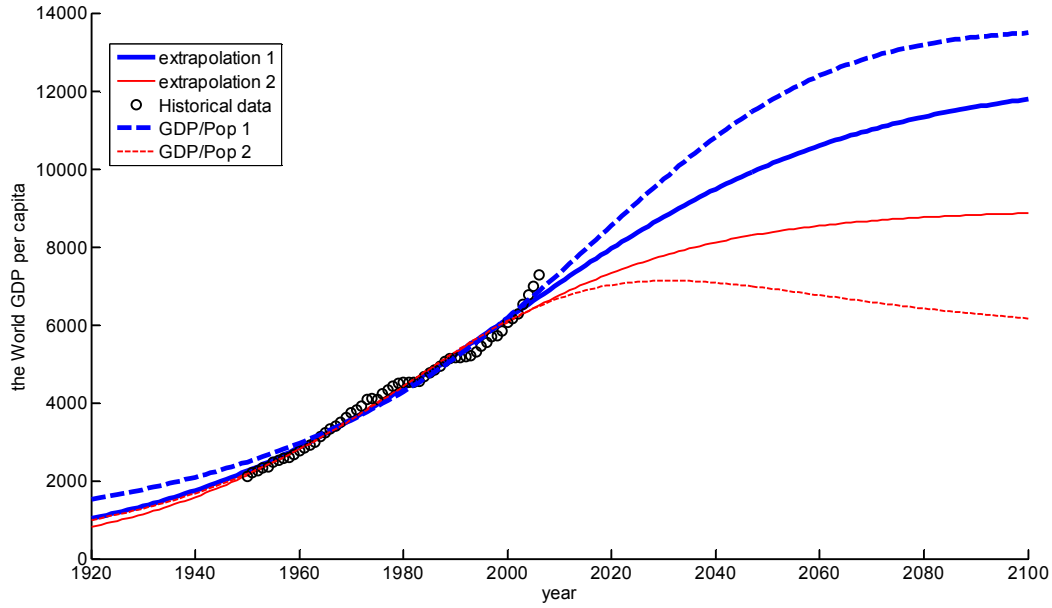
Figure 9. Comparison of the four forecasts of global GDP per capita by the end of the 21st century (Two were made by extrapolating the trends from the years 1950-2006 (continuous lines) and two calculated from the partial projections of global GDP growth and the increase in the world population (dashed lines)

5. SO FAR SO GOOD?

It seems that at this stage our work could be considered as completed – the relevant forecasts have been done. But all the time we ought to be sceptical in relation to the obtained results. The presented forecasts show the great potential of the logistic function in forecasting, although significant differences in the forecasts made applying different criteria to identify the parameters of the logistic function may cause a certain anxiety. It turns out that the selection of other periods to identify the parameters can generate essentially different results, not only in quantitative but also in qualitative terms.

5.1. GLOBAL GDP GROWTH ANALYSIS

Up to now we were using all the available historical data (from 1950 to 2006) to identify trends on which the predictions have been made. To test to what extent shorter identification periods produce similar results we use the historical data from two sub-periods, namely 1950-1971 and 1980-2006 to identify the parameters of logistic and exponential functions. The period 1950-1971 allows us to compare the forecast with real development in years 1972-2006.

It turns out that in that case of the period 1980-2006 the best fit is obtained for the exponential function (see Table 4). Table 4 shows also a few results of logistic identification using a criterion of the average square error (Q_1). As the volume of saturation (K) is growing, the identification error is decreasing, but it is worth noting that very large differences in the values of K (e.g. a hundredfold) have resulted in a slight diminishing of the identification error (the differences at the 6th LSD). The higher the K the better fit, so one could suspect that the best alignment occurs for the exponential function (i.e. when K goes to infinity), and indeed that is the case. However, depending on the fitting criterion we obtained slightly different values of optimal parameters, e.g. for the mean square error criterion the optimal

growth rate (γ) is equal to 3.29%, while for the mean square relative error (Q_2) optimal growth rate is equal to 3.19%. These differences are minor ones, but in the long-term they result in reasonably different predictions (see Figure 10).

More interestingly, while we use the data from the period 1950-1971 to identify the parameters of the logistic and the exponential functions we obtain similar results – better fitting to the historical data is the one for exponential growth (see Table 5). A comparison of exponential growth in the period 1950-1971 with exponential growth in the period 1980-2006 shows a much higher rate of growth in the post-war period (approximately 4.7% compared to 3.2% in the period 1980-2006). The differences in the forecasts of exponential growth for the two criteria are small but clearly visible (see Figure 11). It should be noted that comparing these predictions with the available historical data for 1972-2006 shows shortages in their effectiveness. Error estimates for 1980 are relatively small, but after 1980 they are more and more significant, in 2006 this error is around 40%.

Table 4. Global GDP growth.
The parameters values of the logistic and exponential curves. Historical data for identification: 1980-2006

| Curve/Criterion	K [10^{14} US dol.]	Δt	t_m	Identification error
Logistic Q_1	0.99997717	132.9904	2169.188	712551.0880
Logistic Q_1	97.68471900	133.3967	2308.901	710387.6721
Logistic Q_1	998.55000000	133.4024	2379.482	710367.5573
Logistic Q_1	95917.25000000	133.4024	2518.060	710365.3992
Logistic Q_1	9718381.00000000	133.4023	2658.257	710365.3768
Logistic Q_1	59807200.00000000	133.4025	2713.420	710365.3766
	$A \rightarrow y(1950)$ [10^{13} US dol.]	γ		Identification error
Exponential Q_1	1.9243691	0.032941280		710365.3765
Exponential Q_2	1.9516935	0.031941294		0.02033412209
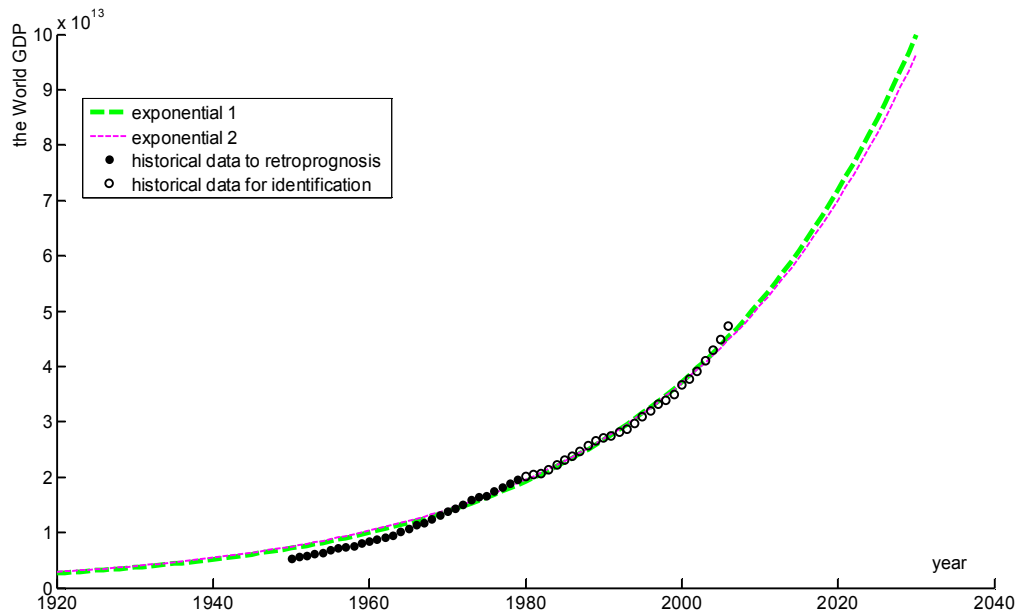
Figure 10. The global GDP forecast (exponential function parameter identification based on historical data from the years 1980 to 2006)

Figure 12 shows the comparison of all our predictions of global GDP growth. It is hard to say which of these predictions is more likely. However, it appears that the forecasts made using the logistic function are more plausible (although the dispersion between the two logistic predictions is very large).

The most intriguing however, is that the inclusion in the identification of a relatively short period of oil shocks (i.e. the period 1972-1979, marked in Figure 12 by the two vertical lines) so radically changes the nature of exponential growth (observed in the periods 1950-1971 and 1980-2006) into the logistic one (based on the whole historical data from 1950 to 2006).

Table 5. Global GDP growth.
The parameters values of the logistic and exponential curves. Historical data for identification: 1950-1971

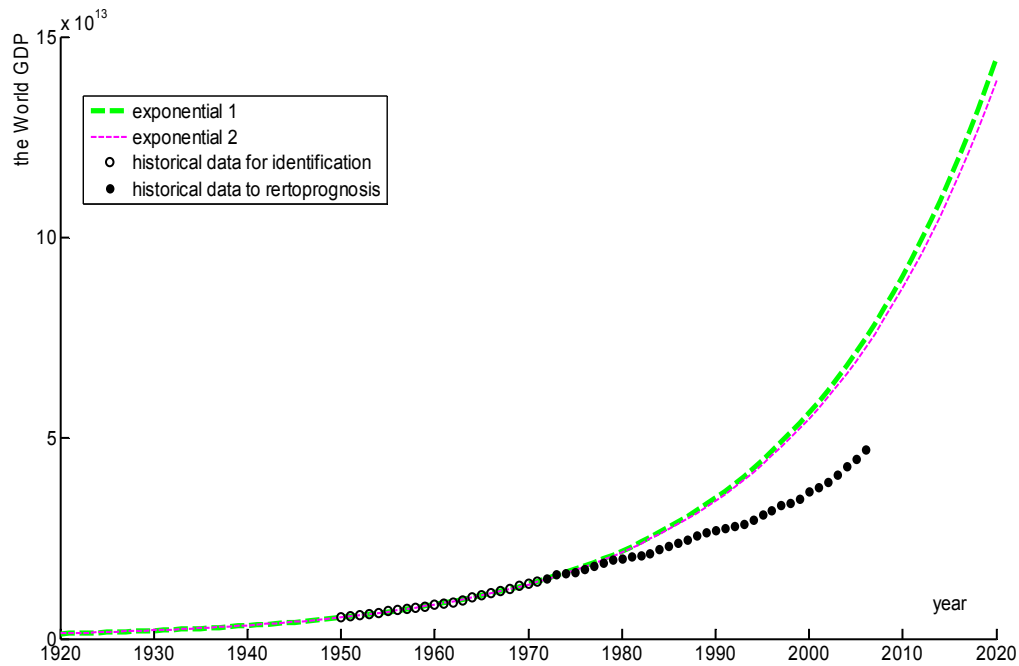| Curve/Criterion	K [10^{15} US dol.]	Δt	t_m	Identification error
Logistic Q_1	7.8277065	92.9378	2201.748	108823.5452
Logistic Q_1	99.9828330	92.9386	2255.624	108820.9534
Logistic Q_1	776.2378700	92.9384	2347.665	108820.7356
	$A \rightarrow y$(1950) [10^{13} US dol.]		γ	Identification error
Exponential Q_1	5.2962144		0.047283458	108820.7328
Exponential Q_2	5.3408785		0.046580132	0.01219099369

Figure 11. The global GDP forecast (exponential function parameter identification based on historical data from the years 1950 to 1971)

5.2. DEMOGRAPHIC GROWTH ANALYSIS

Making similar experiments with global population growth we also obtain qualitatively different results. As we will show, in 1950-1971 the world population growth is better described by the exponential function, while in the period 1980-2008 we observe a slowdown in the growth of world population and the logistic function fits better to that trend. The values of error identification for several values of the logistic function are presented in Table 6. It is seen that in the post-war period 1950-1971, the higher saturation value *K,* the better fit to the logistic curve . This suggests that the exponential curve fits better to the historical data, and that is the case. It is worth noting that for both criteria the identified population growth rate is nearly the same, namely approximately 1.89% per annum. It is true that the exponential trend fits well to the historical data in the period 1950-1971, but a forecast based on the extrapolation of that exponential trend (Figure 13) is relatively good only for the next 20 years

(until 1990), at the end of the 20th century and beginning of the 21st century we observe significant deviations of that trend from the historical data.

If we use historical data from the period 1980-2008 to identify the logistic and exponential curves parameters, we clearly see that a better fit to historical data is obtained for the logistic function (Table 7). In contrast to the earlier identification based on historical data from the years 1950-2008 (see Table 1 and Figure 3), in this experiment, the value of the identified parameters of the logistic function for both the identification criteria are very similar, in particular saturation K is roughly equal to 9.2 billion (Table 7 and Figure 14). The value of this saturation is about 30% smaller than the saturation value obtained for identification based on data for 1950-2008. A comparison of the three experiments (predictions) is shown in Figure 15 (vertical lines indicate the period 1972 to 1979; the oil crises). It seems that for the world population growth, the logistics trend seems more probable and the expected maximum number of people living on the Earth might be between 9 and 12 billion.
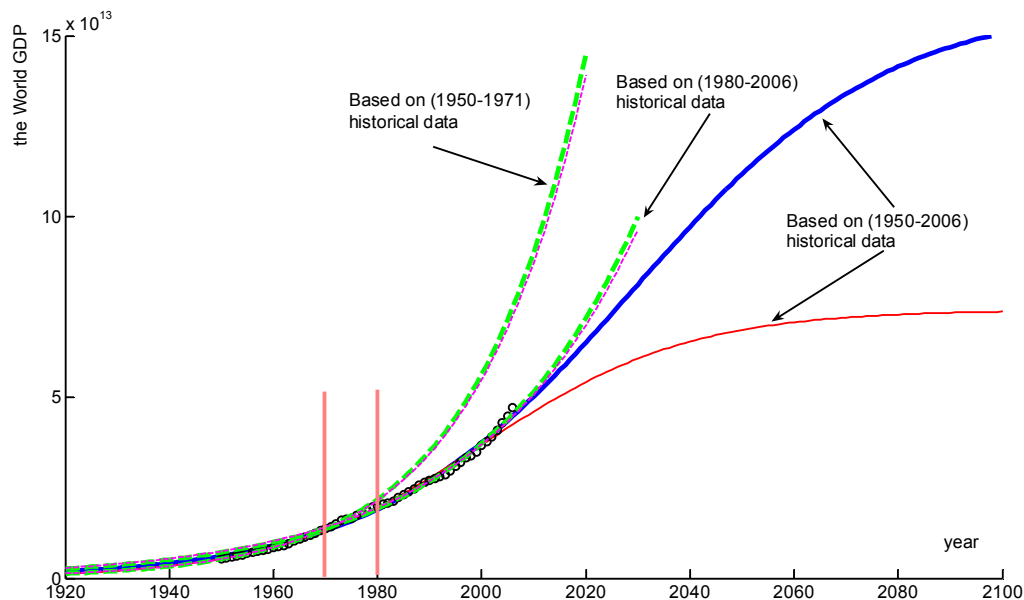

Figure 12. Comparison of the global GDP growth forecasts based on extrapolation of exponential growth in the years (1950-1971) and (1980-2006) and the logistic growth in (1950-2006)

Table 6. The growth of the world population.
The parameters' values of logistic and exponential curves. Historical data (1950-1971)

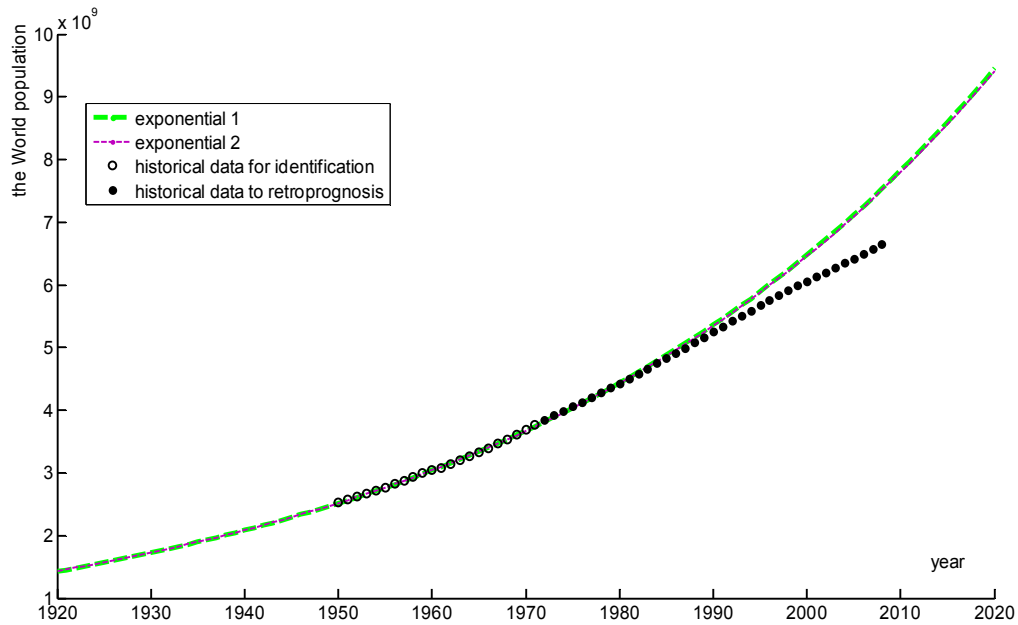| Curve/Criterion	K [10^9 US dol.]	Δt	t_m	Identification error
Logistic Q_1	20.515148	197.2791	2038.442	13635920.27
Logistic Q_1	6287.348200	232.3073	2363.559	11028257.11
Logistic Q_1	38717522.000000	232.4238	2825.282	11021606.83
	$A \rightarrow y(1950)$ [10^9 US dol.]		γ	Identification error
Exponential Q_1	2.5163250		0.018907043	11021605.77
Exponential Q_2	2.5184137		0.018831309	0.00339091178

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Figure 13. The global population growth extrapolation (exponential parameter identification based on historical data from the years 1950 to 1971)

The presented results allow us to understand (and to same extent to justify) the incorrect population projections presented in the First Report for the Club of Rome *The Limits to Growth*, published in 1972. The demographic development up to the 1970s suggested a very rapid, exponential (some even have claimed hyperbolic) trend of world population growth. The authors of *The Limits to Growth* have not taken into account the limits to population growth in their world model, caused by some natural mechanisms (mainly the market ones), which usually contribute to slowing down population growth in the course of increasing population density and growing welfare (this slowdown, as we can see, is observed in the last decades of the twentieth and the first decade of the twenty-first centuries).

Table 7. The growth of world population.
The parameters' values of logistic and exponential curves. Historical data (1980-2008)

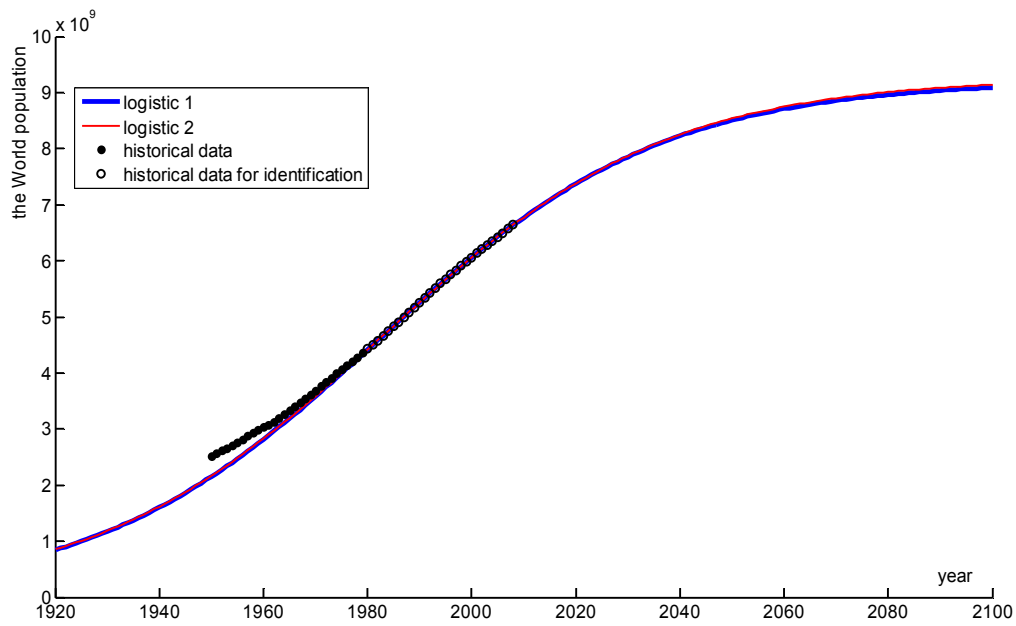| Curve/Criterion	K [10^9 US dol.]	Δt	t_m	Identification error
Logistic Q_1	9.206758	119.2270	1982.23	7028676
Logistic Q_2	9.266125	120.4273	1982.57	0.001387531253
	$A \rightarrow y$(1950) [10^9 US dol.]		γ	Identification error
Exponential Q_1	4.5238956		0.014286828	55615848.68
Exponential Q_2	4.5057450		0.014541383	0.01002837651

Figure 14. Forecast of world population by the end of the 21st century (logistic function parameter identification based on historical data from the years 1980 to 2008)
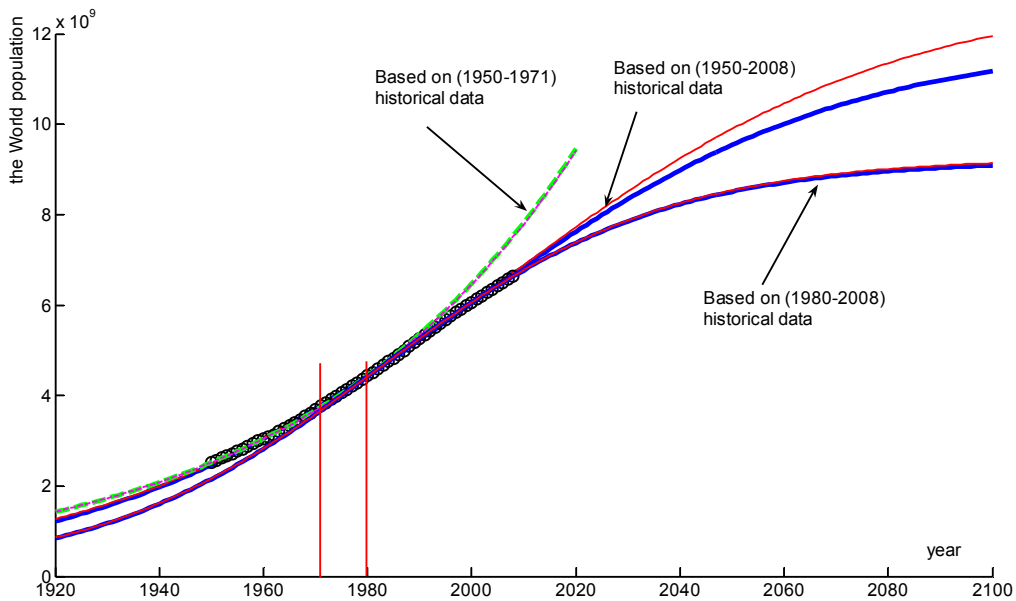

Figure 15. Comparison of the global population growth forecasts based on extrapolation of exponential growth in the years (1950-1971) and the logistic growth in (1980-2006) and (1950-2008)

5.3. GDP PER CAPITA ANALYSIS

A trend analysis of changes of global welfare (measured by the volume of GDP per capita) in the periods 1950-1971 and 1980-2006 shows that, as in the case of global GDP, the development is dominated by an exponential trend. Thus once again we can see that the inclusion of the oil crises (1972-1979) radically changes the nature of the trend (as was shown earlier in Section 3, the 1950-2006 identified trend was a logistic one).

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Table 8 presents the results of the identification of GDP per capita growth based on historical data from the years 1950-1971. The identification error is diminishing for the increasing values of the saturation K; this suggests that a better fit is obtained for the exponential function. The rate of growth of GDP per capita in the years 1950-1971 is similar for both identification criteria. It was indeed a period of rapid growth of prosperity; GDP per capita was growing during this period by approximately 2.8% annually. It should be emphasized that the gap between the forecast and the actual values after 1980 is significant and is widening in subsequent decades, in 2006, the difference is roughly 30% (Figure 16).

The identification of the parameters of logistic and exponential functions using historical data from the years 1980-2006 gives qualitatively similar results. The best fit is for exponential growth, but the growth rate during this period is much smaller than in the post-war period, namely approximately 1.7% (Table 9, Figure 17).

Table 8. GDP per capita.
The parameters' values of logistic and exponential curves. Historical data (1950-1971)

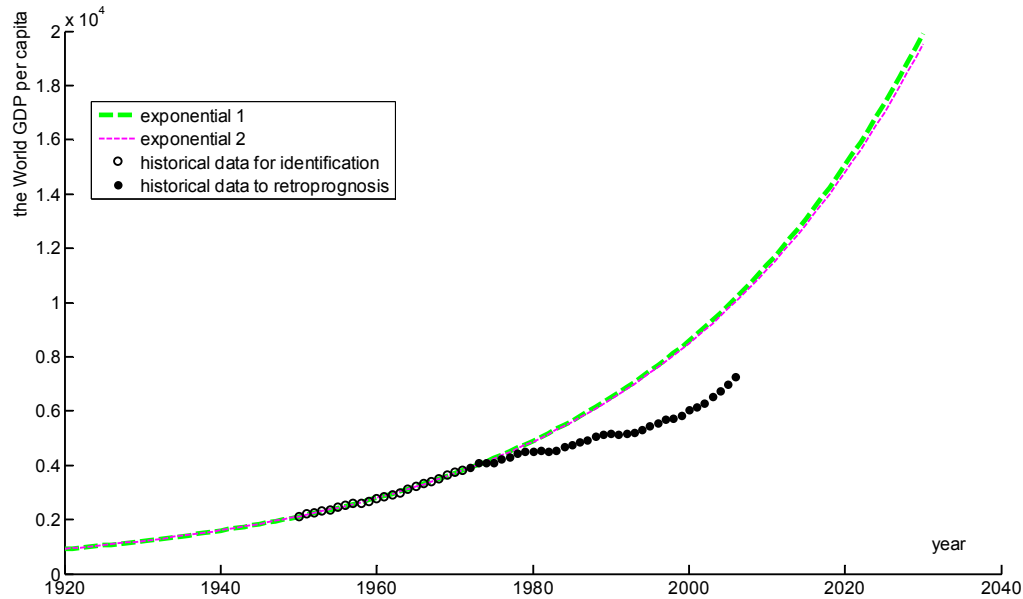| Curves/Criterion	K [US dol.]	Δt	t_m	Identification error
Logistic Q_1	899999.82	156.201	2165.102	94.34445365
Logistic Q_1	8999908.40	156.6601	2247.892	94.13893579
Logistic Q_1	38710930.00	156.6988	2299.994	94.12151201
	$A \rightarrow y$(1950) [US dol.]		γ	Identification error
Exponential Q_1	2114.0825		0.028041745	94.11623718
Exponential Q_2	2120.7042		0.027753573	0.01059338021

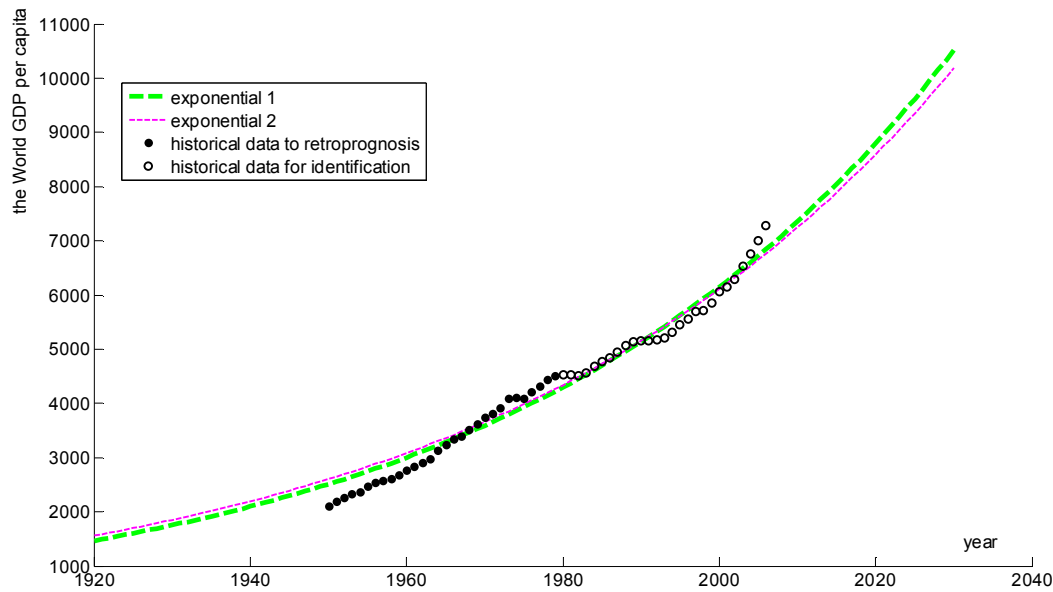Figure 16. GDP per capita (identification period 1950-1971)

Figure 17. GDP per capita (identification period 1980-2006)

Table 9. GDP per capita.
The parameters' values of logistic and exponential curves. Historical data (1980-2006)

Curve/Criterion	K [US dol.]	Δt	t_m	Identification error
Logistic Q_1	18.975492	238.3667	2184.235	538.7584161
Logistic Q_1	9989.583600	245.2912	2541.190	511.3574212
Logistic Q_1	827547.000000	245.3055	2787.785	511.3353354
Logistic Q_1	8005822.300000	245.3055	2914.470	511.3352584
	$A \rightarrow y$(1980) [US dol.]		γ	Identification error
Exponential Q_1	4297.3220		0.017914200	511.3352495
Exponential Q_2	4342.7828		0.017054013	0.02713080275

Figure 18 shows a comparison of these three extrapolative forecasts of GDP per capita. The fastest exponential growth (2.8% per annum) is observed in 1950-1971, and a slower exponential growth (a growth rate of around 1.7%) in the years 1980-2006. Once again the inclusion of the data for the years 1972-1979 in the process of parameters' identification (i.e. for the identification period 1950-2006) makes the logistic growth fit better. The saturation level of the logistic curves is different for different criteria, namely roughly $12,000 for the mean square criterion and $9,000 for the relative mean square error.

An alternative approach to welfare forecasting is to use partial forecasts of global GDP and global population growth and divide the relevant values. It turns out that when we calculate GDP per capita by division of the global GDP by the global population obtained on the basis of historical data from the period 1950-1971 (when, as we remember, the best fit either in terms of GDP and the global population were for the exponential trends) the results are almost the same as for an a simple extrapolation of GDP per capita. A comparison of these predictions is presented in Figure 19. As we can see, the differences between these forecasts are negligible, but (as is mentioned in the discussion of Figure 16) they are very unreliable – after a few years (since the early 1980s) the differences between the forecasts and the actual data are significant, and in the course of time become larger and larger.
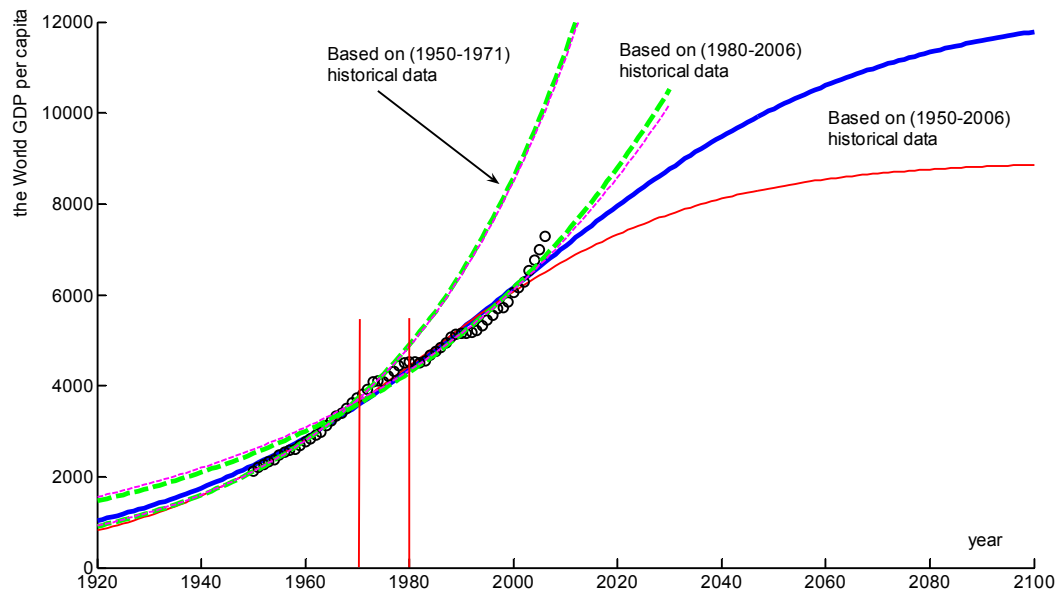
Figure 18. Comparison of the three extrapolative forecast of global welfare

Figure 20 shows a similar comparison of the forecasts on the assumption that the identification is based on historical data from the years 1980-2006. As we remember during this period, the best fit for GDP growth occurred for the exponential curve and for the population growth for the logistic curve. The calculation of GDP per capita by dividing these values produces the trend similar to the 'exponential growth' (there is no tendency to saturation). As we can see in Figure 20, there are significant differences between these forecasts. Naturally it is difficult to say which forecast is better because we have no comparative data (as is the case of identification on the basis of the years 1950 to 1971).
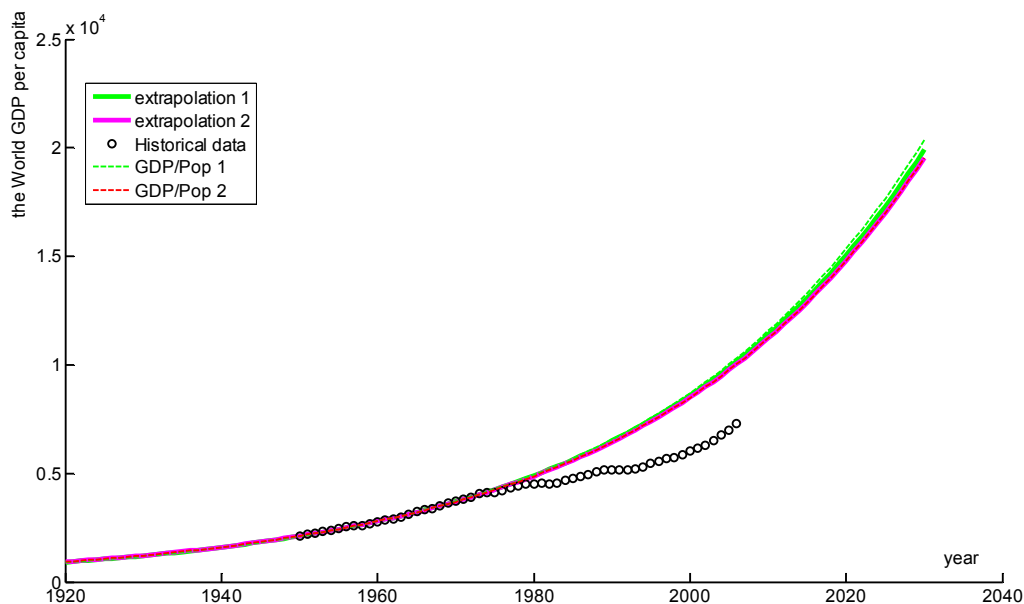

Figure 19. Comparison of the GDP per capita forecasts: extrapolative and calculated on the basis of global GDP and global population (historical data 1950-1971)
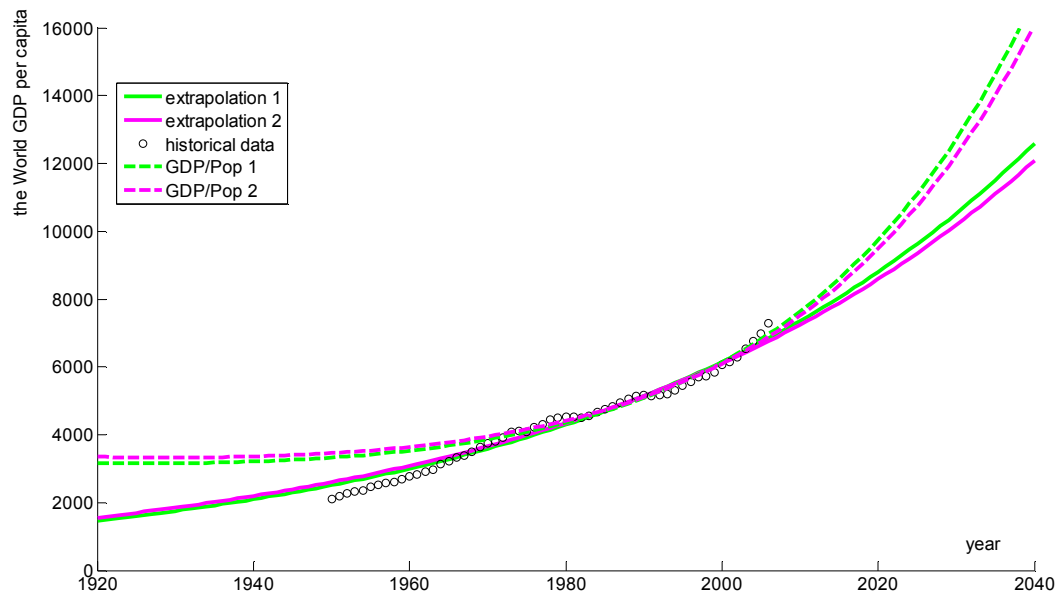
Figure 20. Comparison of the GDP per capita forecasts: extrapolative and calculated on the basis of global GDP and global population (historical data 1980-2006)

6. COMPETITION AND COMPETITIVENESS OF NATIONS

Boretos [6] uses the Logistic Substitution[6] fit of actual GDP contribution for the Western countries, China, and the rest of the world.[7] He concludes that "currently China is at an emerging phase, the West at a decline phase, and the rest of the World is substituting". According to his prediction "[if] the current trend continues, the West will follow a slow declining pace reaching 36% at 2050. The rest of the World is expected to fall gradually to 28% at 2025, while entering the decline phase at almost the same time. China is expected to grow even more in the following years reaching 32% contribution at 2025, and 51% at 2050. China's economy is expected to surpass Western countries' combined economies by 2034, and even earlier at 2023 the rest of the World region."

In the middle of the 1990s we have proposed the evolutionary model of substitution-diffusion processes which can be used to make similar prediction as was done by George Boretos. The model and the procedure of its parameters identification is presented in [9], here we will confine ourselves to describing only the model's basic characteristics.

Let us assume that we have n competing nations (or regions). The dynamics of the share $f_i(t)$ of a nation (region) i in the global GDP in year t can be described by the so called replicator equation (selection equation):

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[6] Logistic Substitution Model II Copyright © 2004 – 2006, International Institute for Applied System Analysis, Transitions to New Technologies Program; http://www.iiasa.ac.at/Research/TNT/WEB/Software/LSM2/lsm2-index.html

[7] the Western countries include: Austria, Belgium, Cyprus, Denmark, Finland, France, Germany (West Germany from 1950-1988, united Germany from 1989-onwards), Greece, Iceland, Ireland, Italy, Luxembourg, Malta, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, Canada, the United States, Australia, New Zealand, China consists of the People's Republic of China and Hong Kong.

$$f_i(t) = f_i(t-1)\frac{c_i(t)}{\bar{c}(t)} \tag{8}$$

where
$c_i(t)$ – competitiveness of the nation (region) i at time t.
$\bar{c}(t)$ – the average competitiveness at time t:

$$\bar{c}(t) = \sum_{i=1}^{n} c_i(t)f_i(t-1) \tag{9}$$

As we can see from the replicator equation, the share of nation (region) i is growing if the competitiveness of that nation is greater than the average competitiveness and is declining for the competitiveness smaller than the average competitiveness.

Let us assume that we identify the replicator equations parameters on the basis of historical data from 1980 to 2006.[8] This will allow us to compare our results with that of George Boretos. The identified competitiveness for the three considered regions and the initial shares are presented in Table 10. We can see that China's competitiveness is much higher than the competitiveness of the West as well as of the Rest the World. The model fits quite well to the historical data (see Figure 21). Our predictions are slightly different than those made by Boretos. According to our extrapolations, in 2050 the West and the Rest will have roughly the same shares in global GDP (equal to 19%), and the share of China will be around 60%. China will surpass the West as well as the Rest at around 2025. This scenario seems to be rather doubtful (as unlikely as is also the scenario proposed by Boretos[9]) and therefore the discussion of reliability of these predictions will be presented in the following part of the paper.

Table 10. Values of the model's parameters: China, the West and the Rest of the World – the identification period 1980-2006

	Competitiveness (c_i)	Initial share $f_i(t_0)$ in 1979
West	0.999152	0.486100
China	1.047807	0.053287
Rest of the World	1.000000	0.460613

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[8] In 1977 Deng Xiaoping became the new leader of China (after Mao Zedong's death) and initiated pro free market economic reforms (based also on the economic policy encouraging foreign trade and foreign investments).

[9] He writes: "It is evident that in the following years China will probably become the largest economy of the World, surpassing even the leading U.S economy. By the year 2024 though it will enter the substitution phase, as our world will most likely experience the emergence of a new "superpower" that will take its place, and once more will change the international landscape as we know it today. One of the best candidates to be that superpower is India which currently accounts for 6% of World GDP and has one of the largest growth rates around the globe (7% CAGR for 2000–2005). If this does happen then our forecast will most likely overestimate China's relative power during 2025–2050, and underestimate the rest of the World and eventually India's contribution for the same period." [6, p.324]
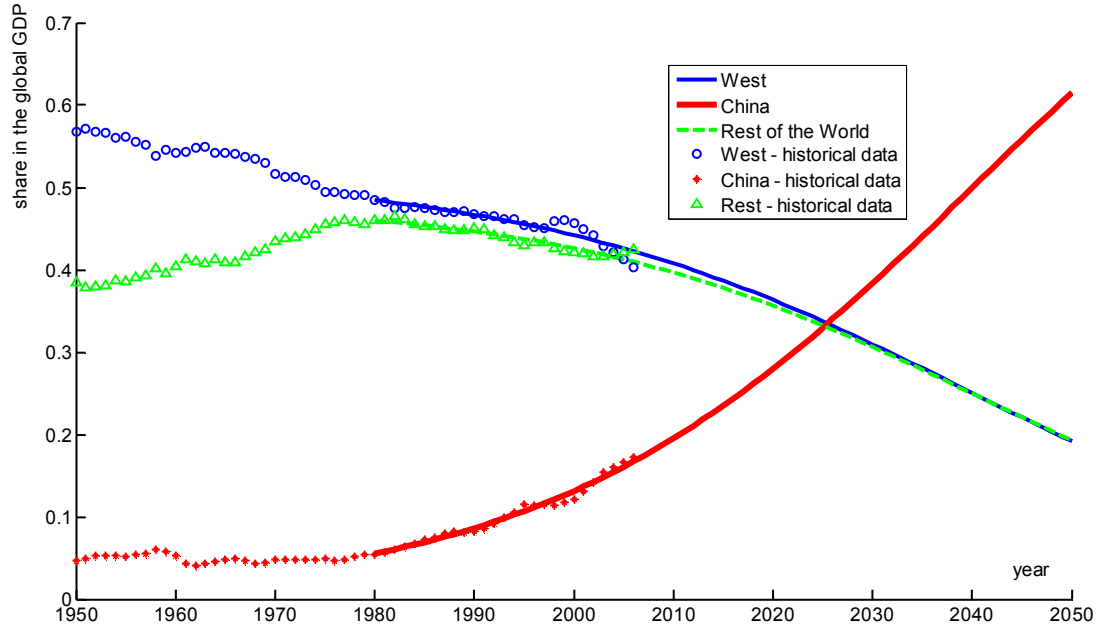
Figure 21. Evolution of the GDP shares of the three regions: China, the West and the Rest of the World (the identification period 1980-2006)

We obtain slightly different results if we use the whole available historical data of the period 1950-2006 for the parameters' identification. The overall competitiveness of China is much lower (see Table 11) and in the middle of the 21st century the share of China in global GDP is almost the same as the share of the West (roughly 29%; see Figure 22). The share of the Rest is equal to 42%. Naturally we may complain that the fitting of the model to historical data is not good (Figure 22). This is understandable because the structure of the Chinese economy of the post-war period up to the end of the 1970s was significantly different than that of the post 1980 one.

We may expect that the competitiveness of the regions is far from being constant and fluctuates in the course of time. Our model allows identifying dynamics of these fluctuations. Namely we are able to assume a much smaller identification period (e.g. a 7 year window) and make the identification of the competitiveness starting from the period 1950-1956 and move the 7 year window up to the last year, i.e. to the period 2000-2006.[10] In such a case we obtain a kind of a 'moving competitiveness'. The result of this experiment is presented in Figure 23.

Table 11. Values of the model's parameters: China, the West and the Rest of the World – the identification period 1950-2006

	Competitiveness (c_i)	Initial share $f_i(t_0)$ in 1949
West	0.992706	0.568897
China	1.020249	0.035354
Rest of the World	1.000000	0.395749

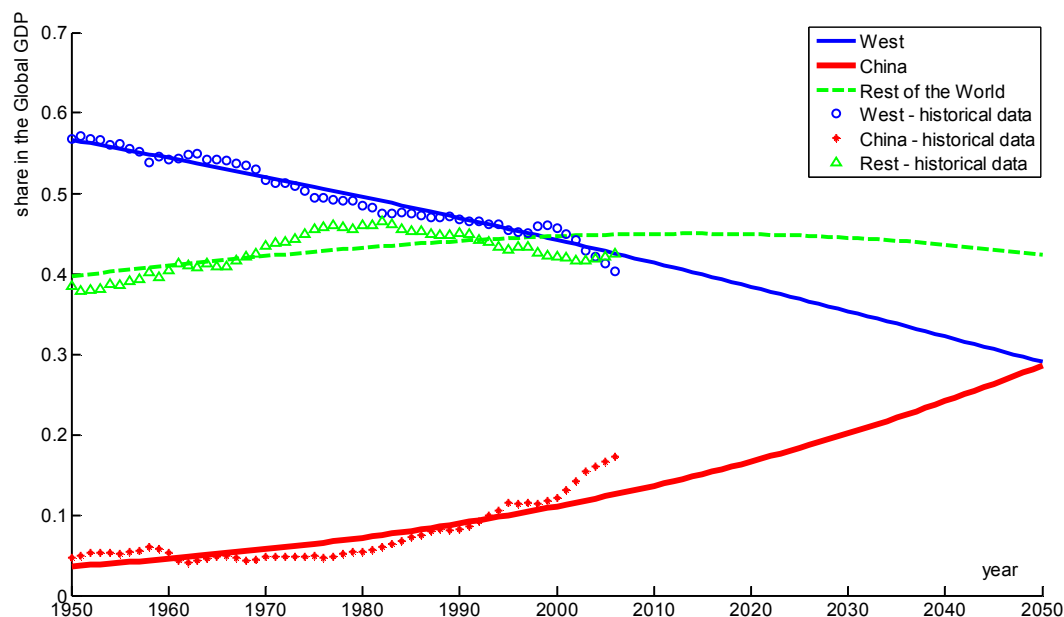[10] this procedure is described in details in [9].

Figure 22. Evolution of the GDP shares of the three regions: China, the West and the Rest of the World (the identification period 1950-2006)

As can be seen (Figure 23) the competitiveness is far from being constant. Up to the end of the 1980s the competitiveness of the West was below the competitiveness of the Rest of the World and usually slightly below China's competitiveness. The West's economies were more competitive from the end of the 1980s, but after the dot.com crisis the West's competitiveness has been declining. It is clearly visible that China's competitiveness started to rise after the Deng Xiaoping reforms and (although fluctuating) was much higher than the West and the Rest's competitiveness. It is difficult to predict the future of the Chinese economy's competitiveness but we may expect that in the near future the advance of China will be sustained. The lesson of Japan may give us a hint as to what may happen in the longer perspective.
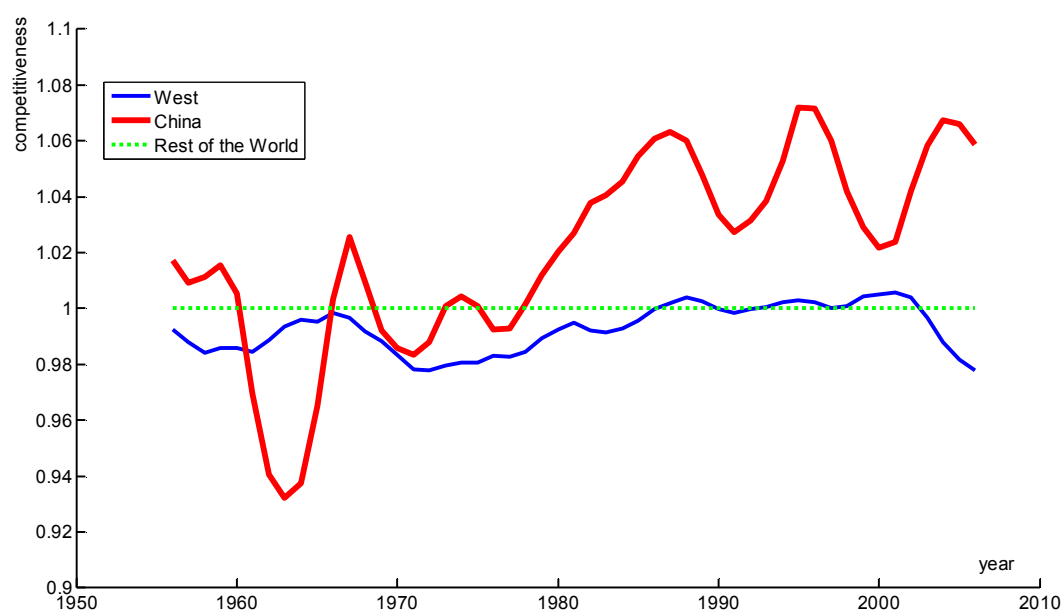

Figure 23. Dynamics of the competitiveness: China, the West and the Rest of the World (identification is

based on the 7 year moving window of historical data)

As is known, Japan's economy was treated as the model for growth in the post-war period up to the beginning of the 1970s. The identified competitiveness of the Japanese economy, based on the historical data from 1950 to 1970, is roughly similar to China's competitiveness for the period 1980-2006 (see Table 12) – the competitiveness was roughly 4% higher than the West and the Rest's competitiveness. The share of Japan's GDP in global production more than doubled in the period 1950-1970 (similar as in the period 1980-2000 for China).

The prediction of the shares in global GDP of Japan and the two other regions are shown in Figure 24. We can see that since the middle of the 1970s the discrepancy between the prediction and the real development has been growing. The prediction based on the trend observed in 1950-1980 suggested that in 2030 the share of Japan's economy will be above 50% (as in the case of China in 2050). According to that prediction we might expect that the share of Japan in the global production in 2006 ought to be 27%, in reality it declined to 6% (see Figure 24).

Table 12. Values of the model's parameters: Japan, the West and the Rest of the World – the identification period 1950-1970

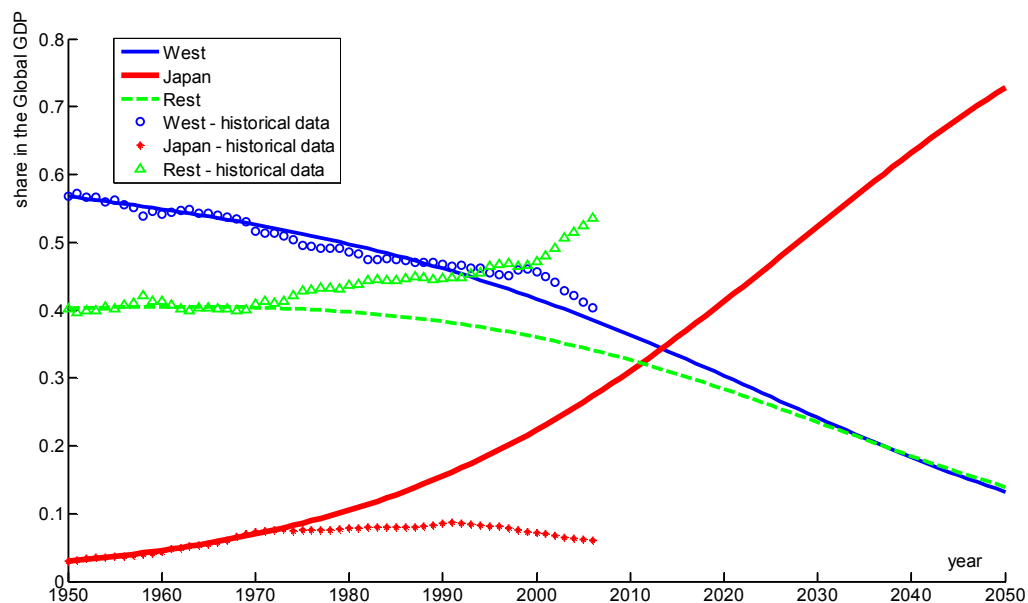|	Competitiveness (c_i)	Initial share $f_i(t_0)$ in 1949
West	0.996064	0.569261
Japan	1.043551	0.028382
Rest of the World	1.000000	0.402356

Figure 24. Evolution of GDP shares of the three regions: Japan, the West and the Rest of the World (the identification period 1950-1970)

The results suggest that it would be good to look at the dynamics of changes of Japan's competitiveness. The results of a similar experiment with moving the 7 year identification window (as in the case of China) are presented in Figure 25. We can see that the pattern of changes of Japan's competitiveness in 1950-1970 is more or less similar to the pattern of the changes of China's competitiveness in 1980-2000 (compare Figures 25 and 23), we can see

the enormous superiority of Japan's and China's economies in the relevant periods. As we can notice (Figure 25) the sharp decline of Japan's competitiveness was observed in the 1970s, the almost constant level of competitiveness in the 1980s and the beginning of the 1990s, and once more the sharp decline at the turn of the 20th and the 21st centuries. We do not claim that a similar pattern will be observed in the case of China's economy in the next few decades, but we would like to point out that we ought to be very cautious in our evaluations of the future of the Chinese economy.
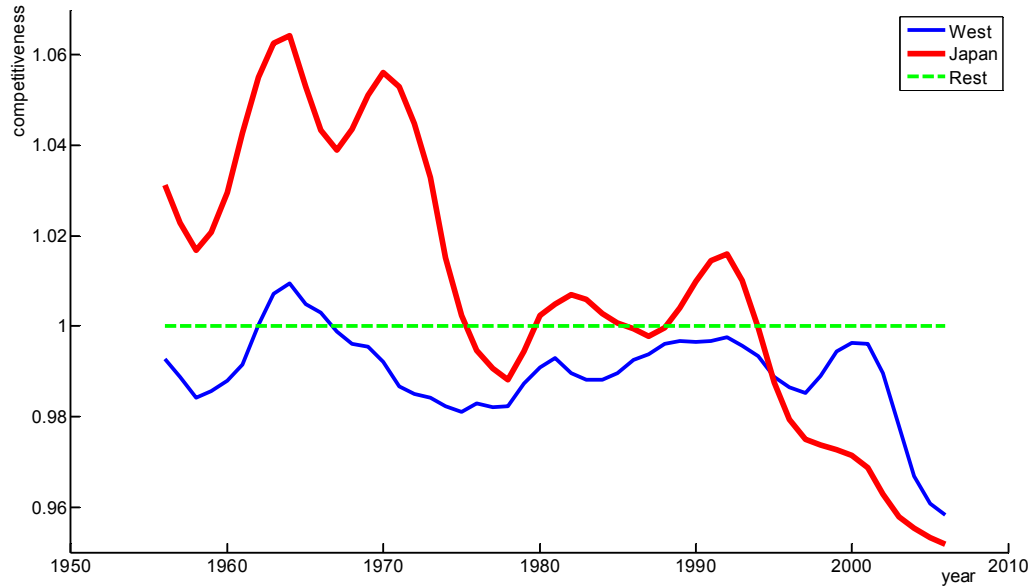

Figure 25. Dynamics of competitiveness: Japan, the West and the Rest of the World (identification is based on the 7 year moving window of historical data)

Table 13. Values of the model's parameters: USA, E12, Japan, China, India and the Rest of the World – the identification period 1950-2006

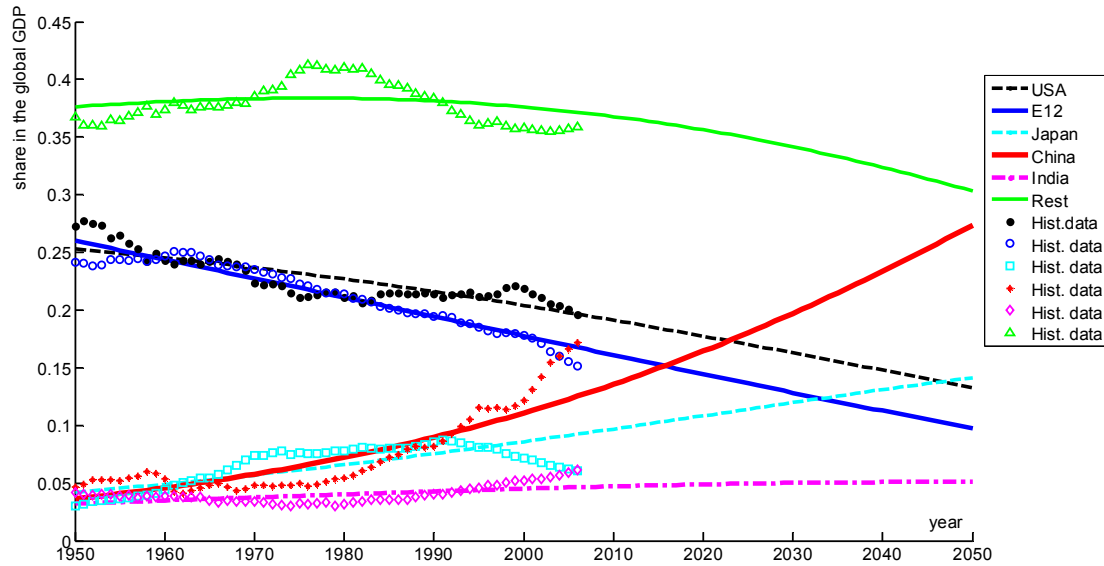|	Competitiveness (c_i)	Initial share $f_i(t_0)$ in 1949
USA	0.995710	0.253936
E12	0.992412	0.261623
Japan	1.014378	0.041473
China	1.022661	0.035302
India	1.006745	0.032042
Rest of the World	1.000000	0.375624

Figure 26. Evolution of the GDP shares of the six regions/countries: USA, E12, Japan, China, India and the Rest of the World (the identification period 1950-2006)

Our model allows us to investigate the evolution of a larger number of countries/regions. As the first experiment in that series, let us assume that the world is divided into six countries/regions, namely: the USA, the E12[11], Japan, China, India and the Rest of the World. The overall competitiveness of those six countries/regions in the post-war period is presented in Table 13. We can see that either the USA or the E12 economies lose their positions in the post-war period: their competitiveness is smaller than the competitiveness of all the other countries/regions. The fit of the model (see Figure 26) is rather poor and is clearly unsatisfactory. Significant differences between the model and the historical data are seen in almost all the countries/regions, but is especially visible in the case of China, Japan, and the Rest of the World. This is caused by significant differences in the mood of development of the World's economy before and after 1980. This is clearly seen when we look at the dynamics of competitiveness in the post-war period (Figure 27). To identify the moving competitiveness we use the 14 year identification window.[12] It is clearly visible that for all the competitiveness the mood of changes up to 1980 is significantly different than that after 1980. The competitiveness of India's economy in the last three decades is only slightly smaller than China's competitiveness; the USA's competitiveness, although smaller than China's and India's, is significantly greater than that of the E12.

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[11] E12 consists of the twelve European countries, namely: Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Sweden, Switzerland, the United Kingdom.

[12] It is necessary to identify 2n-1 parameters in our model (n is the number of countries/regions; namely n-1 competitiveness and n initial shares), therefore the number of historical data ought to be greater than 2n-1 (in our case greater then 11, therefore we select the 14 year identification window).
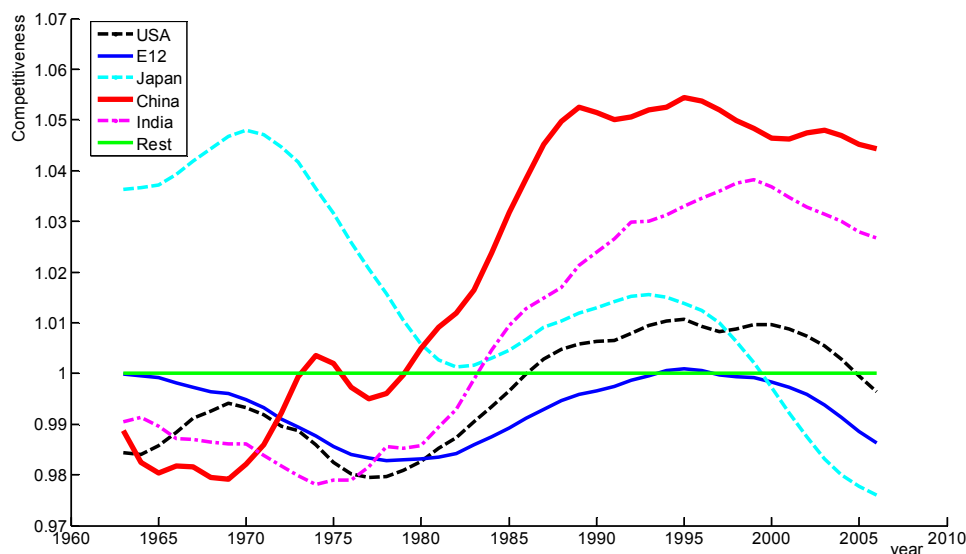
Figure 27. Dynamics of the competitiveness: USA, E12, Japan, China, India and the Rest of the World (identification is based on the 14 year moving window of historical data)

Therefore let us look more closely at the development of the world economy in the last three decades. The average competitiveness in the period 1980-2006 is presented in Table 14, and we can see that it confirms the general impression flowing from Figure 27; Japan and the E12 economies lose their position, but the USA economy tries to compete with China and India. Figure 28 shows the prognosis based on the trends observed in the period 1980-2006. It confirms the suggestions concerning the expected future of the Chinese economy presented in Figure 21 (the share of China's GDP will be around 60% of global GDP). According to that prediction, currently we ought to observe the catching up of the USA by the Chinese economy (in GDP terms). India's economy will exceed the E12's around 2030 and will be at the same level as the USA's in the middle of the 21st century.[13]

Table 14. Values of the model's parameters: USA, E12, Japan, China, India and the Rest of the World – the identification period 1980-2006

	Competitiveness (c_i)	Initial share $f_i(t_0)$ in 1949
USA	1.005344	0.211215
E12	0.994965	0.215214
Japan	0.996753	0.086284
China	1.049823	0.053095
India	1.031486	0.030351

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[13] A more plausible scenario is presented in our working paper on *China, India and the future of the global economy* (available at http://mpra.ub.uni-muenchen.de/32558/1/MPRA_paper_32558.pdf), pp. 23-25. According to that scenario "the Chinese economy will overcome the US in 2011 (with a roughly 20% share of global GDP by both economies) and will still grow to reach the maximum share equal to 28% in 2027, in the next two decades (still being the largest global economy) its share will be dropping to reach 24.5% in 2050. The second largest economy will be the US, but its share will still decline to reach the minimum 18.3% in 2027. From that year the share of the US economy will rise to reach 22% in 2050 (roughly the same as China). The share of the Indian economy will grow steadily to reach almost 16% in 2050 (and being a 3rd world economy). The total share of the twelve European countries (E12) will keep the past tendency to decline, but, due to the reform initiated in the 2030s, in the middle of the century will reach a plateau with a share equal to 10%. The same pattern of development will be experienced by Japan, but the plateau (roughly a 5% share) is reached by the Japanese economy in the beginning of the 2030s."
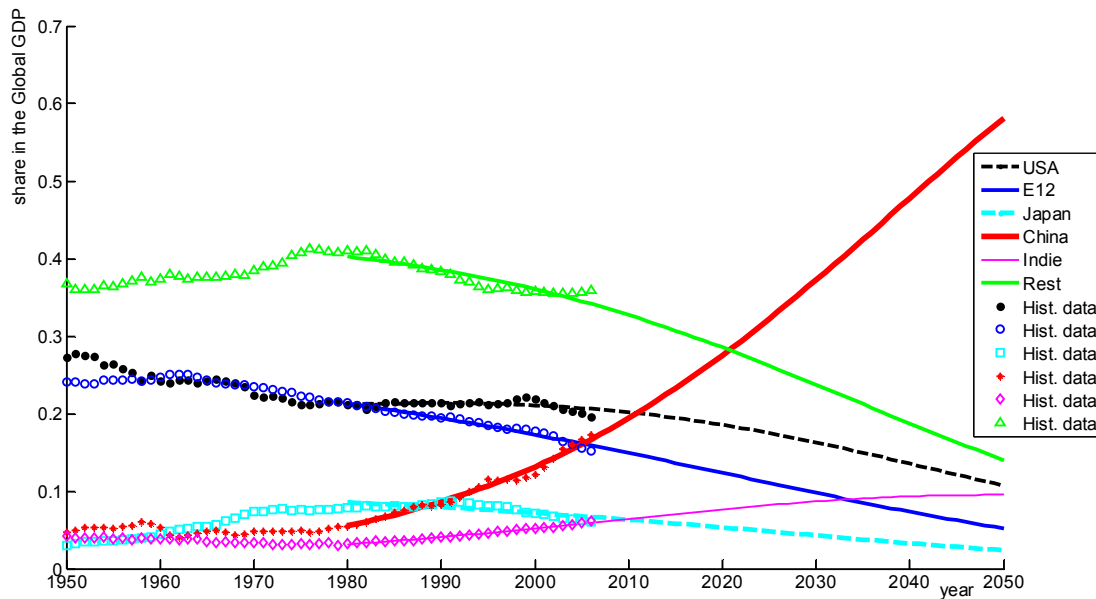
| Rest of the World | 1.000000 | 0.403841 |

Figure 28. Evolution of the GDP shares of the six regions/countries: USA, E12, Japan, China, India and the Rest of the World (the identification period 1980-2006)

The idea of ranking the national economies according to their competitiveness index came to us during working on this paper. The problem is that if we would like to consider, let us say 100 nations, and calculate their competitiveness using our model we ought to have historical data on their GDP for roughly 200 years. Naturally it is not possible to collect such long historical data; therefore we propose a simplified approach. Let us assume that we consider each country separately as competing with the Rest of the World. To identify the competitiveness of that country (against the competitiveness of the Rest, all the time assumed as equal to one[14]) we ought to have historical data on at least four years (usually we assume a longer period, e.g. 7 years for two types (countries)). Just to investigate the relevance of this approach we calculated moving the competitiveness for the five considered countries/regions by making five simulation experiments: each country competes with the rest of the World. The results of these experiments are presented in Figure 29. The general tendency of the competitiveness changes is more or less similar to that observed in the experiment where all countries/nations competed altogether (see Figure 27). Just to show the level of the differences, Figures 27 and 29 are collectively presented in Figure 30 (for all six countries/regions competing (solid lines) and calculated separately for each country competing with the Rest of The World (dashed lines)). The differences are visible, although there is general agreement concerning the observed tendencies and the far reaching similarities in the competitiveness rankings. In Table 15 the rankings of these five countries/regions for 1970, 1980, 1990, and 2000 are presented. The compatibility of rankings obtained for these two approaches is astonishingly good. The only difference is for 1970 where the USA and the E12 interchange their positions (but as we see in Figure 30 their competitiveness are very similar).

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[14] as we explain in [9] one country (type) ought to be treated as the reference country (type) and it is necessary to assume the reference value of the competitiveness of that country (type).
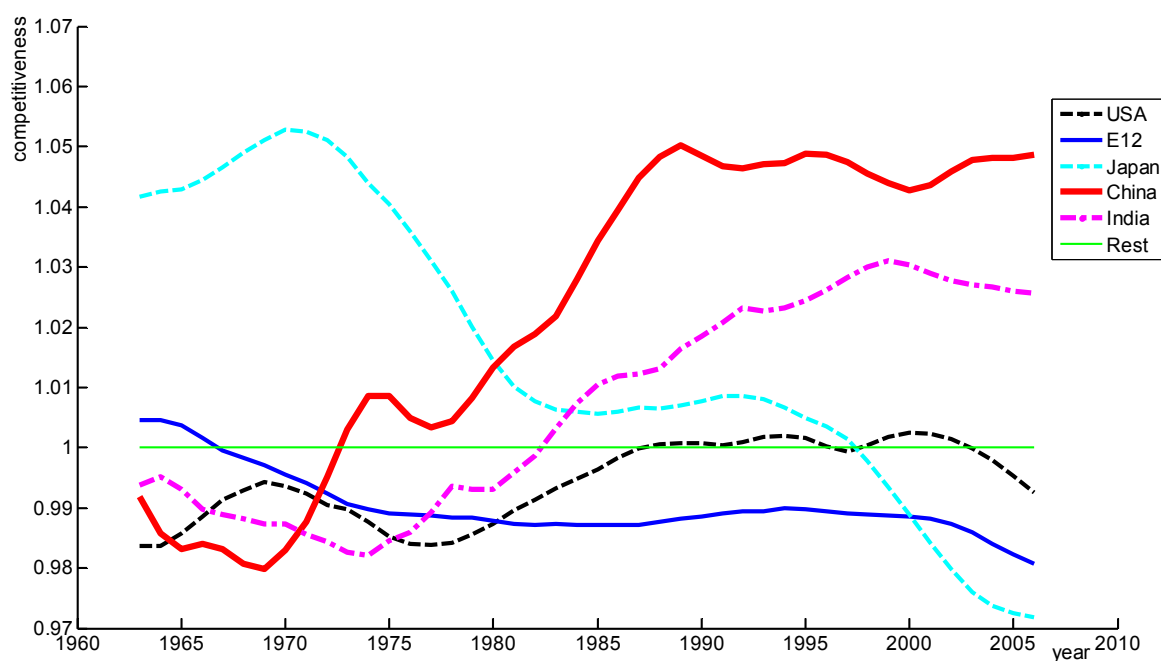
Figure 29. Dynamics of competitiveness: USA, E12, Japan, China, India and the Rest of the World, calculated separately for each country competing with the Rest of The World (identification is based on the 14 year moving window of historical data)

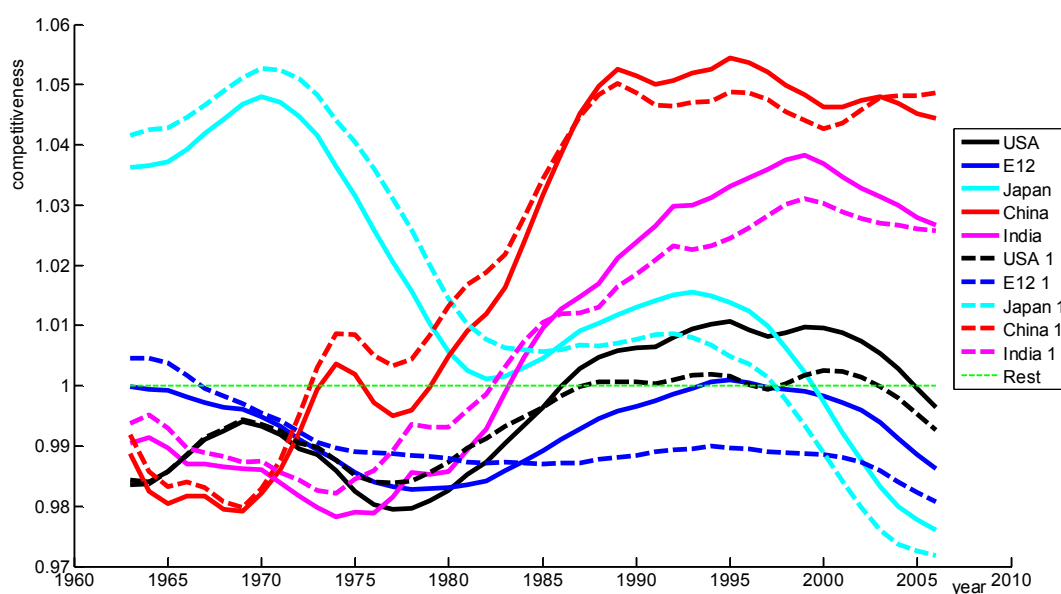Figure 30. Comparison of the dynamics of competitiveness: USA, E12, Japan, China, India and the Rest of the World, for all six countries/regions competing (solid lines) and calculated separately for each country competing with the Rest of The World (dashed lines); (identification is based on the 14 year moving window of historical data)

Table 15. Rankings of competitiveness of different countries/regions for two approaches 'altogether competition' and 'separate competition'

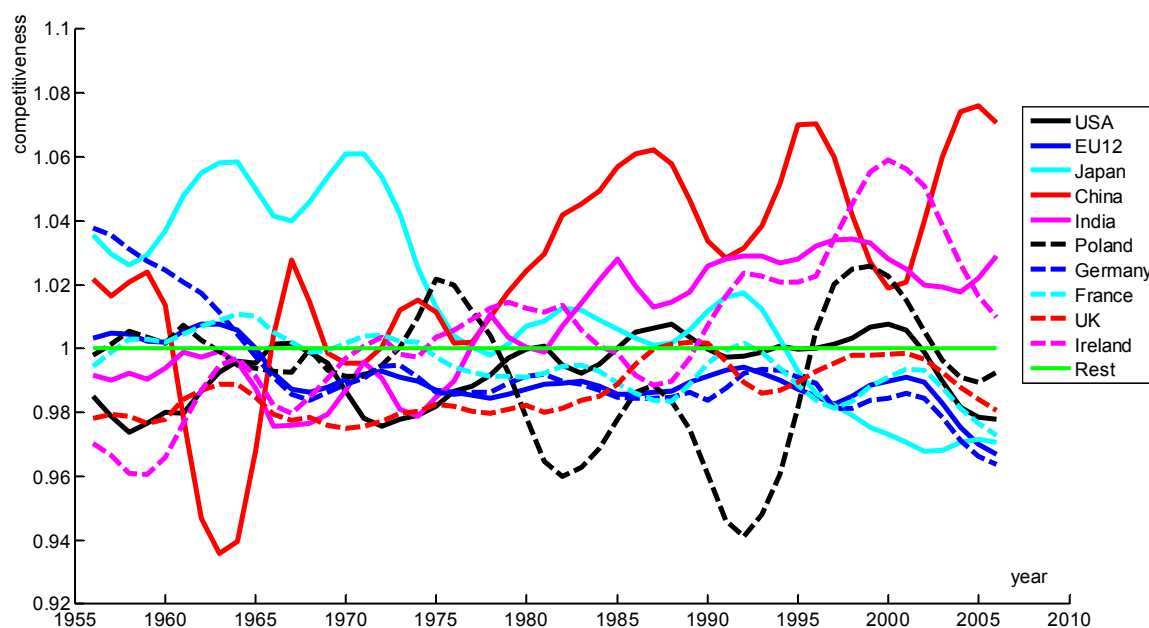|	1970		1980		1990		2000	
	altogether competition	separate competition	altogether competition	separate competition	altogether competition	separate competition	altogether competition	separate competition
USA	**3**	**2**	4	4	4	4	3	3
E12	**2**	**3**	4	4	5	5	4	4
Japan	1	1	1	1	3	3	4	4
China	5	5	1	1	1	1	1	1
India	4	4	3	2	2	2	2	2

Figure 31. Dynamics of the competitiveness of nine countries and E12; calculated separately for each country competing with the Rest of The World (identification is based on the 7 year moving window of historical data)

There is no room to present the rankings of the competitiveness of all the countries in the World but we plan to undertake such a project in the near future. Here, as the first step towards that project we present an experiment for twenty-nine selected countries and the E12 (distinguished as a region competing especially with the USA and China). The dynamics of the competitiveness of the ten selected countries are presented in Figure 31 (for a larger number of countries the figure would be unreadable). Once more we can see the great variability of the competitiveness for almost all the countries since the middle of the 20th century. In Table 16 we present the rankings of the 30 countries/region for selected years. We start from the middle 1950s, and as we can see, Israel, Germany and Japan were the most competitive countries at that time. Due to the market oriented reforms initiated in 1948 by Ludwig Erhard, the German economy was one of the most competitive in the 1950s, but in the course of time Germany has become more and more a welfare state and less and less competitive, in 1980 Germany was ranked 19th, in 1990 25th, and in the last few years was placed at the bottom of the ranking. The same tendency of losing competitiveness is observed for all of the twelve European countries (E12). The growing competitiveness in the last 20-30 years is observed for such economies as: Chile, Ireland, India, and China. Poland, and to some extent also Hungary, are good examples of competitiveness advance due to market oriented

transformations. Hungary and Poland in 1990 were at the bottom of the ranking and now, after 20 years of transformation, are placed in the top ten.

In the last column of Table 16 the competitiveness indices for the latest available historical data (2006) are presented. It is worth noting the strong superiority of China and India over all the advanced economies. The index for China is roughly 10% higher than that of the USA, France, Japan and Germany. Even small differences in the values of the competitive indices result in an enormous advantage/disadvantage of the economy in the long term. For example, there is nearly a 3% difference between the competitiveness of China and the West in the period 1950-2006 (see Table 11), which resulted in an increase of China's share in global GDP from 11% in 2000 to 28% in 2050 and a decrease of the share of the West from 44% to 29% (see Figure 22).

Table 16. Ranking of the competitiveness of selected economies (30 countries and regions)

ranking	1956	1960	1970	1980	1990	1995	2000	2006	2006
1	Israel	Israel	Singapore	Hong Kong	South Korea	China	Ireland	China	1.0707
2	Germany	Japan	Japan	South Korea	Hong Kong	Singapore	India	India	1.0291
3	Japan	Hong Kong	South Korea	Singapore	Singapore	Chile	Singapore	Ireland	1.0098
4	South Korea	Brazil	Israel	Brazil	China	South Korea	Poland	Hong Kong	1.0053
5	Hong Kong	Germany	Spain	Mexico	Chile	Israel	China	Singapore	1.0029
6	China	Mexico	Brazil	China	India	Hong Kong	Finland	South Korea	1.0015
7	Austria	Austria	Mexico	Chile	Japan	India	Chile	Chile	1.0011
8	Italy	China	Hong Kong	Ireland	Spain	Ireland	South Korea	Hungary	0.9992
9	Singapore	Italy	Italy	Norway	Ireland	Norway	Israel	Poland	0.9927
10	Mexico	France	Australia	Japan	Israel	Australia	Netherlands	Spain	0.9893
11	Spain	E12	Netherlands	India	Australia	N. Zealand	Australia	N. Zealand	0.9893
12	Netherlands	Poland	France	Italy	Finland	Mexico	USA	Australia	0.9881
13	Brazil	Hungary	Canada	USA	UK	USA	Mexico	Israel	0.9860
14	E12	Canada	Austria	Canada	USA	Austria	Canada	Sweden	0.9853
15	Canada	South Korea	Ireland	Israel	Canada	Netherlands	Spain	Finland	0.9847
16	Switzerland	Finland	China	Spain	France	Brazil	Hungary	Canada	0.9830
17	Finland	Australia	Finland	Australia	Italy	Denmark	Norway	UK	0.9808
18	Poland	Singapore	Chile	Austria	Brazil	Japan	Sweden	Brazil	0.9799
19	N. Zealand	Switzerland	Poland	Germany	Netherlands	Spain	UK	Norway	0.9793
20	France	Denmark	Norway	France	Austria	Germany	Denmark	Mexico	0.9790
21	Norway	N. Zealand	E12	Netherlands	Switzerland	Canada	Hong Kong	USA	0.9777
22	India	Chile	Denmark	E12	E12	UK	Austria	Austria	0.9742
23	Australia	India	Switzerland	Finland	Sweden	France	N. Zealand	Denmark	0.9733
24	Hungary	Netherlands	Sweden	Denmark	Norway	E12	France	France	0.9730
25	USA	Spain	Germany	Hungary	Germany	Italy	Brazil	Switzerland	0.9719
26	Chile	Norway	India	UK	Denmark	Poland	E12	Netherlands	0.9707
27	Sweden	Sweden	USA	Poland	Mexico	Switzerland	Italy	Japan	0.9707
28	UK	USA	Hungary	Sweden	N. Zealand	Sweden	Switzerland	E12	0.9670
29	Denmark	UK	UK	Switzerland	Hungary	Finland	Germany	Italy	0.9648
30	Ireland	Ireland	N. Zealand	N. Zealand	Poland	Hungary	Japan	Germany	0.9638

Possible scenario of development

The extrapolation of the future development of structure of global GDP, as presented in Figure 28, seems to be rather improbable, mainly because it is hardly possible that the competitiveness of the selected six countries/regions will be constant over the next 40 years. Let us make an experiment and assume the future development of competitiveness of these

six regions. The initial competitiveness of those six regions are as presented in Table 14 (i.e. based on the identification period 1980-2006). Future competitiveness (up to 2050) is assumed to change as follows (as illustrated in Figure 32): the USA's competitiveness will be stable (and equal to 1.005344) up to 2020 and from that year will grow steadily (in a linear form) over the next 30 years, to reach 1.02 in 2050; the E12 competitiveness will remain constant (and equal to 0.994965) up to 2030, from that year it will grow steadily to reach 1.01 in 2050; the same pattern is assumed for Japan, although it is assumed that the reform will start earlier than in Europe, and the steady growth of Japan's economy's competiveness will start in 2020, to reach the same value 1.01 in 2050; China's economy's competitiveness will be the highest (and equal to 1.49823) up to 2015, and then will drop significantly to reach 1.0 in 2030, from that year it will be constant and equal 1.0 (so it is assumed that the pattern is similar to that of Japan in the 1970s and 1980s); India's competitiveness will grow from the initial 1.031486 to 1.04 in 2025 and from that year will diminish steadily to 1.01 in 2050; the competitiveness of the rest of the world as the reference competitiveness is assumed to be constant for the whole period, and equal to 1.0.
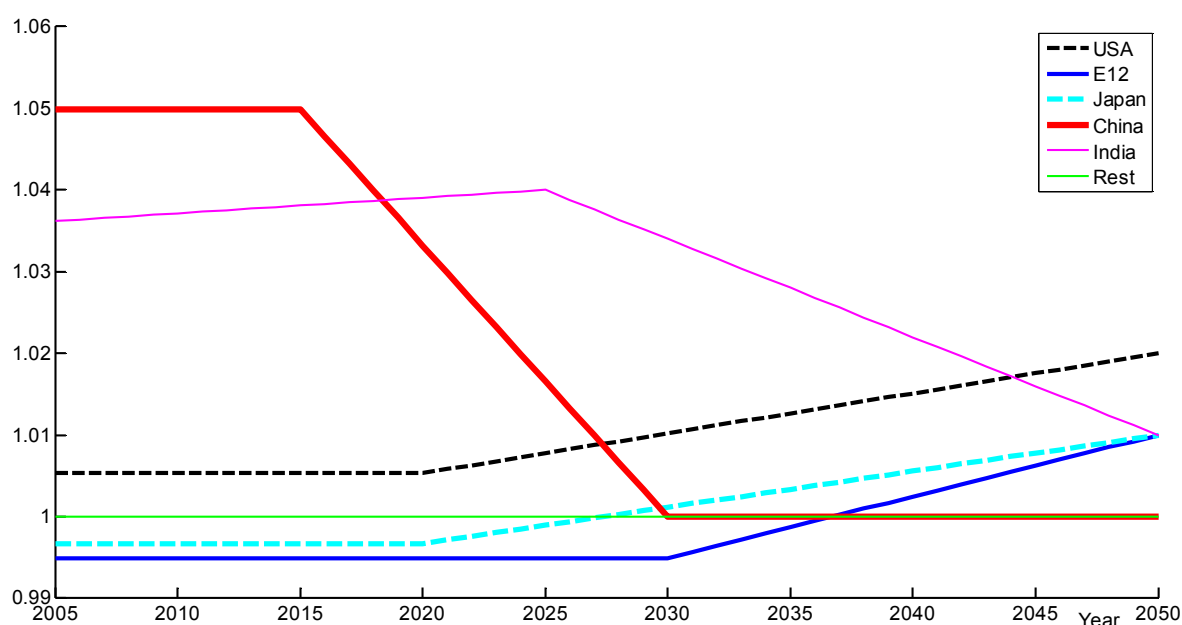

Figure 32. Assumed evolution of the competitiveness of the six countries/regions in the proposed scenario

In short, we assume that the US economy will be able to recover in the next ten years and will return to its relatively high competitiveness after 2020, the European countries (mainly due to the bureaucratic burden of the EU) will start the necessary reforms ten years later and will slowly revive after 2030. Japan will follow the same pattern of reforms as the US, although their results will be not so impressive (therefore the final competitiveness in 2050 of Japan is slightly lower than the US in 2050). China will be able to become the most competitive economy in the next decade, but mainly due to the lack of the political reform the economy will lose its vigorousness after 2020. Thanks to the democratic system and openness of the Indian economy, India will be the most competitive economy from 2019 to 2044.

In Figure 33 the evolution of the structure of global GDP (under the above assumptions) is presented. The Chinese economy should overtake the US in 2011 (with roughly a 20% share of global GDP by both economies) and will still grow to reach the maximum share equal to 28% in 2027, in the next two decades (still being the largest global economy) its share will be

dropping to reach 24.5% in 2050. The second largest economy will be the US, but its share will still decline to reach the minimum 18.3% in 2027. From that year the share of the US economy will rise to reach 22% in 2050 (roughly the same as China's). The share of the Indian economy will grow steadily to reach almost 16% in 2050 (becoming the third economy in the world). The total share of the twelve European countries (E12) will keep the past tendency to decline, but, due to the reform initiated in 2030s, in the middle of the century will reach a plateau with a share equal to 10%. The same pattern of development will be experienced by Japan, but the plateau (roughly a 5% share) will be reached by the Japanese economy in the beginning of the 2030s.
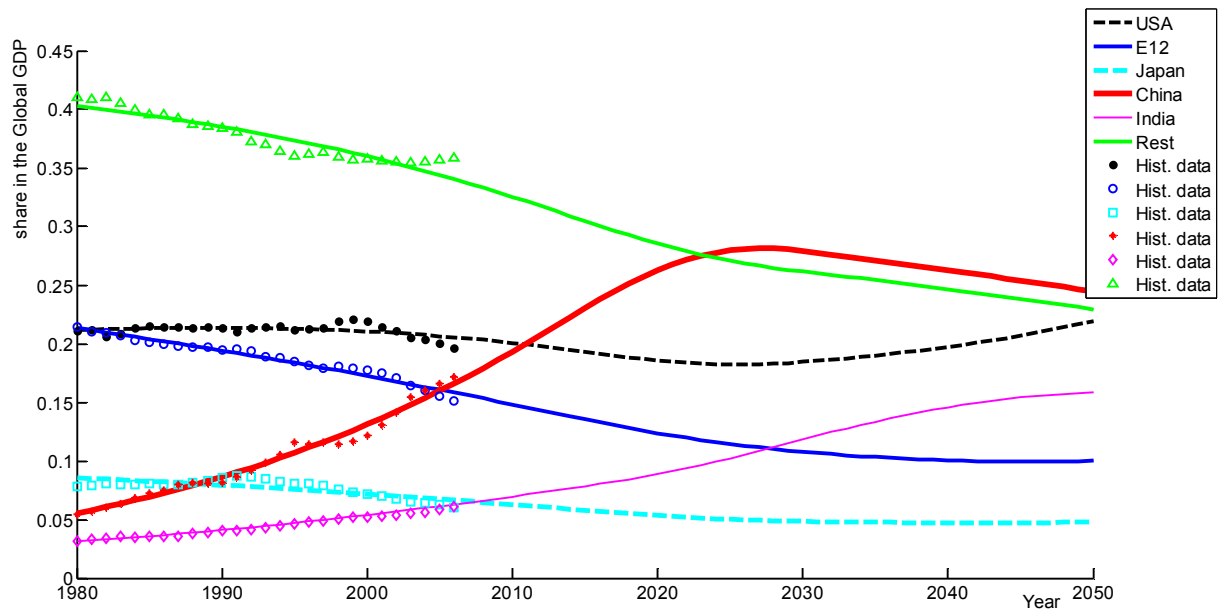

Figure 33. Scenario of development of future structure of global GDP – the six regions/countries: USA, E12, Japan, China, India and the Rest of the World

SUMMARY

One of the goals of this paper was to add new insight into the frequently mentioned (e.g. by Joseph P. Martino) far reaching skepticism in using trend analysis in the forecasting of socio-economic processes. The problem of the quality of statistical (historical) data and its impact on the accuracy of forecasts were not discussed in this paper. Instead, we have pointed out two important aspects, namely:

- selection of the identification period for a model calibration may highly influence the generated forecasts (not only in quantitative terms but, what is more important, in qualitative terms).
- the selected identification criterion (i.e. a measure of trend fitting to the historical data) has an essential influence on the quality of the generated forecast.

The prognoses of global economic development (in terms of global GDP) and demographic prognoses (in terms of the world's human population) presented in the first section has been generated on the basis of a relatively long time series of historical data (from 1950 to 2006-2008). Someone may suppose that such a long historical period will result in a

much more reliable prognoses, but as is shown in the paper, it is hard to decide which period, e.g. shorter or longer, allows the generation of more reliable forecasts.

The extension of the logistic curve into the substitution-diffusion model allows to evaluate the future share of national/regional economies in global GDP and to estimate the competitiveness of these economies. It turns out that the competiveness of nations/regions is far from being constant.

An interesting question stated in the article concerns the possible way of development of the Chinese economy. To what extent the history of the Japanese economy in the post-war period may suit us as a metaphor/analogy for the future development of China?

The proposition of building competitiveness ranking is presented. The problem not stated in the paper (due to the limited space of the regular article) is to what extent the proposed ranking is compatible with the well-known Doing Business ranking,[15] The Global Competitiveness Report,[16] The World Competitiveness Yearbook,[17] or Index of Economic Freedom rankings[18] and Economic Freedom of the World.[19] This problem will be undertaken in future studies.

In the final section a possible scenario of the development of the five countries/regions (namely the USA, the E12, Japan, China, India) is presented. The future development of the competitiveness of the six regions was assumed. Naturally it is fully subjective estimation, but we evaluate is as highly probable.

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[15] http://www.doingbusiness.org/
[16] http://www.weforum.org/en/initiatives/gcp/Global%20Competitiveness%20Report/index.htm
[17] http://www.imd.org/research/publications/wcy/index.cfm
[18] http://www.heritage.org/index/
[19] http://www.cato.org/pubs/efw/ or http://www.freetheworld.com/index.html