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Logistic Forecasting of GDP Competitiveness

Arnab K. Ray ⋆
Dhirubhai Ambani Institute of Information and Communication Technology, Gandhinagar 382007, Gujarat, India

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ABSTRACT
The growth of the nominal GDP of national economies is modelled by the logistic function. Applying it on the GDP data of the World Bank till the year 2020, we forecast the outcome of the competitive GDP growth of Japan, Germany, the UK and India, all of whose current GDPs are very close to one another. Fulfilling one of the predictions, the GDP of India overtook the GDP of the UK in 2022. We further forecast that in 2047 the GDP of India will exceed the GDPs of both Japan and Germany. When trade saturates, large and populous countries (like India) have the benefit of high domestic consumption to propel their GDP growth.

Key words: Economics and econophysics; Dynamics of social systems; Nonlinear dynamics; Systems obeying scaling laws

1 INTRODUCTION

The logistic equation is a standard example of a first-order autonomous nonlinear dynamical system (Strogatz 1994). Introduced originally to study population dynamics (Braun 1983; Strogatz 1994), it was later applied to multiple problems of socio-economic and scientific interest (Mansfield 1961; Montroll 1978; Braun 1983; Strogatz 1994; Ray 2010; Kakkad and Ray 2023). This is because the growth of many natural systems is modelled quite accurately by the logistic equation, the growth of species being one of many such examples (Braun 1983). Hence, the logistic equation is organically compatible with natural evolution in a free and fertile environment. This principle can be extended to the evolution of economic systems as well, a point of view that is supported by the successful logistic modelling of the GDP and trade dynamics of some leading national economies (Kakkad and Ray 2023).

The GDP (an abbreviation of Gross Domestic Product) of a country is the market value of goods and services produced by the country in a year (Samuelson and Nordhaus 1998; Ángeles Serrano 2007; Garlaschelli et al. 2007). GDP thus quantifies the aggregate outcome of the economic activities of a country that are performed all round the year. As such, the GDP of a national economy is a dynamic quantity and its evolution (commonly implying growth) can be followed through time. To this very end, the logistic equation turns out to be a simple and convenient mathematical tool, as has been shown in an earlier study on the GDP and trade dynamics of countries that are ranked high globally in terms of their nominal GDPs (Kakkad and Ray 2023).

From a macroeconomic perspective, GDP is a standard yardstick with which the state of a national economy is gauged, and in a global comparison of national economies, the GDP of a country is a reliable point of reference. By this criterion, globally the top six economies pertain to the USA, China, Japan, Germany, the UK and India. At present these six countries account for nearly 60% of the global GDP and nearly 40% of the global trade. China, India and the USA are the three most populous countries in the world, accounting for almost 40% of the world population. On the scale of strategic economic regions, the three most dominant economies in the North-Atlantic region are the USA, Germany and the UK. Likewise, the three most dominant economies in the Indo-Pacific region are China, Japan and India. All six countries are members of important economic blocs like G7 and BRICS. The USA, Japan, Germany and the UK belong to the former bloc, while China and India belong to the latter. Besides, all of these countries are the leading global representatives of three types of economic systems, namely, free economies (the USA, Japan, Germany and the UK), controlled economies (China) and mixed economies (India). That only six countries should exert such an overarching influence on the global economy is in keeping with the scale-free (power law) degree distribution of GDP (Garlaschelli and Loffredo 2004; Garlaschelli et al. 2007), because in scale-free distributions the disproportionate dominance of a few elements is a natural occurrence (Albert and Barabási 2002). To this the global economic order is no exception. Summing up these facts, we now argue that our study on a restricted scale of six countries (which are global leaders in terms of their nominal GDPs) adequately represents the essence of the GDP growth of more countries on a larger scale (like the twenty countries of G20) (Kakkad and Ray 2023).

Economic forecasts are useful in making informed policy decisions. As a discipline, economic forecasting is well-established by now,

⋆ E-mail: arnab_kumar@daiict.ac.in; arnab.kr311@gmail.com

with a wide scope and advanced methodologies (Holden et al. 1990; Clements and Hendry 2004; Carnot et al. 2005; Elliott et al. 2006). Precise forecasting in economic and social systems requires quantitative techniques and mathematical models of progressively increasing accuracy (Forrester 1961). Within this general framework, the specific objective of our present study is forecasting the outcome of the competitive GDP growth (a subject of macroeconomic interest) of some prominent national economies. Our mathematical tool is the nonlinear logistic equation. Nonlinearity is inherent in real industrial and economic systems (Forrester 1961), for which a linear model proves inadequate at times. The nonlinear approach to economic forecasting has been made already from several directions (Teräsvirta 2006; White 2006; Stock and Watson 2006; Elliott and Timmermann 2008), and to the same end, the logistic equation opens a new avenue. There are certain advantages that the logistic equation affords. First, the dynamics of an organically evolving system that converges to a finite limit, such as the economy in its various dimensions, is often modelled by the logistic equation (Mansfield 1961; Montroll 1978; Braun 1983; Strogatz 1994; Ray 2010; Kakkad and Ray 2023). Secondly, the deterministic nature of the logistic equation expresses a system variable as a known function of time. Thus, starting with an initial condition, the entire dynamic trajectory of the variable becomes known, making predictions about the future of the system feasible. We exploit these features of the logistic equation in our economic forecasting exercise here.

Country-wise annual GDP data, on which our modelling and analysis are based, have been collected from the World Bank website (USA GDP data n.d.; China GDP data n.d.; Japan GDP data n.d.; Germany GDP data n.d.; UK GDP data n.d.; India GDP data n.d.) up to 2020 (pre-Covid-pandemic years). The basic mathematical theory of the logistic equation and its application on the GDP data are laid out in Sec. 2. The numerical and statistical analyses of the modelling are summarized in Table 1. In Sec. 3 we consider the competitive GDP growth of Japan, Germany, the UK and India. Extrapolating the theoretical logistic functions (all calibrated by actual GDP data) beyond 2020, we predict the specific years in which the GDP of one country will overtake the GDP of another. Three such overtakes are to occur, one of which, the overtake of the UK GDP by the GDP of India, has already happened in 2022, in precise agreement with our forecast. The remaining two overtakes are to happen by 2047, following which, the nominal GDP of India is to be the third largest in the world after the GDPs of the USA and China. In Sec. 4 we remark on policies and unforeseen events that may have an impact on GDP growth.

2 LOGISTIC MODELLING OF GDP GROWTH

The nominal GDPs of all the six countries in this study are measured in US dollars. Quantifying GDP by the variable $G(t)$, in which t is time (measured in years), we set up a first-order autonomous dynamical system for $G(t)$ as (Strogatz 1994; Kakkad and Ray 2023)

$$\dot{G} \equiv \frac{\mathrm{d}G}{\mathrm{d}t} = \gamma G \left(1 - \frac{G}{k}\right). \tag{1}$$

Eq. (1) is the well-known logistic equation. Its integral solution, under the initial condition of $G(0) = G_0$, is

$$G(t) = \frac{G_0 e^{\gamma t}}{1 + (G_0/k)\left(e^{\gamma t} - 1\right)} = \frac{k}{1 + \left[(k/G_0) - 1\right] e^{-\gamma t}}, \tag{2}$$

which is the logistic function. The time scale that is implicit in Eq. (2) is γ^{-1}. On early time scales, when $t \ll \gamma^{-1}$, the growth of G in Eq. (2) is approximately exponential, i.e. $G \simeq G_0 \exp(\gamma t)$. This gives $\ln G \sim \gamma t$, which is linear in a linear-log plot. We interpret $\gamma \simeq \dot{G}/G$ as the relative growth rate (per annum) in the early exponential regime. However, this exponential growth is not indefinite, and on time scales of $t \gg \gamma^{-1}$ (or $t \longrightarrow \infty$) there is a convergence to the limit of $G = k$ (in US dollars). Thus, according to Eq. (2), growth saturates to a finite limit on long time scales. The transition from the exponential regime to the saturation regime occurs when $t \sim \gamma^{-1}$.

The initial year of the GDP data for the USA, China, Japan, the UK and India is 1960. For Germany the data begin from 1970. All data sets end either in 2019 or 2020. Hence, our study spans across six decades in all cases but one. The USA, Germany and the UK are the top three economies in the North-Atlantic region, and China, Japan and India are likewise in the Indo-Pacific region. Moreover, the USA and China are the top two economies of the world, with their respective GDPs being of the order of US $20 trillion as of 2023. The GDPs of Japan, Germany, the UK and India are each approximately a quarter of the GDPs of either the USA or China. Hence, on the largest scale of global competitiveness, we exclusively compare the GDP growth of the USA and China in Fig. 1. After China, the two competing economies in the Indo-Pacific region are Japan and India. Their GDP growth is compared jointly in Fig. 2. Similarly, after the USA, the two competing economies in the North-Atlantic region are Germany and the UK, whose GDP growth is compared together in Fig. 3. The early exponential growth of the GDP and its later convergence to a finite limit, as implied by Eq. (2), are modelled in all the linear-log plots in Figs. 1, 2 and 3. The uneven lines follow the movement of the real GDP data, available from the World Bank (USA GDP data n.d.; China GDP data n.d.; Japan GDP data n.d.; Germany GDP data n.d.; UK GDP data n.d.; India GDP data n.d.). The smooth dotted curves theoretically model the real data with Eq. (2). The values of γ (the relative annual growth rate of GDP in the early stage) and k (the predicted maximum value of GDP), calibrated through the model fitting in all the cases, are to be found in Table 1. The most convincing match of the GDP data with the logistic function is seen in Fig. 1, for the USA. Consistent fitting of the GDP data with the logistic function also follows for Japan, Germany, the UK and India, as can be seen in Figs. 2 and 3. Similar consistency, however, is not observed in the model fitting of the GDP data for China, as we note from the lower plot in Fig. 1. These observations about the model-fitting of the GDP data are statistically summarized in Table 1, which sets down the mean μ and the standard deviation σ of the yearly relative variations of the actual GDP data about the model logistic function. Going by the values in Table 1, we contend that the natural and balanced growth of the GDP of a country can be gauged from the closeness between the model logistic function and the actual GDP data. In support of this view, the GDP growth of the USA is a compelling example. Conditions that favour such a GDP growth are discussed in Sec. 3.

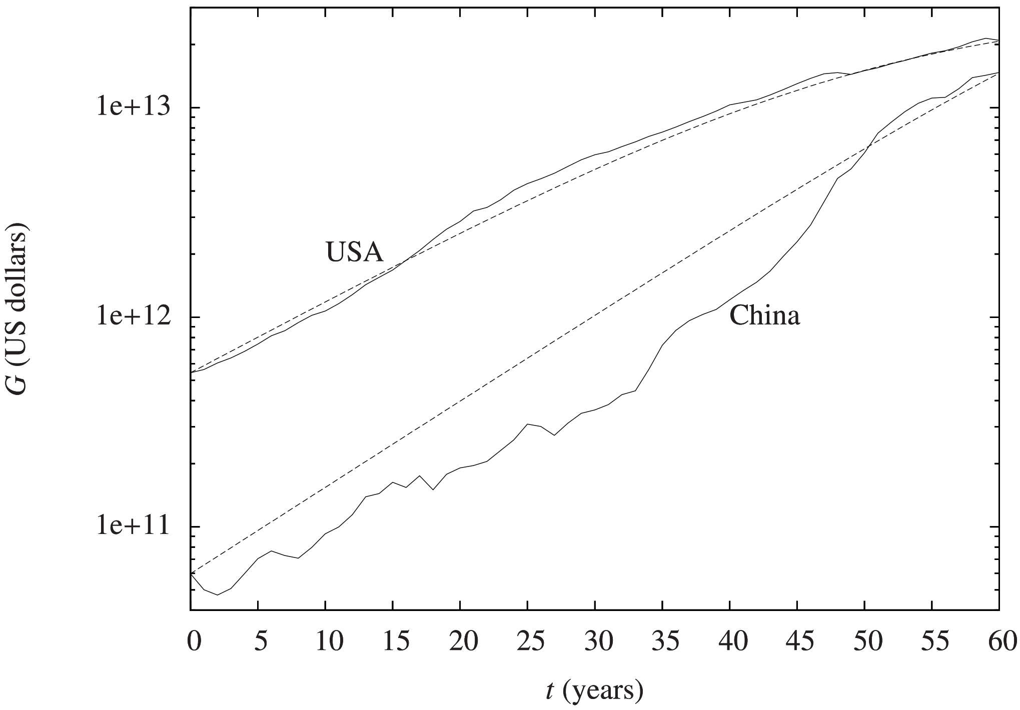

Figure 1. Comparing the GDP growth of the USA and China, which are, respectively, the countries with the highest and the second highest GDPs in the world. The smooth dotted curves model the GDP growth of both countries according to Eq. (2), with the values of γ and k in Table 1. The World Bank data of the annual GDP from 1960 ($t = 0$) to 2020 (USA GDP data n.d.; China GDP data n.d.) show a much more ordered progression for the USA than for China. Consequently, the logistic modelling of the GDP growth of the USA shows a greater closeness with the actual data than what it does in the case of China.

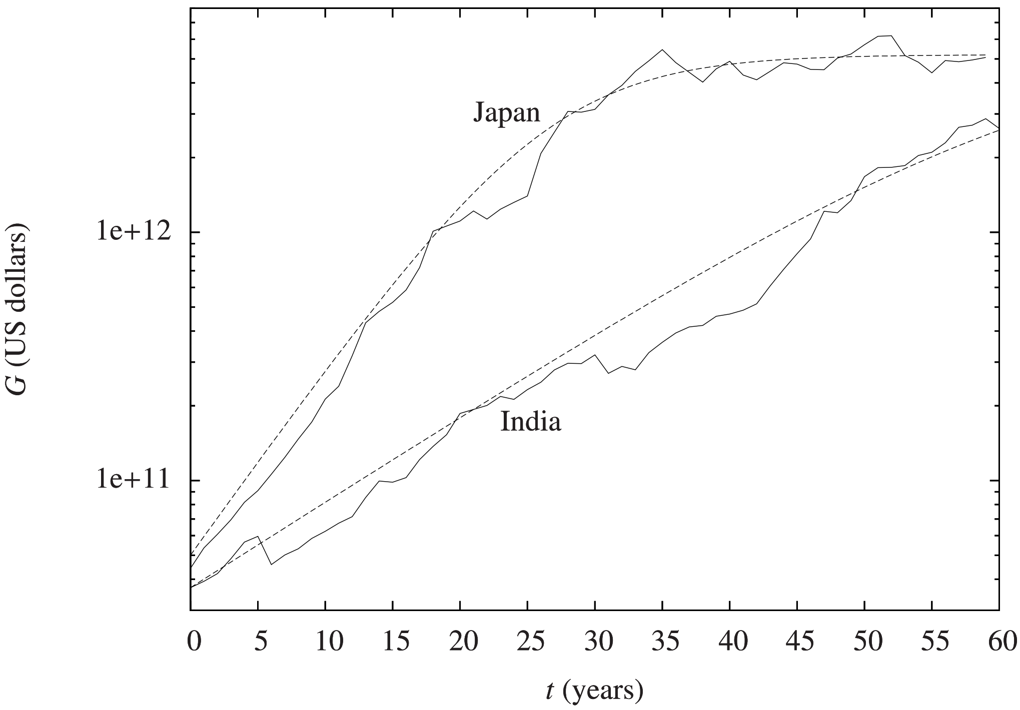

Figure 2. Comparing the GDP growth of Japan and India, which, after China, are, respectively, the countries with the second and the third highest GDPs in the Indo-Pacific region. The World Bank data of the annual GDPs of both countries start from 1960 ($t = 0$) (Japan GDP data n.d.; India GDP data n.d.). The GDP data end in the year 2019 for Japan, and the year 2020 for India. The GDP growth of Japan has a steep gradient in the early years, but by the year 2000, the growth has visibly stagnated. Both of these features are modelled closely by the logistic function — the smooth dotted curve. In contrast, the GDP growth of India has been slow but on the whole steady, and by the year 2020, the GDP of India grows with a higher gradient than the GDP of Japan. At this rate, the GDP of India will eventually overtake the GDP of Japan. This forecast is theoretically modelled in Fig. 4 by extrapolating the logistic curves of Japan and India beyond 2020. These two theoretical logistic curves model the GDP growth of both countries according to Eq. (2), with the values of γ and k in Table 1.

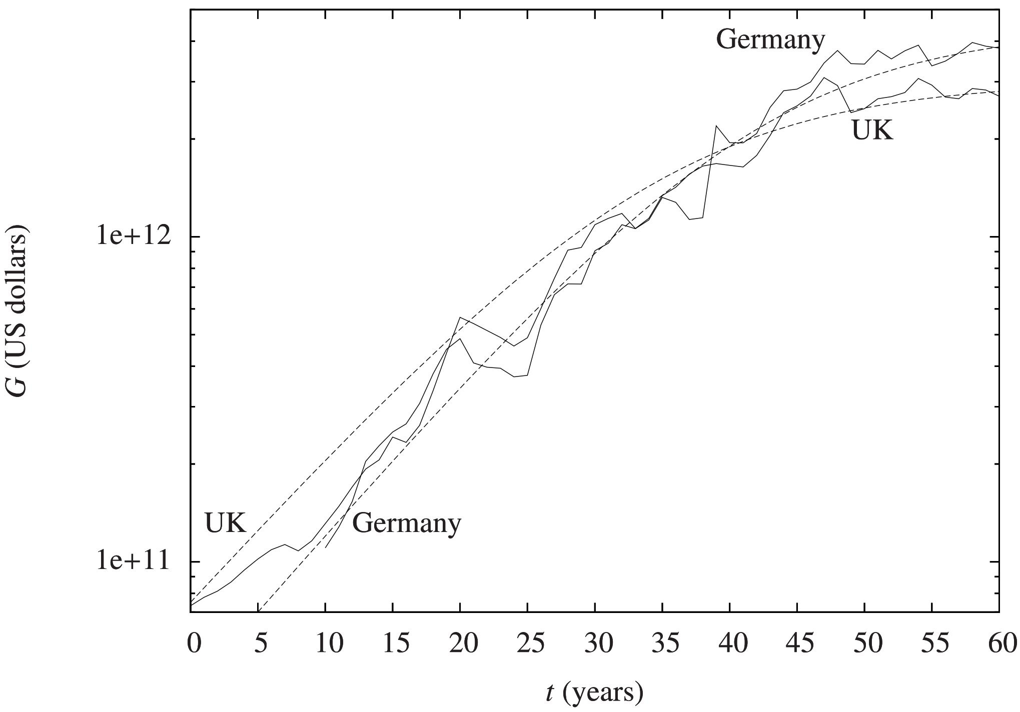

Figure 3. Comparing the GDP growth of Germany and the UK, which, after the USA, are, respectively, the countries with the second and the third highest GDPs in the North-Atlantic region. The World Bank data of the annual GDP of the UK start from 1960 ($t = 0$) and end in 2020 (UK GDP data n.d.). For Germany, however, the GDP data (Germany GDP data n.d.) start from 1970 ($t = 10\,\mathrm{years}$). Till 1999-2000, both countries ran each other very close in terms of their GDP growth. Thereafter, the GDP of Germany has led the GDP of the UK. The beginning of the lead for Germany is theoretically captured by the intersection of the smooth dotted curves around the year 2000 (shown in Fig. 4). These two theoretical logistic curves model the GDP growth of both countries according to Eq. (2), with the values of γ and k in Table 1. In the case of Germany the theoretical logistic curve has been extrapolated backward before 1970.

Table 1. Parameter values and statistical analyses of the logistic modelling of the World Bank GDP data of the six countries that are listed in the first column. The country-wise ranking is in the order of decreasing GDP till the year 2020 (since 2022 India is in the fifth position and the UK is in the sixth). The second and third columns list the values of the parameters γ and k for fitting Eq. (2) with the GDP data.The data have been plotted and modelled in Figs. 1, 2 and 3. The fourth and fifth columns list, respectively, the mean μ and the standard deviation σ of the yearly *relative* variations of the GDP data with respect to the logistic model. Going by the values of μ and σ, the data and the model are most closely matched for the USA and least closely matched for China.

Country	γ (per annum)	k (trillion US dollars)	μ	σ
USA	0.080	30.0	0.0492	0.0873
China	0.095	80.0	−0.3568	0.2504
Japan	0.175	5.2	−0.0833	0.1395
Germany	0.110	4.4	0.0489	0.1744
UK	0.105	3.0	−0.1089	0.1651
India	0.080	6.0	−0.1359	0.1743

3 FORECASTING GDP COMPETITIVENESS

From the GDP values in Figs. 1, 2 and 3 we realize that the USA and China are at present the top two national economies in the world, both with an emphatic lead over the other four countries. Although it is unlikely that in the near future the GDP of Japan, Germany, the UK or India may surpass the GDP of either the USA or China, between the USA and China themselves, the GDP gap is reducing progressively, as Fig. 1 shows. At this rate the GDP of China may surpass the GDP of the USA. The year of this overtake can be identified as the year when the extrapolated logistic function of the China GDP crosses the extrapolated logistic function of the USA GDP. However, while the GDP growth of the USA is modelled accurately by the logistic function (a claim supported by the clean fit of the upper plot in Fig. 1, and the low values of μ and σ for the USA in Table 1), the same observation does not apply to China. The inadequacy of the logistic function to model the GDP growth of China is evident from the lack of closeness between the logistic function and the erratic GDP data in the lower plot in Fig. 1, as well as from the high values of μ and σ for China in Table 1. That the logistic function falls short in modelling the GDP growth of China is known (Kakkad and Ray 2023). It has been argued that the logistic function properly models the GDP growth of countries that foster a democratic polity, are free of military conflicts on their borders, and promote free economic growth without excessive interference from the state (Kakkad and Ray 2023). The cumulative effect of these conditions is conducive to a natural development of material well-being. The

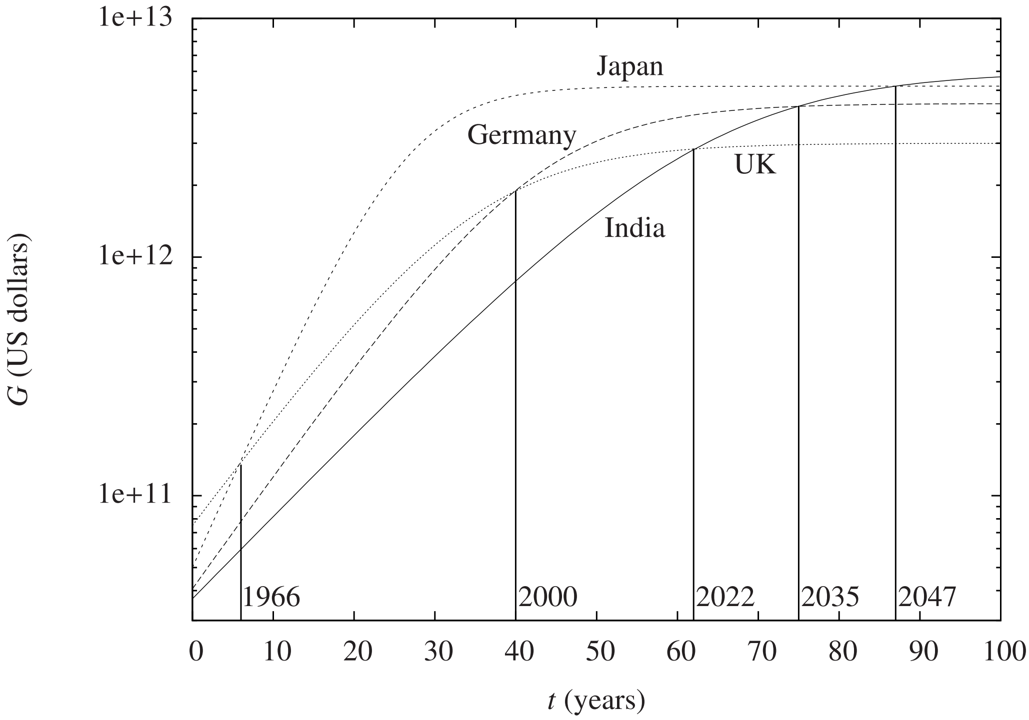

Figure 4. Forecasting the long term outcome of the GDP competitiveness among Japan, Germany, the UK and India. The four theoretical logistic functions, pertaining to the aforementioned countries, are calibrated with the World Bank GDP data till 2020 (Japan GDP data n.d.; Germany GDP data n.d.; UK GDP data n.d.; India GDP data n.d.). Two crossings of the logistic functions occur before 2020, one in 1966, when the GDP of Japan overtook the GDP of the UK, and the other in 2000, when the GDP of Germany overtook the GDP of the UK. The years of these intersections are correctly borne out by the World Bank GDP data. The remaining three intersections are to occur after 2020, and, hence, are predictive in nature. The first of these, in 2022, has already happened, when the GDP of India overtook the GDP of the UK. Thereafter, overtakes of the GDPs of Germany and Japan by the GDP of India are predicted for the years 2035 and 2047, respectively. The UK, with a greater GDP than the other three countries in 1960, brings up the rear of the group from 2022 onwards. In contrast, India, with a smaller GDP than the other three countries in 1960, is to lead the group from 2047 onwards.

absence of any one of the aforementioned conditions causes imbalance, as happens in the case of China. On the other hand, in the other five countries, all of the three foregoing conditions prevail in varying degrees, and as such, the logistic function becomes effective in modelling the GDP growth of these countries (Kakkad and Ray 2023). This argument is substantiated by all the related plots in Figs. 1, 2 and 3, along with the corresponding values of μ and σ in Table 1.

Considering that China is an anomalous case in modelling the dynamics of nominal GDP with the logistic equation, we make no further attempt to compare the logistic growth of the GDPs of the USA and China for predicting the year in which the GDP of the latter will overtake the GDP of the former. Instead we study the competitiveness of the GDPs of the other five countries. However, the GDP of the USA is so far ahead of the others that in the foreseeable future none of the GDPs of Japan, Germany, the UK and India is likely to grow close enough to the GDP of the USA. In that case, a study of the competitiveness of GDP growth is meaningful only among Japan, Germany, the UK and India. Accordingly, it is for these four countries that we forecast the outcome of competitive GDP growth. Our method consists of extrapolating the model logistic functions of the GDPs of Japan, Germany, the UK and India beyond the year 2020 in a single graph, and noting the crossing points among the function curves. At the crossing points the GDP of one country overtakes the GDP of another. Since the four logistic functions have been calibrated with the GDP data available up to 2020, any crossing beyond this year enables us to forecast future outcomes of GDP competitiveness among the four countries. The result of this whole exercise is to be seen in Fig. 4.

We first note that Fig. 4 has five crossing points. Of these, two occur in the years 1966 and 2000, in both of which the GDP of the UK was successively overtaken by the GDPs of Japan and Germany. The actual GDP data (Japan GDP data n.d.; Germany GDP data n.d.; UK GDP data n.d.) do agree with these intersections, and thus confirm the fundamental correctness of the logistic modelling of GDP growth. While the crossings of 1966 and 2000 occur within the range of the available GDP data, i.e. till the year 2020, there are three more crossing points beyond 2020. These are in the years 2022, 2035 and 2047, in all of which, the GDP of India is predicted to successively overtake the GDPs of the UK, Germany and Japan. As it happens, fulfilling the first prediction precisely, the GDP of India did overtake the GDP of the UK in 2022. This certainly inspires confidence in the predictive power of the logistic modelling of GDP growth.

Another noteworthy aspect of Fig. 4 is that in the year 1960 (at $t = 0$ in the graph) it shows India to have the lowest GDP among the four national economies that we compare. The explanation for this lies in the history of the latter half of the twentieth century. In the years following the Second World War, which ended in 1945, it became a policy imperative for the USA (mainly due to the Cold War against the erstwhile Soviet Union) to aid and expedite the economic revival of both war-ravaged Japan and Western Europe (the latter under the

Marshall Plan). Guided by the USA thus, Japan, Germany (then West Germany) and the UK achieved political peace and economic prosperity by 1960. In contrast, during the same period, India, freed from colonial rule about a decade earlier, did not experience the advantages that regenerated the economies of Japan, Germany and the UK. Two factors, more than any other, impeded the GDP growth of India. The first is restrictive government policies in economic matters, and the second is a series of wars in which India was embroiled in the initial three decades of its sovereign existence. Unsurprisingly then, the GDP growth of India is seen to trail those of the other countries in Fig. 4 from 1960 to 2020. And yet from 2047 onwards, the GDP of India is projected in Fig. 4 to lead the GDPs of the other three countries. Along the way, the GDP of India is expected to reach the values of US $4 trillion in 2032 and US $5 trillion in 2043. These estimates can be made from Eq. (2) by recasting it as $t \equiv t(G)$.

Growth as predicted above will be possible only because India has maintained a steady GDP growth rate over an extended duration. One reason for this sustained growth rate is that India is a country of sub-continental proportions with a large population, unlike Japan, Germany and the UK. Now, a study of the World Bank data shows that the annual GDP of a country (G) is scaled by its annual trade T as

$$G(T) \sim T^{\alpha}, \tag{3}$$

in which $\alpha\,(> 0)$ is the scaling exponent (Kakkad and Ray 2023). For the countries that we study here, the power-law scaling implied by Eq. (3) holds true over at least two orders of magnitude (Kakkad and Ray 2023). What is more, the exponent α distinguishes the economies of countries with large geographical areas and populations from the economies of countries with small geographical areas and populations (Kakkad and Ray 2023). In the former type, which includes India (as well as the USA and China), α has a relatively low value (Kakkad and Ray 2023). In the latter type, which includes Japan, Germany and the UK, α has a higher value (Kakkad and Ray 2023).

We now explain how the distinction between the two types of national economies can cause a difference in trading patterns, with a concomitant effect on the GDP growth. A country with a large population has the advantage of a proportionately large domestic consumption of its own products, which in turn makes a proportionately greater contribution to the GDP, as compared to the contribution from trade. Consequently, the contribution of trade to the overall GDP growth reduces, a condition that is reflected by a lower value of α. The same feature is also known for the USA and China, which like India, are geographically extended countries with large populations (Kakkad and Ray 2023). Countries with small populations, on the other hand, are bereft of the high domestic consumption that attends a large population, and thus they have to rely more on trade with other countries to enhance their GDPs (Frankel and Romer 1999). This condition is reflected by a higher value of α, as is known to happen in the case of Japan, Germany and the UK (Kakkad and Ray 2023). Now, the growth of trade also saturates according to the logistic function (Kakkad and Ray 2023), and since trade is highly correlated with GDP (Kakkad and Ray 2023), a saturation of trade implies a corresponding saturation of the GDP. Therefore, countries that depend more on external trade than on domestic consumption will see their GDP growth saturate when their trade saturates due to market-driven inhibitors. This is what we see for Japan, Germany and the UK in Fig. 4, whereas the GDP of India, despite its slow start, will outpace the GDPs of the other three countries on the strength of its large volume of domestic consumption.

4 CONCLUSIONS AND REMARKS

The suitability of the logistic equation to model the dynamics of GDP and trade has been established already (Kakkad and Ray 2023). In the present study we proceed further to show that the logistic equation is also effective in forecasting the outcome of GDP competitiveness among some leading national economies. Our logistic forecasting method has been vindicated both retrospectively and for future times. In the former case, it has correctly estimated the years when the GDPs of Japan and Germany overtook the GDP of the UK (1966 and 2000, respectively). In the latter case, going forward in time, the logistic method has also been successful in forecasting 2022 as the year in which the GDP of India is to overtake the GDP of the UK. What now remains to be seen is the fulfillment of the forecast that the GDP of India will overtake the GDPs of Germany and Japan in 2035 and 2047, respectively. The emergence of India as the third largest economy in the world is, in fact, a question of widespread interest at the moment, with predictions about its year varying from 2025 to 2050 (Japan Centre for Economic Research 2022; Deutsche Bank Research; Goldman Sachs Economics Research 2022). These predictions are not based on the logistic equation. Therefore, a comparison of the technical methods behind these predictions and our logistic forecasting approach could be a subject of more in-depth studies so that more refined forecasting techniques might be developed in the future.

GDP growth, as modelled by the logistic equation, displays two distinct phases — an early phase of rapid exponential growth and a slow long-term convergence towards a limiting value (Kakkad and Ray 2023). In the latter phase, an economy becomes almost stagnated. Stagnation of economic growth is the overall macroeconomic effect of multiple causes like the finiteness of resources for production and the shrinking of markets. Hence, forecasting the time scale of the onset of economic stagnation (Kakkad and Ray 2023) is helpful in devising corrective policies in advance to sustain appreciable GDP growth. If the policies have a positive impact on the economic condition, then in the logistic model, as given by Eq. (1), they will be reflected through augmented values of γ and k. Since GDP and trade are interrelated (Tinbergen 1962; Anderson 2010; De Benedictis and Taglioni 2011; Kakkad and Ray 2023), enhancing trade is a common way to improve GDP growth. This is especially true for countries that rely more on external trade than on domestic consumption. Such countries may experience a stagnation in their GDP growth whenever their external trade saturates (Kakkad and Ray 2023). This eventuality can, however, be averted by regenerating market demands through innovation and manufacturing of technologically superior products.

All that said, we have to remember that the subject of our present study is the dynamics of social systems (national economies). Hence, it must depend on real socio-economic data. For instance, the logistic functions in Fig. 4, which are at the core of our forecasts, have all been calibrated with the GDP data of the World Bank till 2020 (USA GDP data n.d.; China GDP data n.d.; Japan GDP data n.d.; Germany GDP data n.d.; UK GDP data n.d.; India GDP data n.d.). However, unforeseen natural, social, demographic and political factors can compromise our forecasts by recalibrating the parameters of the logistic equation. Examples of such unforeseen factors can be found in some recent events of global significance. Even in the first quarter of 2020 no one anticipated that within two years the global economy was to receive three major shocks. These are, first, Covid-19, which became a global pandemic by the middle of 2020 and whose aftereffects were felt even in late 2022. The second shock has been the war in Ukraine, which broke out in early 2022, even before the world economy could fully recover from the damage it had suffered due to the Covid-19 pandemic. The Ukraine war, by now protracted beyond all expectations, has disrupted global supply chains and energy markets. The third shock has been unfavourable environmental conditions in Europe and China, which are bound to affect crucial sectors like power and agriculture. Considering that Europe and China belong to two major economic regions of the world, the former in the North-Atlantic and the latter in the Indo-Pacific, adverse climatic events in these regions will have an adverse impact on production globally.

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