The future of global development – sustainability and competition

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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 the logistic curve. 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 welfare (the GDP per capita). The important feature of the proposed approach is that we try to examine the impact of different identification criterion on the obtained predictions. One of the goals of that paper was to point out of necessity of far reaching skepticism in using trend analysis in forecasting of socio-economic processes.

In the second part of the paper the extension of the logistic curve into the substitution-diffusion model is proposed. It allows to evaluate future shares of national/regional economies in global GDP and to estimate competitiveness of those economies. It turns out that competiveness of nations/regions is far from being constant. The interesting question stated in the article relates to the possible future development of Chinese economy. We try to answer the question: 'To what extend the history of Japanese economy in the post-war period may suit us as a metaphor/analogy for future development of China?'.

In the end of the paper a proposition of building the competiveness ranking of nations/regions is presented.

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

Growth with saturation (with upper limit) is frequently observed in real processes. This is natural phenomena from economic point of view: limited resources (limited growth factors) are usual situation in socio-economic processes. Therefore so called logistic curve (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. Application of logistic curve, e.g. to describe evolution of population (in biology and demographics) or diffusion of new technologies and products, as well as, in general, economic growth, is very illustrative and appealing (mainly due to nice graphic representation). Popularity of logistic curve in description of variety of real phenomena dates from the middle of the 20th century, and relevant literature is enormous.[1]

[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 1920s by Raymond Pearl, Lowell Reed and Alfred J. Lotka (who in 1925 proposed to call it the *law of population growth*). Application of the logistic equation to describe other processes beside population growth was spurred by B. Ryan, N. Gross who published in 1943 paper on "The diffusion of hybrid seed corn in two Iowa communities".

It is worth to mention two researchers who have laid the ground for steady growing popularity of logistic curve application in numerous areas, namely Cesare Marchetti and Theodore Modis. Large number of their publications related to logistic growth are 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* is good and friendly platform to present recent advancement in research on logistic growth. It is not possible to list all relevant papers published in *TF&SCh* in the last decades, but some of them published in the last years have spurred the current author to write that paper, among them are [1-5], and especially [6].

There are two main findings of the paper, namely that we ought to be cautious in application of logistic curve for prediction of ongoing processes and that extension of the logistic growth into multi type diffusion (so called multi type technological substitution) and its application to global development can produce some interesting insights.

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) than 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:

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

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

where:
K – saturation level (sometimes called the capacity of the environment),
r – maximum growth rate.

Usually (unfortunately, often unconsciously), a logistic description of the continuous model is applied in a case of discrete time and discrete units of measure of y. This may be partly justified, when the discrete values of y are very large numbers (as in the case of the number of people in the world, or the number of bacteria in a Petri dish). We can then expect that this approximation will give us satisfactory results. Although this is not justified when the discrete measure of growth is relatively small natural numbers (such as the number of white-tiled eagles in Poland).

It is worth to note that the logistic models corresponding to discrete and continuous flow of time can behave qualitatively entirely different. One of the properties of the logistic model with continuous time is that it cannot generate fluctuations. This is not the case with discrete time model. There is no place for wider discussion, but as an example the result of the logistic model simulation (1) with parameter values $K = 25$, $r = 0.108$, $y_0 = 3$ are presented in Figure 1, and in Figure 2 results of simulation of continuous model (2) with the same values of the parameters are presented.

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

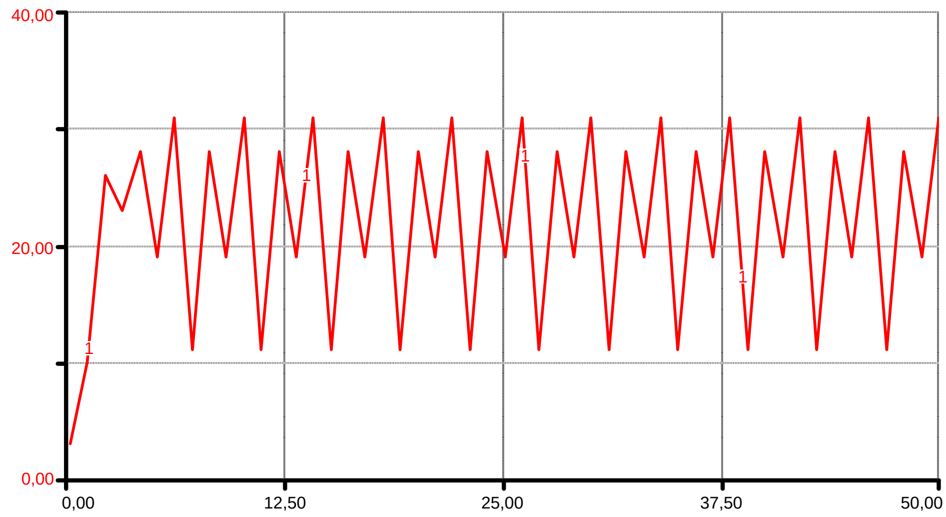

Figure 1. Logistic model – discrete time and discrete values of characteristics of the development *y*

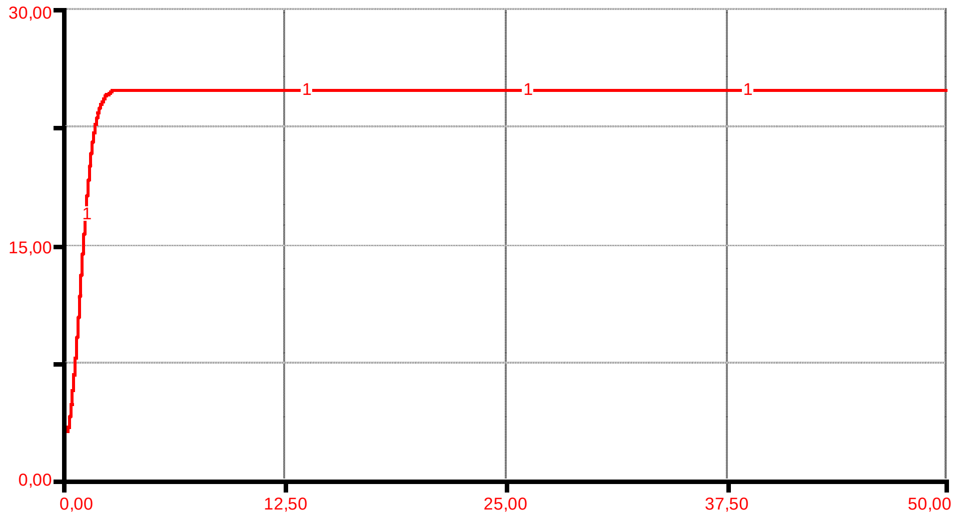

Figure 2. Logistic model – continuous time and discrete values of characteristics of the development *y*

Logistic model in version (2) has some analytical advantages and traditionally is used to describe the situation of the development of discrete characteristics (such as demographic processes), when the values of these characteristics are sufficiently large (e.g., order of a few millions, or billions, of people with demographic processes).These requirements are fulfilled by the processes discussed in this work. Therefore, we will also use the logistic equation in continuous form. This choice is motivated by a need to comparing our results with 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:

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

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 logistic function parameters more intuitive, this function is often presented in the following form (e.g., [7]):

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

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 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.

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

Figure 3 illustrates the logistics growth in a qualitative way.

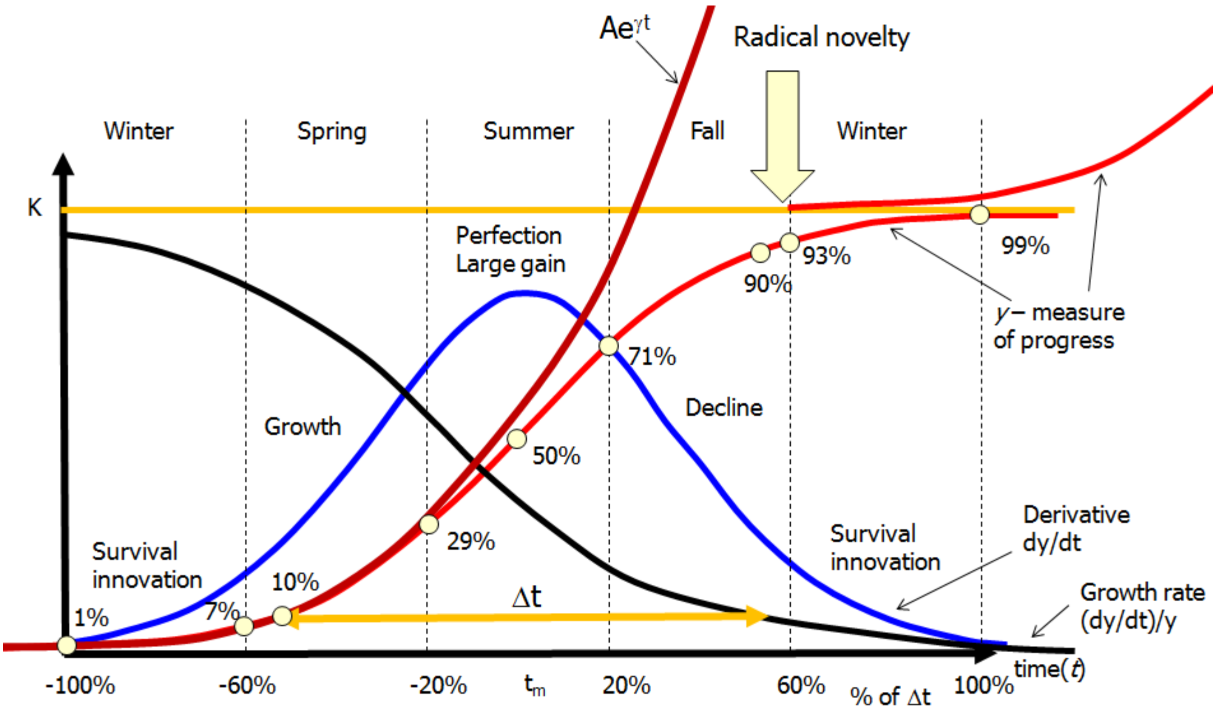

Figure 3. Qualitative characteristics of the logistic growth

Thodore Modis [1] has proposed to divide 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 seasonal metaphor allows for distinguishing specific phases of development associated with the emergence of successive radical innovations. It suggest a relatively rapid growth associated with the spread of a radical innovation (in the *Spring*), the maturity of development (during the *Summer*), exhausting of potential for further growth based on a particular radical innovation (the *Autumn*). Next *Winter* is related to the emergence of another radical innovation, this allow to enters 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 in economic growth (*Autumn*) we observe an increase of the intensity of search for breakthrough innovation. Usually, as an effect of this intensive exploration another radical innovation emerges (mostly in late *Autumn*/*Winter*) which enable further growth, along qualitatively different trajectory of development (at a different logistic curve). Full cycle (i.e., increase the value y from about 1% of the saturation K to about 99% of K) is equal to $2\Delta t$. So the parameter Δt informs us also on the length of the cycle. It is worth to note that the total period it takes to increase 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.

In the very long-term perspective socio-economic development can be described by a sequence of logistic curves, each of which is initiated by another radical innovation (qualitatively illustrated in Figure 4).

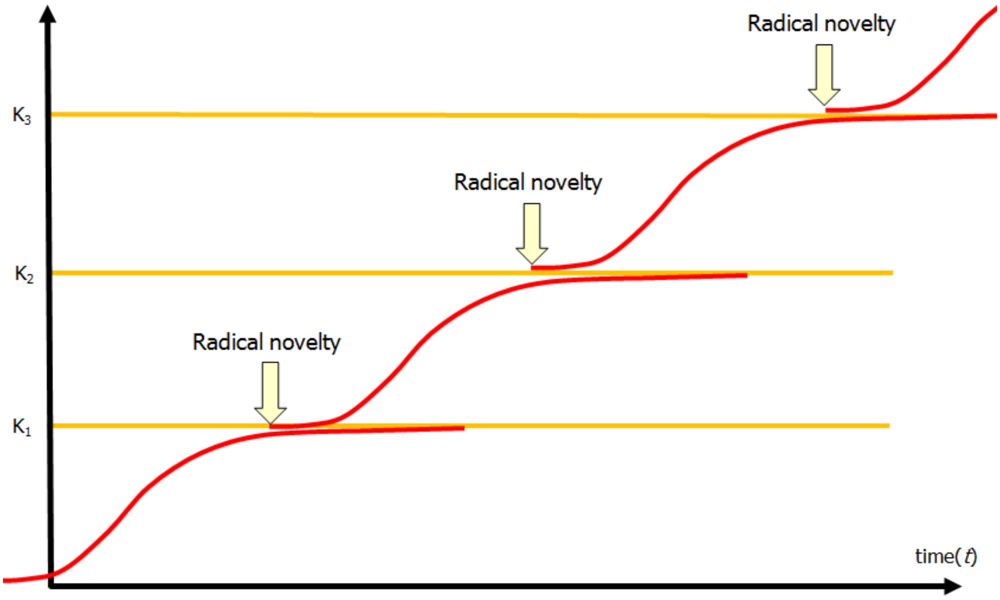

Figure 4. Long-term waves of development

In this work we deal with the possibility of predicting long-term development in a single cycle depicted by logistic curve. 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, Δt, t_m) of the logistic function in such a way that this function fits 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 at *The Conference Board Total Economy Database* website.[2] The data was downloaded on the 19th of November 2009. The available data concerned 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]

As identification criteria we have adopted two most widely used, 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, fitting the logistic curves to the historical data we will try to state the values of K, Δt, i t_m to minimize one of the following criteria:

[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 chosen 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 the relative and absolute criterions, but also the different metrics (not only the mean square metric).

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

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

where:

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

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

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

In some cases 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 is added (i.e., the logistic function when K tends to infinity, see equation (5)).

2. THE WORLD POPULATION GROWTH

Let's start with the identification of parameters of the logistic function and the exponential function given that we use to identify all 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 5. As we see, for the both criteria the identification error is much smaller for the logistic function (Figure 5, Table 1). Thus, it is appropriate to use the logistic function for forecasting of population growth. The forecast is presented in Figure 6, and as we see, in spite of 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

Differences in these parameters cause significant differences in the estimated world population, especially while approaching the end of the 21st century. Although by 2040 the differences are relatively small, but 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 13 billion.

This and many other experiments, 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]

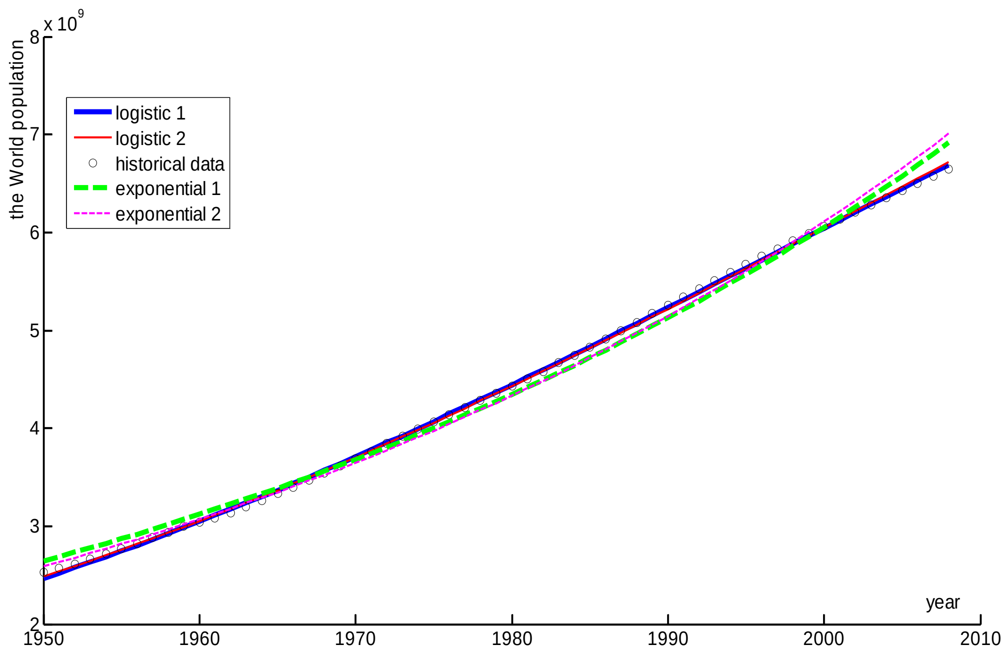

Figure 5. The world population in 1950-2008. Approximation of real data by logistic and exponential curves

[5] Problem of 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 to undertake this and probably we will embark on that project in the future. In such project it would necessary to increase the number of identification criteria, not limit it to only the two ones presented in this article.

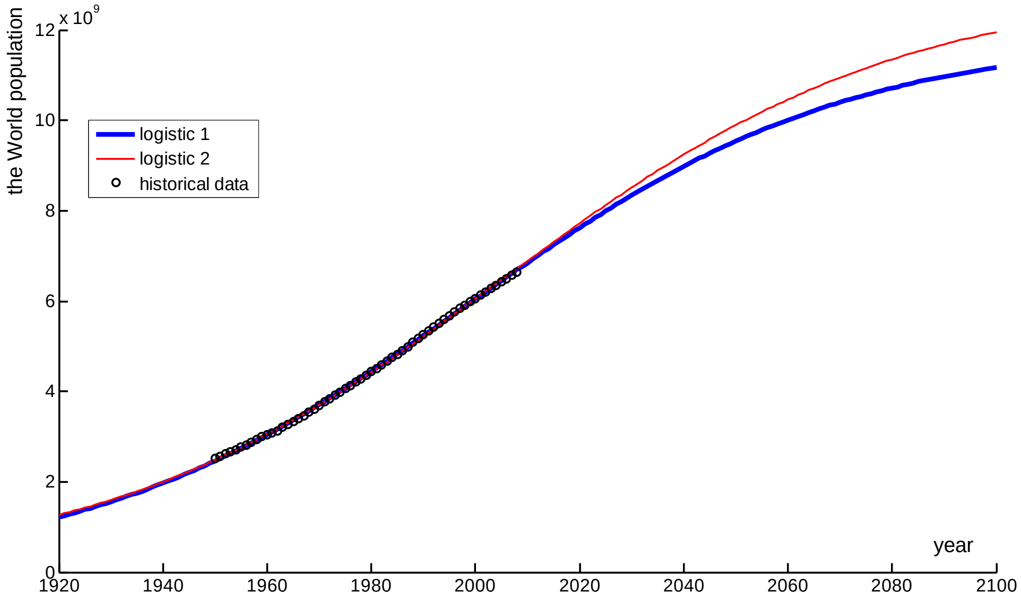

Figure 6. Forecast of the World population by the end of the 21st century (logistic function parameter identification based on historical data from the years 1950 to 2008)

3. GLOBAL ECONOMIC GROWTH

Available statistics on the 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 7. As in the case of approximation of global population growth, a better fit is obtained in the case of logistic functions. Clearly, 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 forecast the World GDP growth in the twenty-first century. However, while the differences in growth projections of world population for both criterions 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 more than double of 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 8. As early as in 2020 there is almost 10% difference in the projections made by the two logistic functions:

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

$$y_2 = \frac{7.417883\ 10^{13}}{1+e^{-\frac{\ln(81)}{86.85134}(t-2000.2162)}}$$ for the relative mean square error (Q_2).

In the course of the time the gap is widening, up to almost 100% in the end of the twenty-first century (Figure 8).

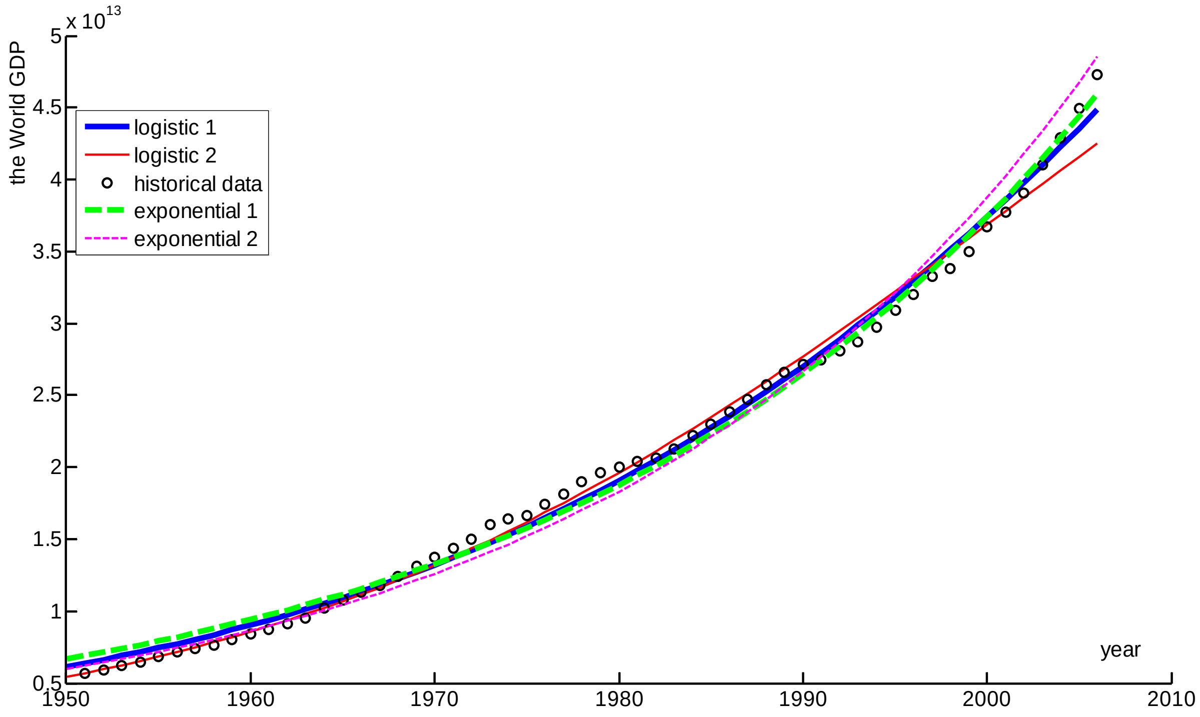

Figure 7. Global GDP in 1950-2006. Approximation of real data by logistic and exponential curves

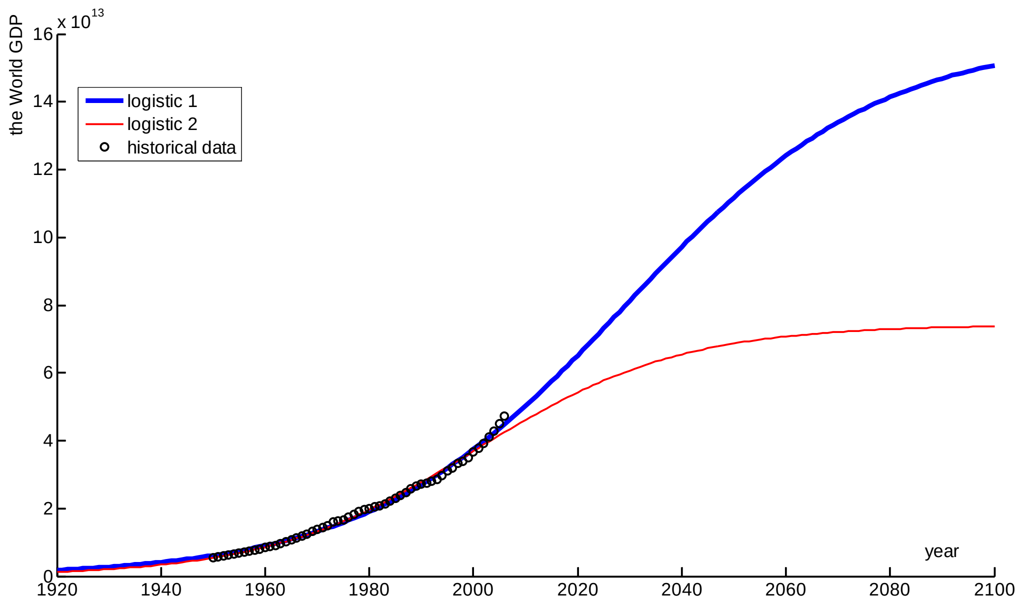

Figure 8. The global GDP forecast (logistic function parameter identification based on historical data from the years 1950 to 2006)

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 the GDP growth and the global population growth (i.e., by dividing these values and obtain the desired estimates of GDP per capita).

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 9). Again, the logistic curve fit is clearly better than the exponential curve (see the errors of identification in Table 3). Thus there is justification for the choice of logistic curves to make predictions. Once more we observe large differences in the optimum values of parameters of logistic functions (Table 3). 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 forecast GDP per capita are following:

$y_1 = \frac{12387.948}{1+e^{-\frac{\ln(81)}{147.21609}(t-2000.3777)}}$, for the mean square criterion (Q_1),

$y_2 = \frac{8956.403}{1+e^{-\frac{\ln(81)}{115.55678}(t-1980.4634)}}$, for the relative mean square criterion (Q_2).

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

We get radical different forecasts when we make them by dividing the values obtained from the forecasts of GDP growth (Figure 8) and the values of the forecast of the World population (Figure 6). The results of this experiment are shown in Figure 11. First, the value of GDP per capita calculated using forecast the mean square error criterion (Q_1) in the end of the twenty-first century is higher than in both extrapolative forecasts (Figure 10). Secondly, 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 rising GDP per capita and then, up to the end of the twenty-first century, a slow decline (lower curve in Figure 11). To compare the results of these two approaches all four forecasts are presented in Figure 12. It is seen that extrapolative forecasts are between the two projections calculated by dividing the global GDP and the population of the world. It is also worth to note that all four trends fit quite well to the real data from the period 1950-2006, but long-term extrapolations give significantly different projections.

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

Krzywa/kryterium	*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

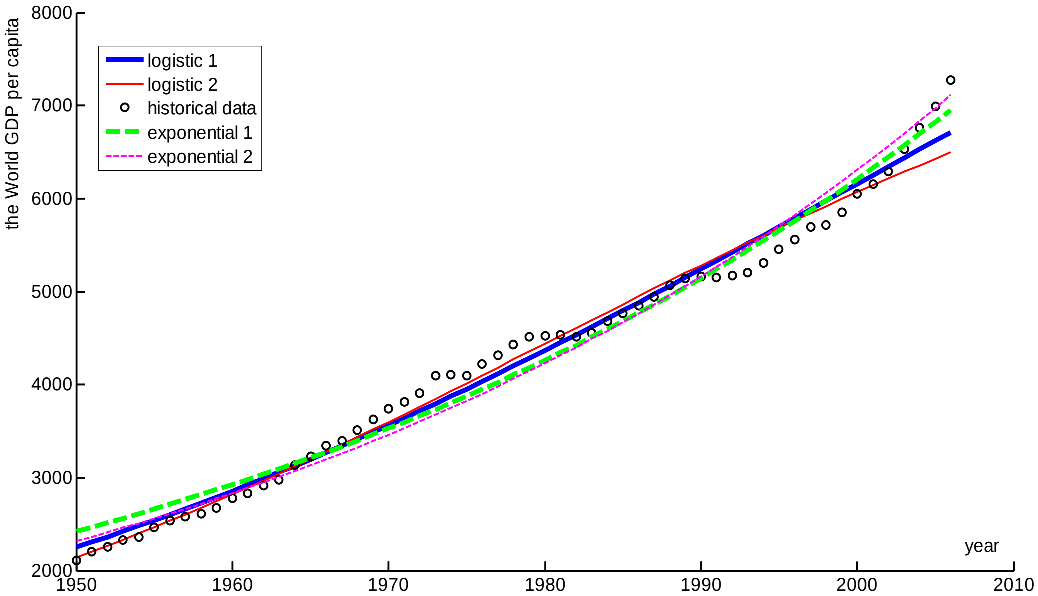

Figure 9. Global GDP per capita in 1950-2006. Approximation of historical data by logistic and exponential curves

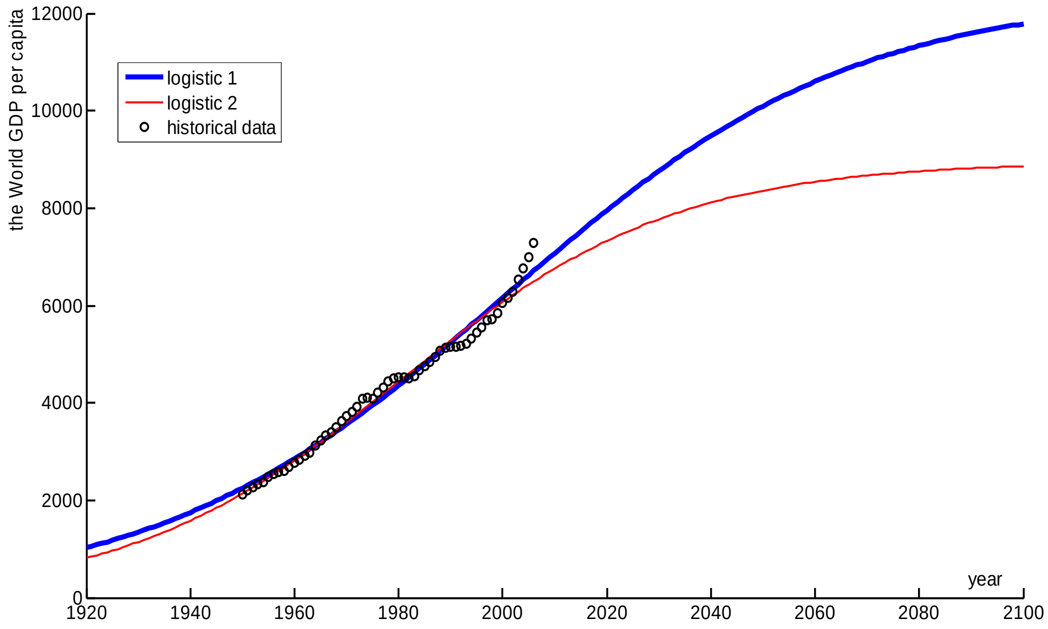

Figure 10. Forecast of the global GDP per capita growth by the end of the 21st age (logistic function parameter identification based on historical data from the years 1950 to 2006)

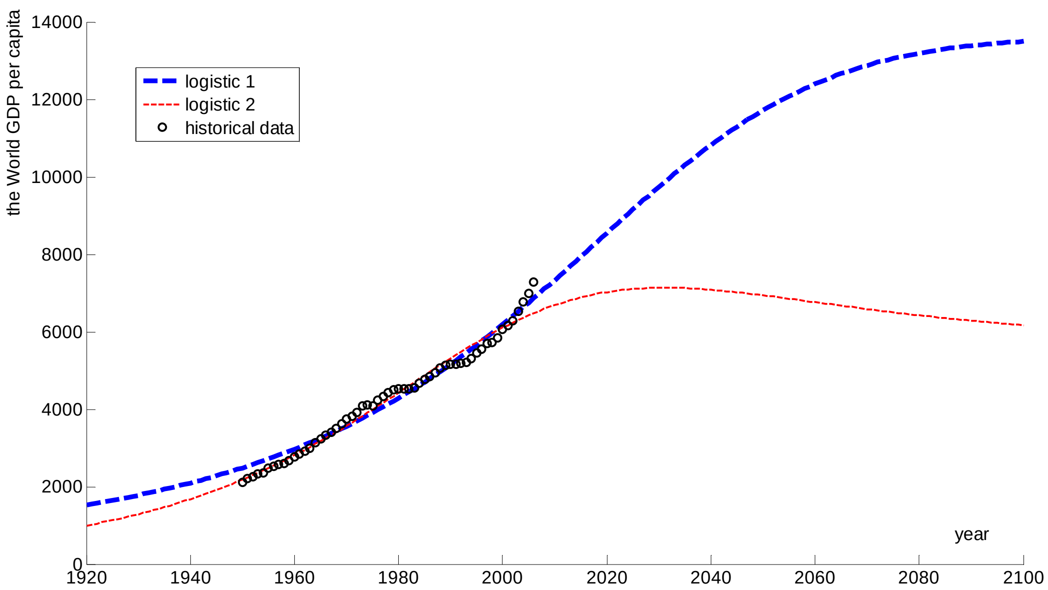

Figure 11. The forecasts of the global GDP per capita growth by the end of the 21st age calculated from the partial projections of global GDP growth and increase the World population

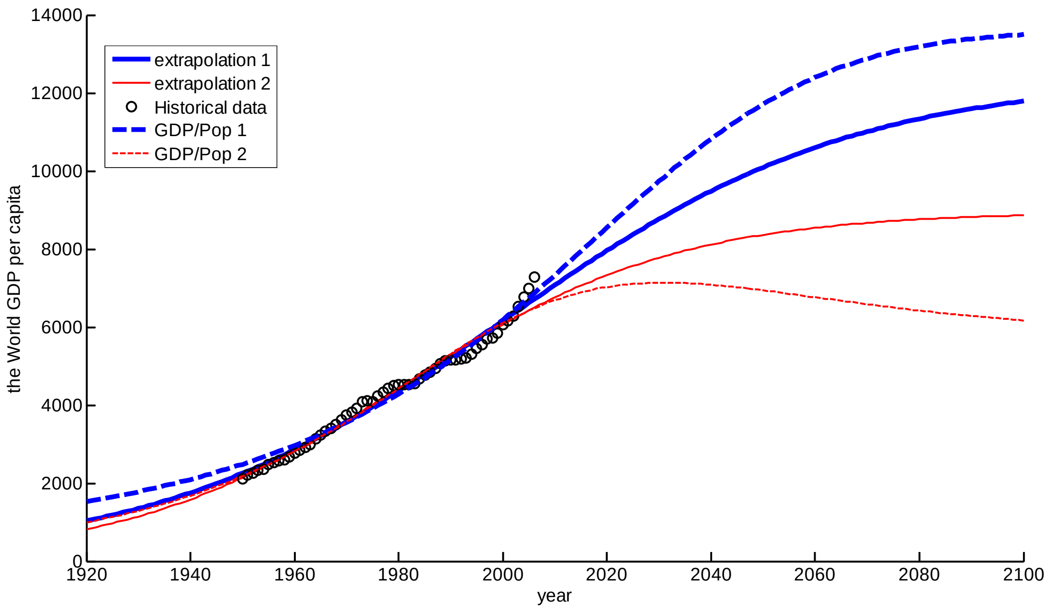

Figure 12. Comparison of the four forecasts of the global GDP per capita by the end of the 21st century (Two made by extrapolating the trends from the years 1950-2006 (continuous lines) and two calculated from the partial projections of global GDP growth and increase the world population (dashed lines)

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 obtained results. Presented forecasts show great potential of logistic function in forecasting, although significant differences in the forecasts made with applying different criteria to identify the parameters of logistic function may cause 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 available historical data (from 1950 to 2006) to identify trends on which the predictions have been made. It sounds reasonable that better forecasts can be made using more recent historical data. To test it we use the historical data from the period 1980-2006 to identify the parameters of logistic and exponential functions. It turns out that in that case the best fit is obtained for the exponential function (see Table 4). Table 4 shows also a few results of logistic identification with 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 note that very large differences in the values of K (e.g., a hundredfold) has resulted in a slight diminishing of 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 it is. However, depending on the fitting criterion we obtained slightly different values of optimal parameters, e.g., for 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 sensible different predictions (see Figure 13).

More interestingly, if 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 for the exponential growth (see Table 5). Comparison of the exponential growth in the period 1950-1971 with the 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 in the identification of the two criteria are small but clearly visible (see Figure 14). It should be noted that comparing these predictions with the available historical data for the years 1972-2006 shows shortages in their effectiveness. Error estimates for 1980 is relatively small, but after 1980 is more and more significant, in 2006 this error is equal to about 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

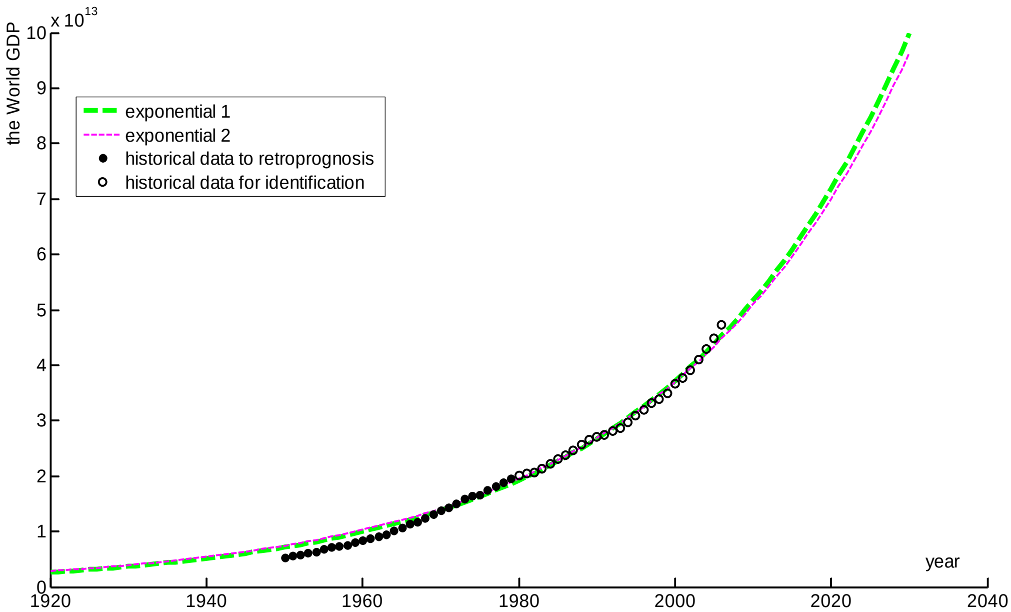

Figure 13. The global GDP forecast (exponential function parameter identification based on historical data from the years 1980 to 2006)

Figure 15 shows the comparison of all our predictions of global GDP growth. It's 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 dispersion between the two logistic predictions is very large).

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 15 with 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
	$A \to y(1950)$ [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	

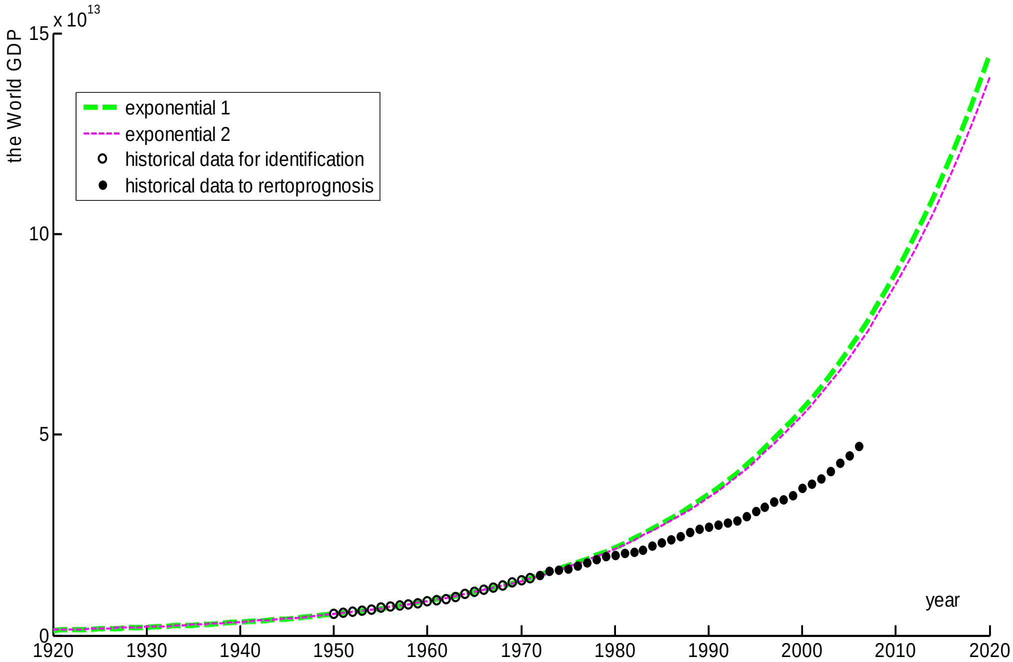

Figure 14. The global GDP forecast (exponential function parameter identification based on historical data from the years 1950 to 1971)

5.2. DEMOGRAPHIC GROWTH ANALYSIS

By doing similar experiments with global population growth also obtain qualitatively different results. As we will show, in the 1950-1971 the world population growth is better described by the exponential function, while in the period 1980-2008 we observe 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 for the post-war period 1950-1971 the higher saturation value K, the better the match to the logistic curve is. This suggests that the exponential curve fits better to the historical data, and that is the case. It is worth to note that for both criterions 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 forecast based on extrapolation of that exponential trend (Figure 16) is relatively good only for the next 20 years (until 1990), in 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 6), 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 9.2 billion (Table 7 and Figure 17). The value of this saturation is about 30 percent smaller than the saturation value obtained for identification based on data for 1950-2008. Comparison of three experiments (predictions) is shown in Figure 18 (vertical lines indicate the period 1972 to 1979; the oil crises). It seems that for the World population growth logistics trend seems more probably and the expected maximum number of people living on the Earth might be between 9 and 12 billion.

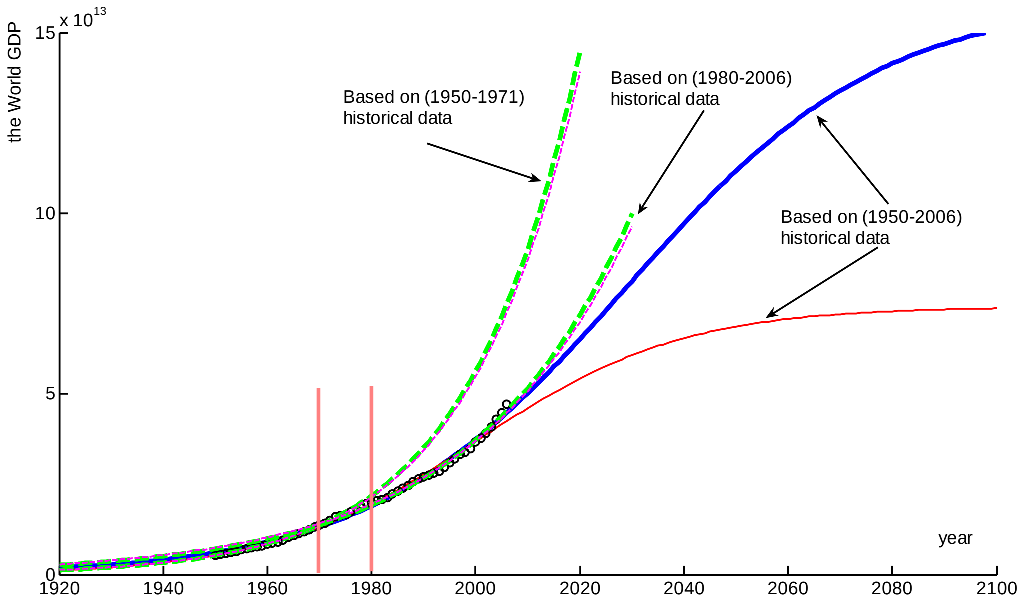

Figure 15. Comparison of the global GDP growth forecasts based on extrapolation of exponential growth in the years (1950-1971) and (1980-2006) and the logistic growth in (1950-2006)

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

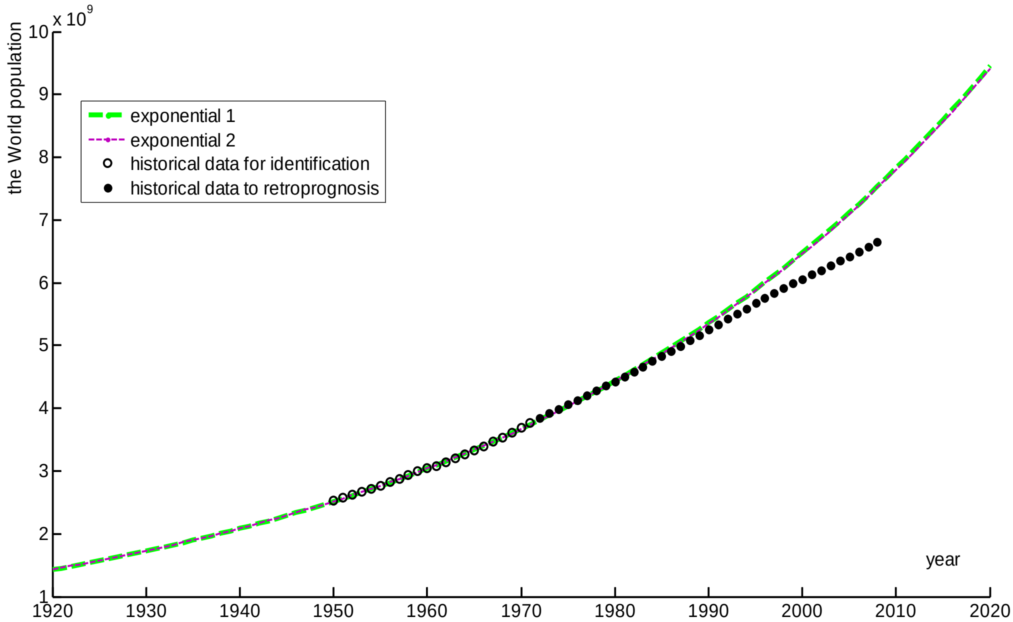

Figure 16. The global population growth extrapolation (exponential parameter identification based on historical data from the years 1950 to 1971)

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

Table 7. The growth of the 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

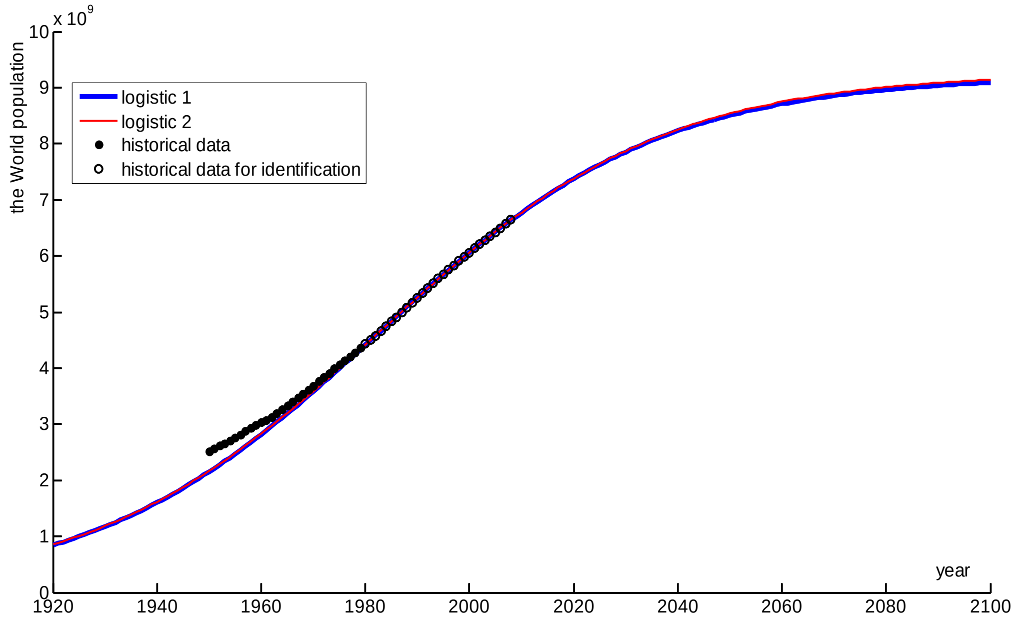

Figure 17. Forecast of the World population by the end of the 21st century (logistic function parameter identification based on historical data from the years 1980 to 2008)

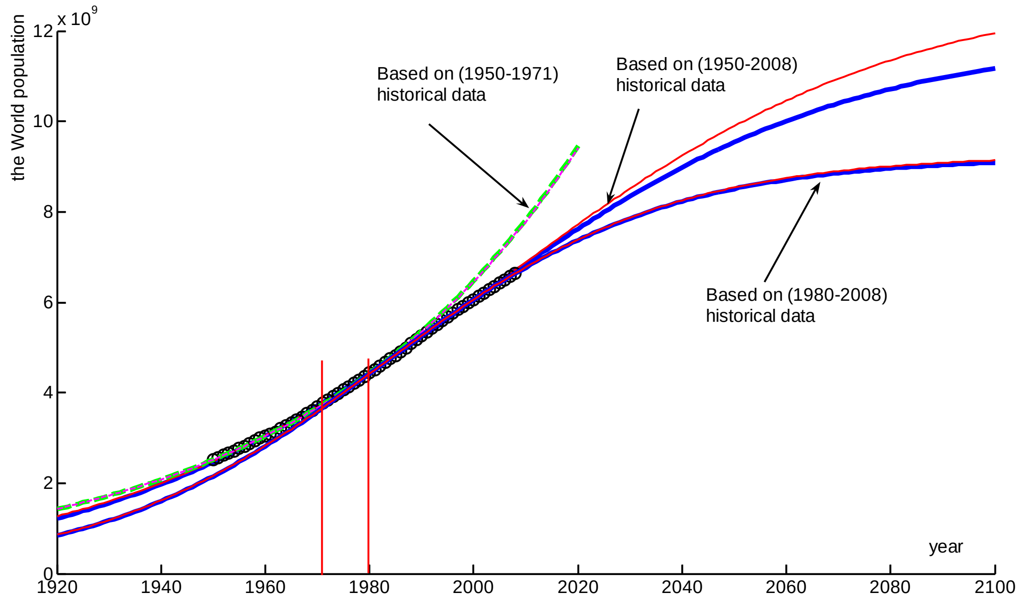

Figure 18. Comparison of the global population growth forecasts based on extrapolation of exponential growth in the years (1950-1971) and the logistic growth in (1980-2006) and (1950-2008)

5.3. GDP PER CAPITA ANALYSIS

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

Table 8 presents the results of the identification of per capita GDP based on historical data from the years 1950-1971. For increasing values of the saturation K identification error is diminishing, this suggests that a better fit is obtained for the exponential function. The rate of growth of prosperity in the years 1950-1971 is similar for both identification criteria. This was indeed a period of rapid growth in prosperity; GDP per capita grew during this period approximately 2.8% per year. 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 19).

Identification of 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 growth rate during this period is much smaller than in the post-war period, namely approximately 1.7% (Table 9).

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
	$A \to y(1950)$ [US dol.]		γ	*Identification error*
Exponential Q_1	2114.0825		0.028041745	94.11623718
Exponential Q_2	2120.7042		0.027753573	0.01059338021

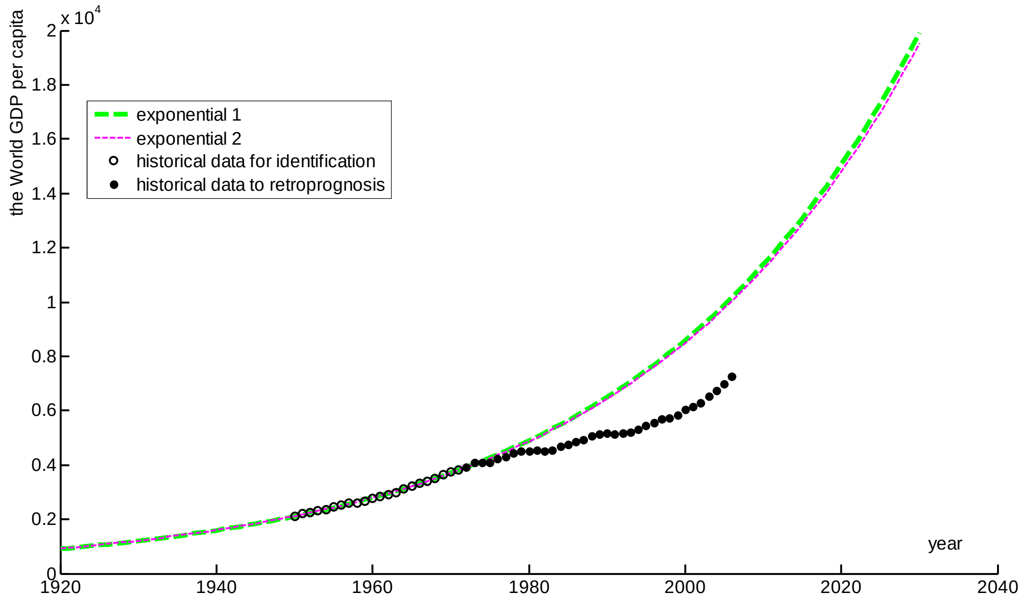

Figure 19. GDP per capita (identification period 1950-1971)

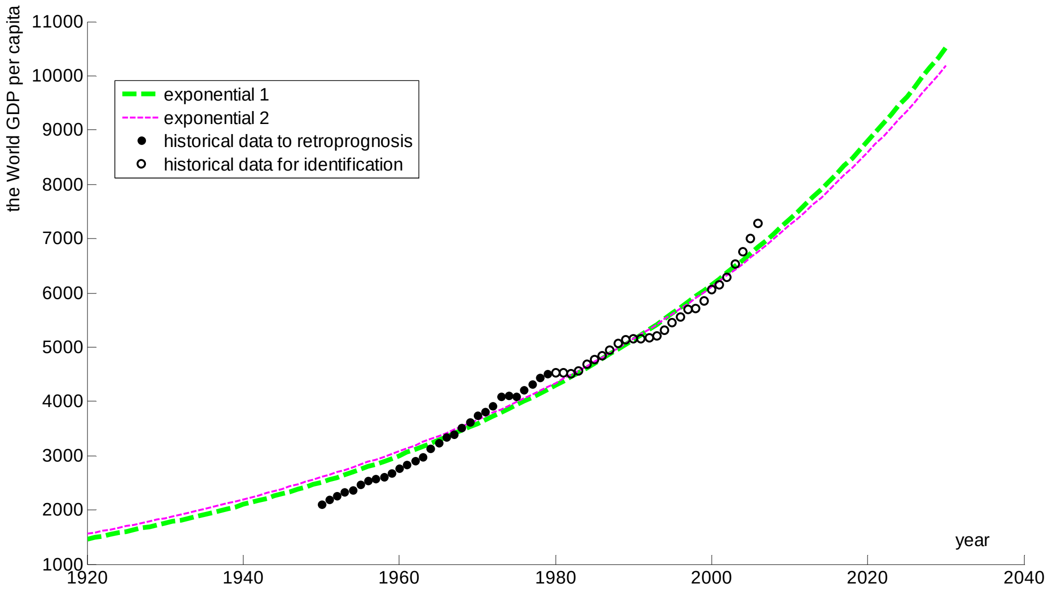

Figure 20. GDP per capita (identification period 1980-2006)

Table 8. 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
	$A \to y(1980)$ [US dol.]		γ	*Identification error*
Exponential Q_1	4297.3220		0.017914200	511.3352495
Exponential Q_2	4342.7828		0.017054013	0.02713080275

Figure 21 shows a comparison of these three extrapolative forecasts of GDP per capita. The fastest exponential growth (2.8% per year) observed as a result of the identification parameters based on the historical data for the years 1950 to 1971, slower exponential growth (the growth rate around 1.7%) suggest the historical data from the years 1980-2006. The inclusion of the data for the years 1972-1979 in the process of identification and the parameters identification based on the whole available data, namely period 1950-2006, show that the logistic growth fits 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 the welfare forecasting is to use partial forecasts of the global GDP and the global population growth and divide the relevant values. It turns out that when we calculate the GDP per capita by division of the global GDP by the global population obtained on 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. Comparison of these predictions is presented in Figure 22. As we can see the differences between these forecasts are small, but (as is mentioned in the discussion of Figure 19) they are very unreliable – after a few years (since the early 1980s) differences between forecasts and actual data are significantly large, and in a course of time become bigger.

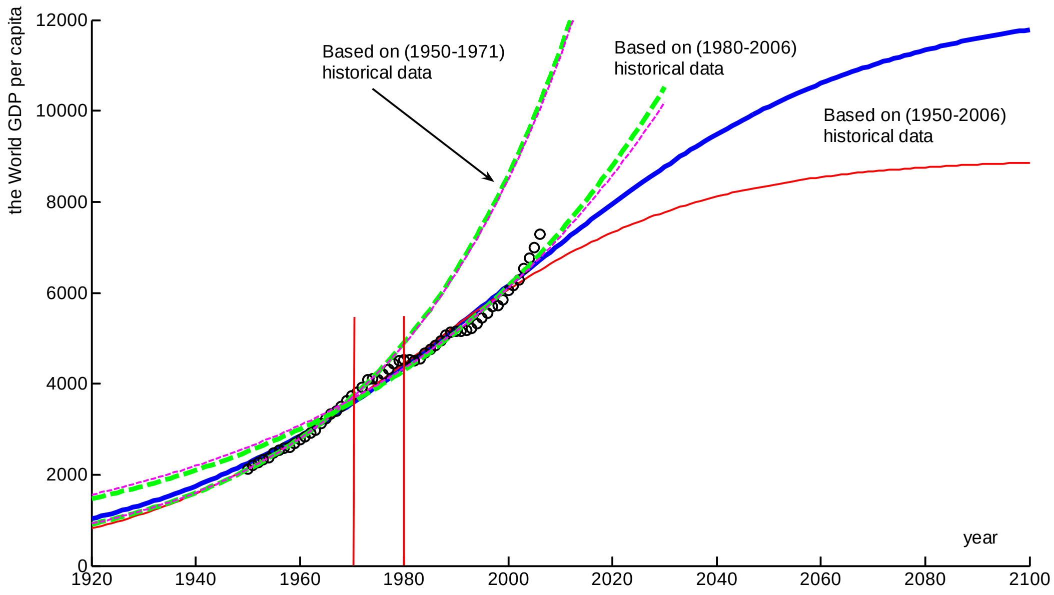

Figure 21. Comparison of the three extrapolative forecast of the global welfare

Figure 23 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 the GDP growth has occurred for the exponential curve and for the population growth for the logistic curve. 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 see in Figure 23, in that case there are significant differences between that forecast and the extrapolation forecast calculated on the GDP per capita data and population growth trend. Naturally it is difficult to say which forecast is better because we have no comparative data (as it is in the case of identification on the basis of the years 1950 to 1971).

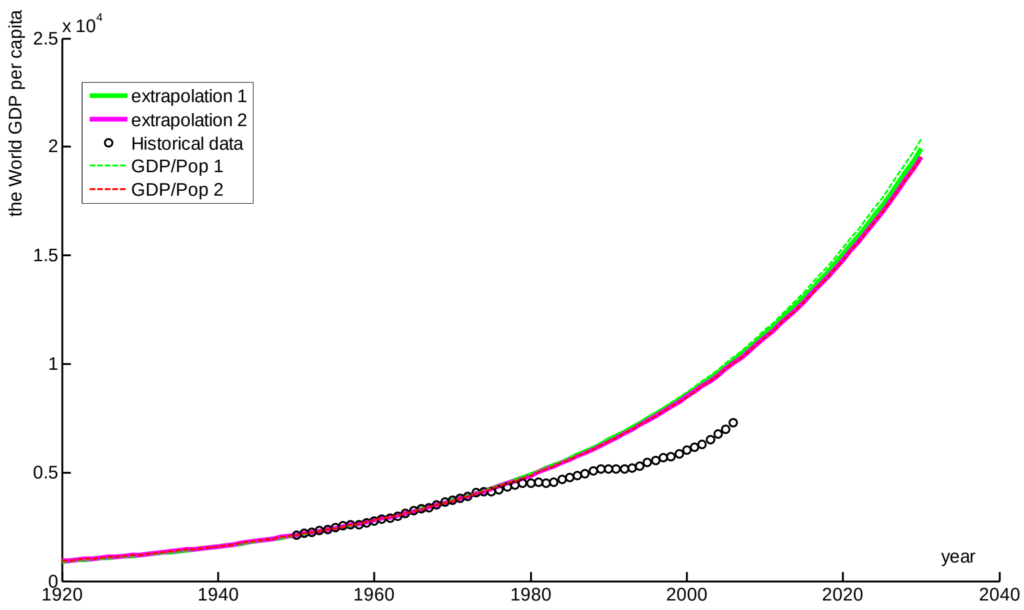

Figure 22. Comparison of the GDP per capita forecasts: extrapolative and calculated on the basis of the global GDP and the global population (historical data 1950-1971)

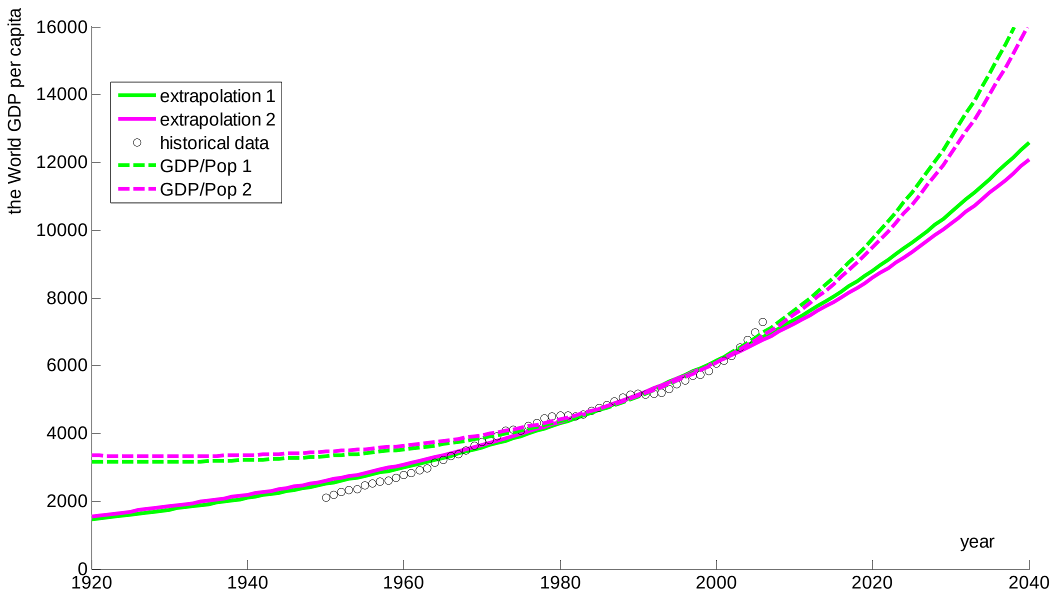

Figure 23. Comparison of the GDP per capita forecasts: extrapolative and calculated on the basis of the global GDP and the global population (historical data 1980-2006)

6. COMPETITION AND COMPETITIVENESS OF NATIONS

Boretos [6] use the Logistic Substitution fit of actual GDP contribution for the Western countries, China, and the rest of the World.[6] Although it is not fully clear what procedure is used by George Boretos to fit the model to historical data the generated figure looks convincingly. 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 "[i]f 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 it was done by Goerge Boretos. The model and the procedure of its parameters identification is presented in [8], here we will confine ourselves to describe only the model's basic characteristics.

Let's 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 so called replicator equation:

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

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

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

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

As we 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 competeviness.

Let's assume that we identify the replicator equations parameters on the basis of historical data from years 1980 to 2006.[7] It will allow us to compare our results with that of George Boretos. Identified competeviness for three considered regions and the initial shares are presented in Table 9. We see that the 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 24). 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 the global GDP (equal to 19%), and the share of China will be around 60%. China will surpass the West as well as the Rest around 2025. This scenario seems to be rather improbably (as improbably is also scenario proposed by Boretos) and the discussion of reliability of those predictions will be presented in the following part of the paper.

Table 9. Values of the model's parameters: China, 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

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

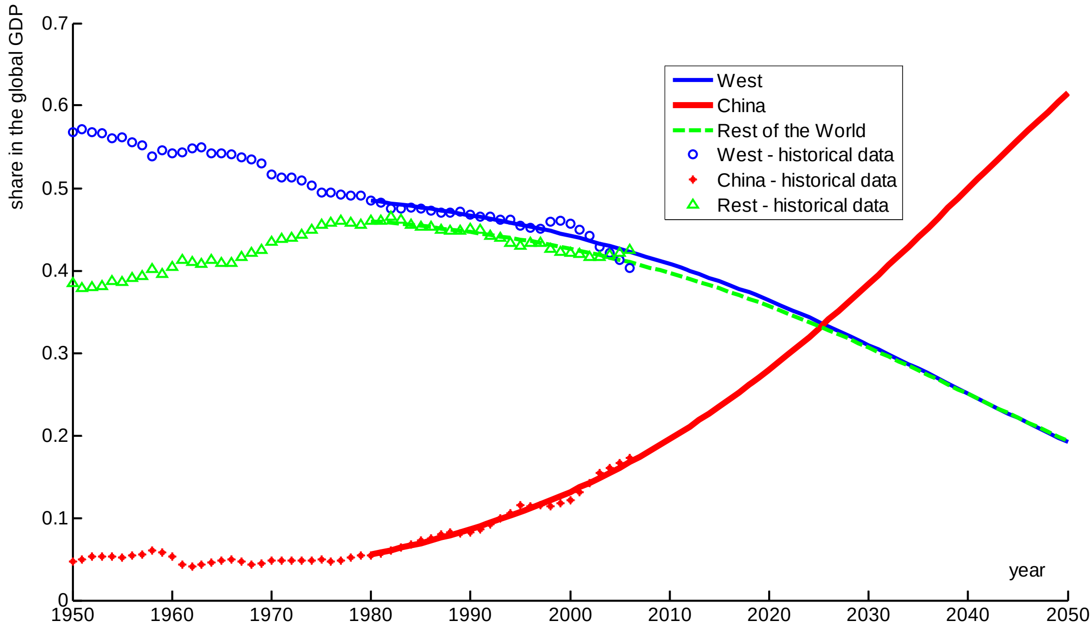

Figure 24. Evolution of the GDP shares of the three regions: China, West and the Rest of the World (the identification period 1980-2006)

We obtain slightly different results if we use the whole available historical date of the period 1950-2006 for the parameters' identification. The overall competitiveness of China is much lower (see Table 10) and in the middle of the 21st century the share of the China in the global GDP is almost the same as the share of the West (roughly 29%; see Figure 25). 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 25). It is understandable because the structure of Chinese economy of the post-war period up to the end of the 1970s was significantly different than that of post 1980 one.

We may expect that the competitiveness of those regions is far from being constant and fluctuates in the course of time. Our model allows identifying dynamics of those fluctuations. Namely we are able to assume much smaller identification period (e.g., 7 years window) and make the identification of the competitiveness starting from the period 1950-1956 and move the 7 years window up to the last year, that is to the period 2000-2006.[8] In such a case we obtain a kind of a 'moving competitiveness'. The result of this experiment is presented in Figure 26.

Table 10. Values of the model's parameters: China, 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

[8] this procedure is described in details in [8].

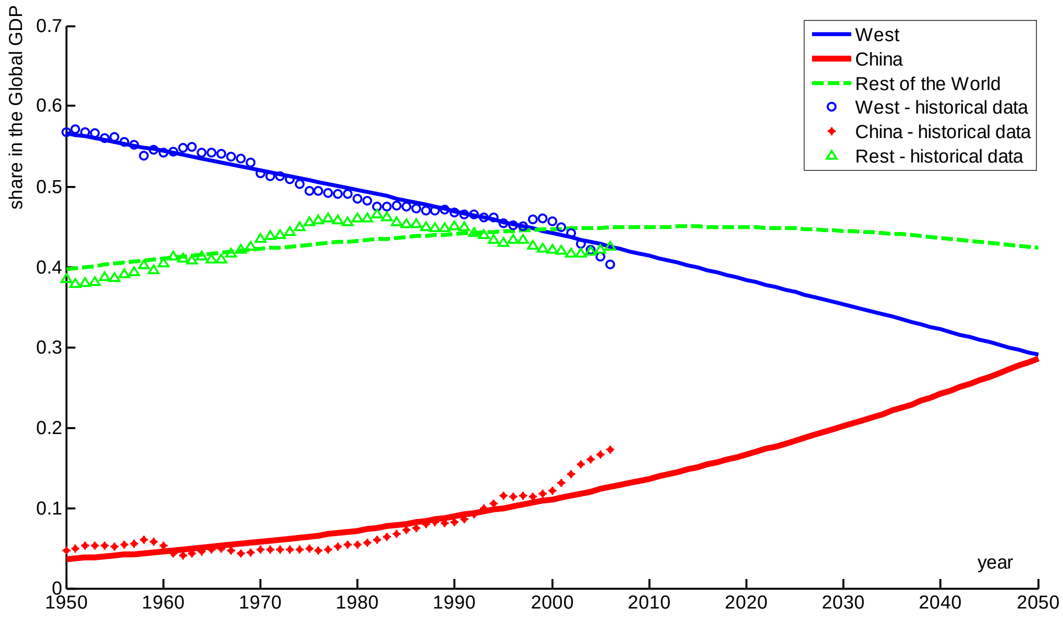

Figure 25. Evolution of the GDP shares of the three regions: China, West and the Rest of the World (the identification period 1980-2006)

As it is seen (Figure 26) 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 below China competitiveness. The West economies were more competitive since the end of 1980s, but after the dot.com crises the West competitiveness is declining. It is clearly seen that the China competitiveness started to rise after the Deng Xiaoping reforms and (although fluctuating) was much higher than the West and the Rest competiveness. It is hardly to predict the future of the Chinese economy competiveness but we may expect that in near future advance of China will sustain. Lesson of Japan may give us a hint what may happen in longer perspective.

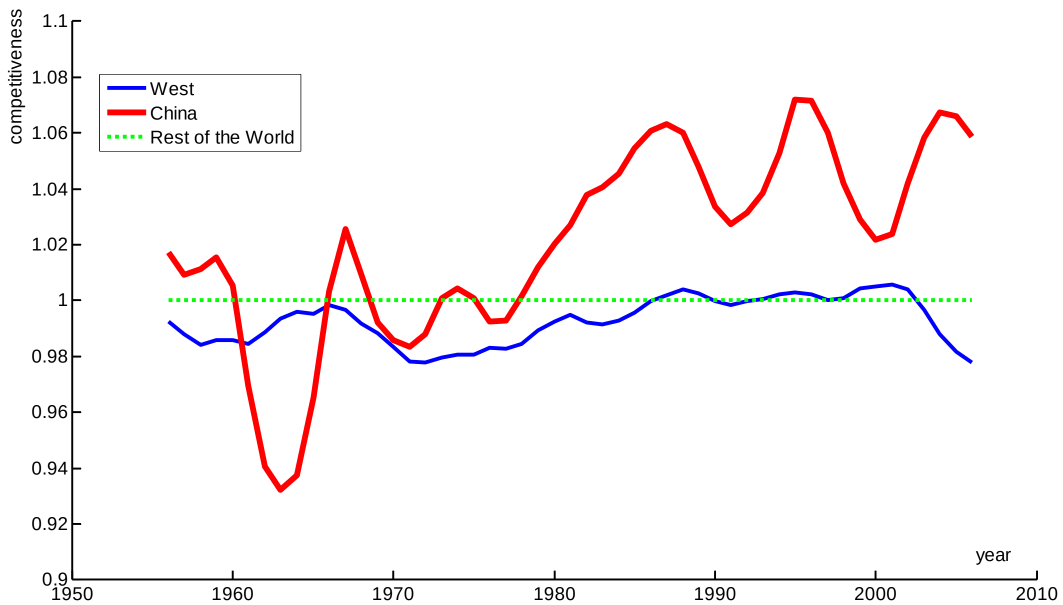

Figure 26. Dynamics of the competitiveness: China, West and the Rest of the World (identification is based on the 7 years moving window of historical data)

As it is known, Japan economy was treated as a pattern for growth in post-war period up to the beginning of the 1970s. Identified competitiveness of Japanese economy, based on the historical data from 1950 to 1970 is roughly similar as the China competitiveness for the period 1980-2006 (see Table 11) – the competitiveness was roughly 4% higher than the West and the Rest competitiveness. The share of Japan GDP in global production more than doubled in the period 1950-1970 (similar as it was in the period 1980-2000 for China).

The prediction of the shares in global GDP of Japan and two other regions are shown in Figure 27. We see that since the middle of the 1970s the discrepancy between the prediction and the real development is growing. Prediction based on the trend observed in 1950-1980 suggested that in 2030 the share of Japan economy will be above 50% (as in the case of China in 2050). According to that predictions 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 27).

Table 11. Values of the model's parameters: Japan, 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

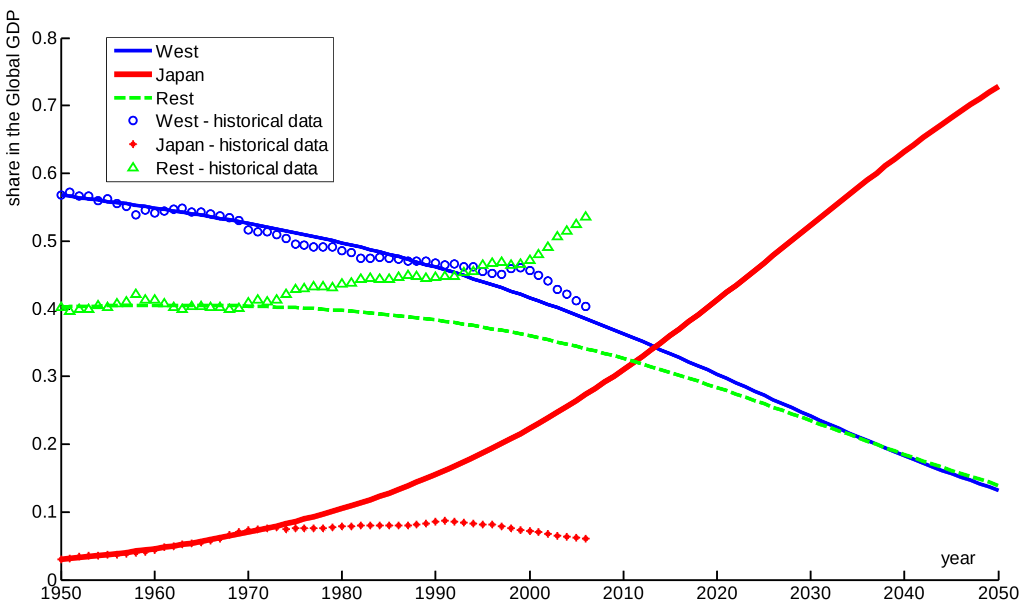

Figure 27. Evolution of the GDP shares of the three regions: Japan, West and the Rest of the World (the identification period 1950-1970)

Those results suggest that it would be good to look at the dynamics of changes of the Japan competitiveness. Results of similar experiment with moving 7 years identification window (as in the case of China) are presented in Figure 28. We see that the pattern of changes of Japan competitiveness in the 1950-1970 is more or less similar to the pattern of changes of the China competitiveness in 1980-2000 (compare Figures 28 and 26), we see enormous superiority of Japan and China economies in the relevant periods. As we can notice (Figure 28) the sharp decline of the Japan competitiveness was observed in the 1970s, almost constant level of teh competitiveness in the 1980s and beginning of the 1990s, and once more sharp decline in the turn of the 20th and the 21st centuries. We do not claim that the similar pattern will be observed in the case of the China economy in the next few decades, but we would like to point that we ought to be very cautious in our evaluations of future of Chinese economy.

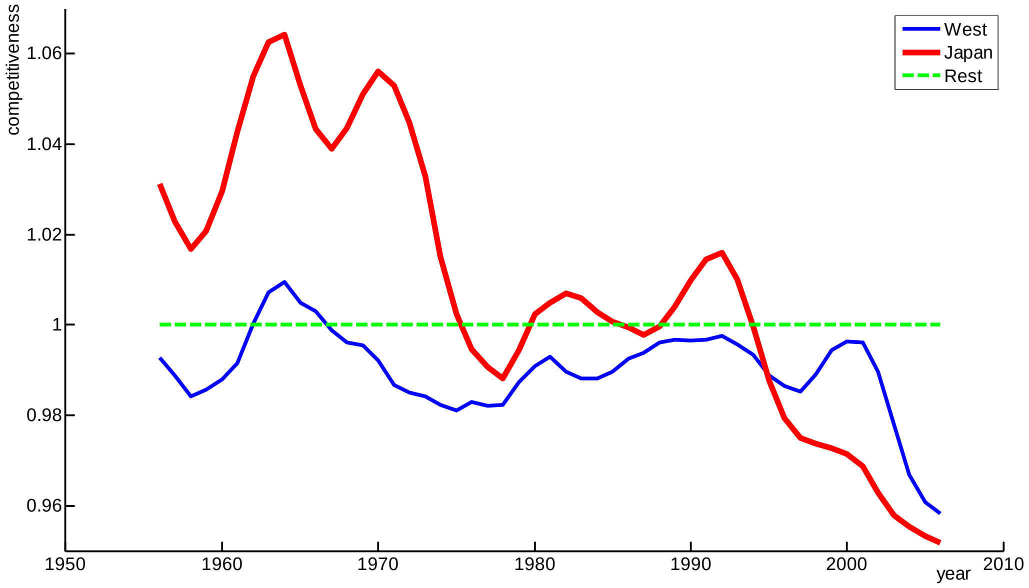

Figure 28. Dynamics of the competitiveness: Japan, West and the Rest of the World (identification is based on the 7 years moving window of historical data)

Table 12. 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

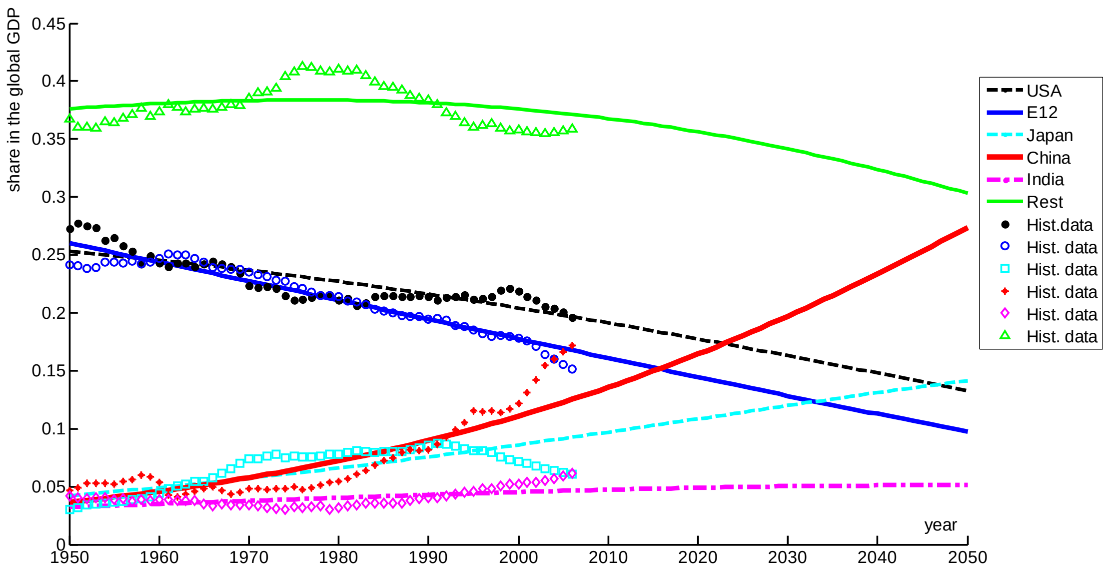

Figure 29. Evolution of the GDP shares of the six regions/countries: USA, E12, Japan, China, India and the Rest of the World (the identification period 1950-2006)

Our model allows to investigate the evolution of 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: USA, E12[9], 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 12. We see that either USA or E12 economies lose their positions in the post-war period: their competitiveness is smaller than competitiveness of all other countries/regions. The fit of the model (see Figure 29) is rather poor and is clearly unsatisfactory. Significant differences between the model and the historical data are seen in almost all countries/regions, but especially visible in a case of China, Japan, and the Rest of the World. This is caused by significant differences in the mood of development of the World economy before and after 1980. It is clearly seen when we look at the dynamics of competitiveness in the post-war period (Figure 30). To identify the moving competiveness we use the 14 years identification window.[10] It is clearly visible that in all competitiveness the mood of changes up to 1980 is significantly different than that after 1980. It is worth to notice that in the last three decades the competitiveness of India economy is only slightly smaller that the China competitiveness, and that the USA competitiveness, although smaller than Chinese and Indian, is significantly greater than that of E12.

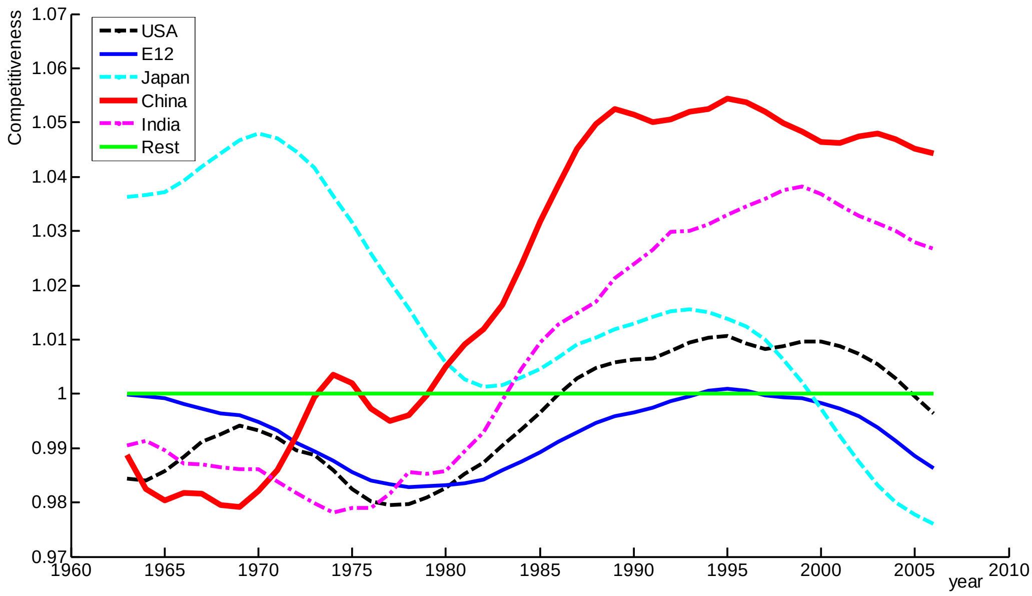

Figure 30. Dynamics of the competitiveness: USA, E12, Japan, China, India and the Rest of the World (identification is based on the 14 years moving window of historical data)

Therefore let's look more closely on the development of the world economy in the last three decades. The average competitiveness in the period 1980-2006 are presented in Table 13, and we see that it confirm general impression flowing from Figure 30; Japan and E12 economies lose their position, but USA economy tries to fight with China and India. Figure 31 shows the prognosis based on the trends observed in the period 1980-2006. It confirms the

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

[10] It is necessary to identify 2*n*-1 parameters in our model (*n* is the number of countries/regions; namely *n*-1 competiveness and *n* initial shares), therefore the number of historical data ought to be greater then 2*n*-1 (in our case greater then 11, therefore we select 14 years identification window).

suggestions concerning the expected future of Chinese economy presented in Figure 24 (the share of China GDP will be around 60% of the global GDP). According to that prediction, currently (in 2010) we ought to observe catching up of USA by Chinese economy (in GDP terms). India economy will exceed the E12 around 2030 and will be at the same level as USA in the middle of the 21st century.

Table 13. 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
Rest of the World	1.000000	0.403841

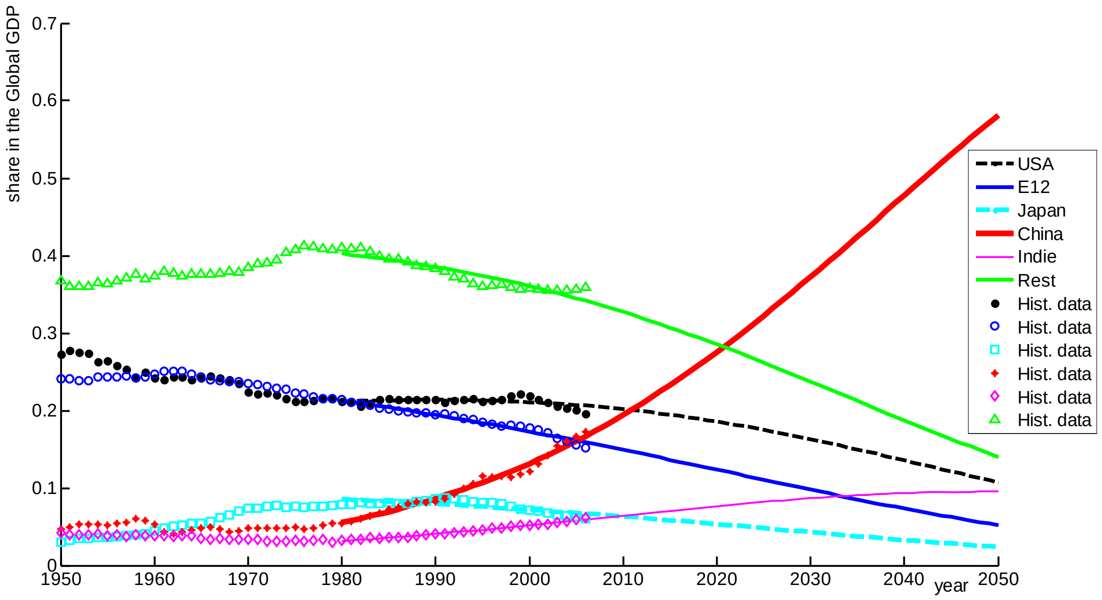

Figure 31. Evolution of the GDP shares of the six regions/countries: USA, E12, Japan, China, India and the Rest of the World (the identification period 1980-2006)

An idea of ranking the national economies according to their competitiveness index has come to us during the working on that paper. The problem is that if we would like to consider let's 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's assume that we consider each country separately as competing with the Rest of the World. To identify the competitiveness of that country (against the competeveness of the Rest, all time assumed as equal to one[11]) we ought to have historical data on at least four years (usually we assume longer period, e.g. 7 years for two types (countries)). Just to enquire the relevance of that approach we calculated moving competeveness for the five considered countries/regions by making five simulation experiments: each country compete with the rest of the World. The

[11] as we explain in [8] 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).

results of those experiments are presented in Figure 32. The general tendency of the competiveness changes is more or less similar to that observed in the experiment where all countries/nations competed altogether (see Figure 30). Just to show the level of the differences, the Figures 30 and 32 are collectively presented in Figure 33 (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 clearly visible although there is general agreement concerning observed tendencies and far reaching similarities in the competitiveness rankings. In Table 14 the rankings of these five countries/regions for the years 1970, 1980, 1990, and 2000 are presented. The compatibility of rankings obtained for those two approaches is astonishingly good. The only difference is for the year 1970 where USA and E12 interchange their positions (but as we see in Figure 33 their competitiveness are very similar).

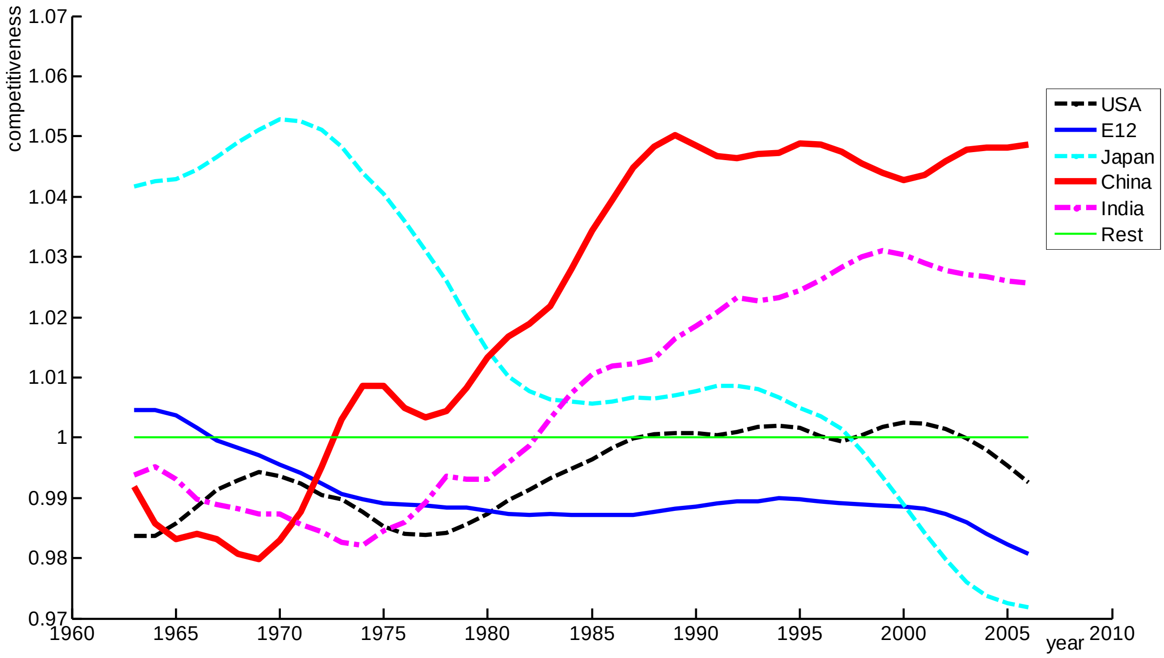

Figure 32. Dynamics of the competitiveness: USA, E12, Japan, China, India and the Rest of the World, calculated separately for each country competing with the Rest of The World (identification is based on the 14 years moving window of historical data)

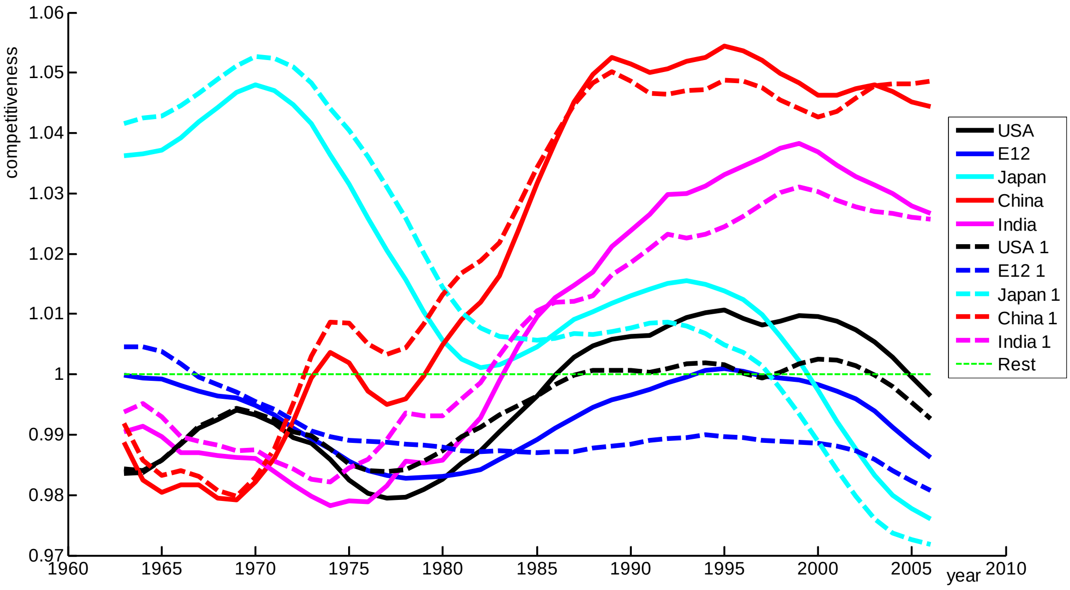

Figure 33. Comparison of the dynamics of the competitiveness: USA, E12, Japan, China, India and the Rest of the World, for all six countries/regions competing (solid lines) and calculated separately for each country competing with the Rest of The World (dashed lines); (identification is based on the 14 years moving window of historical data)

Table 14. 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

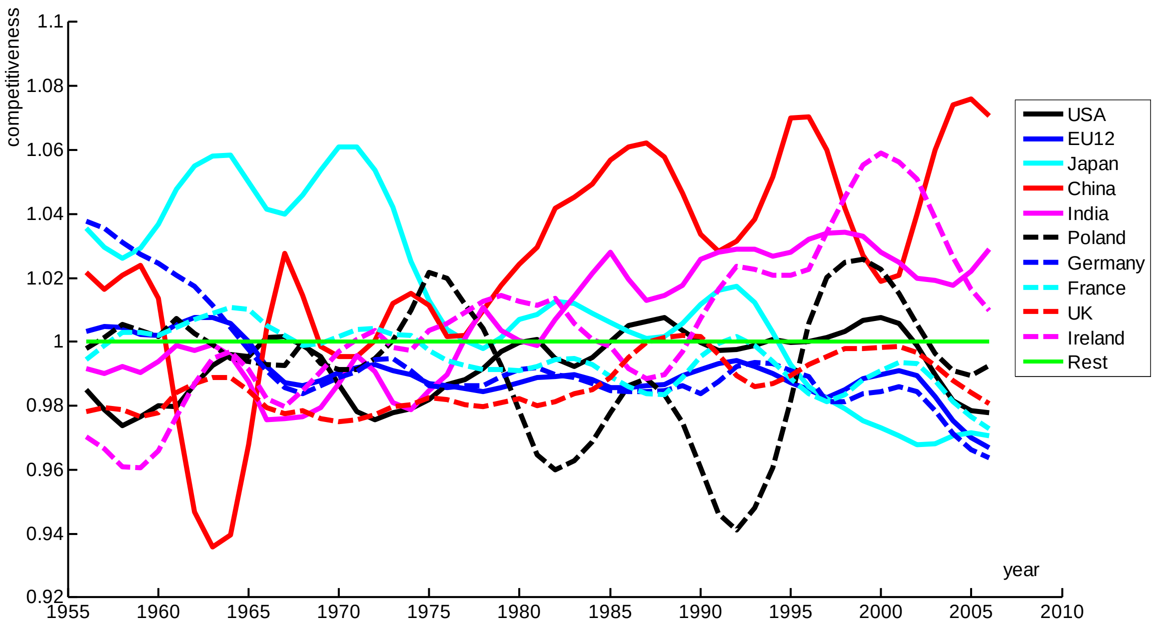

Figure 34. Dynamics of the competitiveness of nine countries and E12; calculated separately for each country competing with the Rest of The World (identification is based on the 7 years moving window of historical data)

There is no place present the rankings of competitiveness of all countries in the World but we plan to endeavour such project in near future. Here, as the first step toward that project we present the experiment for twenty nine selected countries and E12 (distinguished as a region competing especially with USA and China). Dynamics of the competitiveness of ten selected countries are presented in Figure 34 (for larger number of countries the figure would be unreadable). Once more we see great variability of the competitiveness for almost all countries since the middle of the 20th century. In Table 15 we present the rankings of those 30 countries/region for selected years. We start from the middle 1950s, and as we 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 a course of time Germany become more and more welfare state and became less and less competitive, in 1980 was ranked 19th, in 1990 25th, and in the last years was placed in the bottom of ranking. The same tendency of losing the competitiveness is observed for whole twelve European countries (E12). Growing competitiveness in the last 20-30 years is observed for such economies as: Chile, Ireland, India, and China. Poland, and to some extend also Hungary, are good examples of competitiveness advance due to the market oriented transformations. In 1990 these two counters was at the bottom of the ranking and now, after 20 years of transformation are placed in the top ten positions.

In the last column of the Table 15 the competitiveness indices for the last available historical data (2006) are presented. It is worth to notice high superiority of China and India over all advanced economies. The index for China is roughly 10% higher than these of USA, France, Japan and Germany. Even small differences in the values of the competitive indices result in enormous advantage/disadvantage of the economy in the long perspectives. For example nearly 3% difference between competitiveness of China and the West in period 1950-2006 (see Table 10) resulted in increase of China's share in global GDP from 11% in 2000 to 28% in 2050 and decrease of the share of the West from 44% to 29% (see Figure 25).

Table 15. Ranking of the competiveness 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

SUMMARY

One of the goals of that paper was to point out of necessity of far reaching skepticism in using trend analysis in forecasting of socio-economic processes. The problem of quality of statistical (historical) data and its impact on the goodness of forecasts were not discussed in that paper. Instead of that we have pointed 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., measure of trend fitting to historical data) has essential influence on quality of generated forecast.

Presented in the first section prognoses of global economic development (in terms of the global GDP) and demographic prognoses (in terms of the World human population) has been generated on the basis of relative long time series of historical data (from 1950 to 2006-2008). Someone may suppose that such long historical period will result in much more reliable prognoses, but as it is shown in the paper, it is hard to decide which period, e.g., shorter or longer, allows to generate more reliable forecasts.

Extension of the logistic curve into the substitution-diffusion model allows to evaluate future shares of national/regional economies in global GDP and to estimate competitiveness of those economies. It turns out that competiveness of nations/regions is far from being constant. The interesting question stated in the article concerns the possible way of development of Chinese economy. To what extend the history of Japanese economy in the post-war period may suit us as a metaphor/analogy for future development of China?

In the end of the paper a proposition of building the competiveness ranking is presented. The problem not stated in the paper (due to the limited space of the regular article) is to what extend the proposed ranking is compatible with well known Doing Business ranking,[12] The Global Competitiveness Report,[13] The World Competiveness Yearbook,[14] or Index of Economic Freedom rankings[15] and Economic Freedom of the World.[16] This problem will be undertaken in the next paper.

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