

Multidecadal dynamics project slow 21st-century economic growth and income convergence

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Future economic growth will affect societal well-being and the environment, but is uncertain. We describe a multidecadal pattern of gross domestic product (GDP) per capita growth rising, then declining, as regions become richer. An empirically fitted differential-equation model and an integrated assessment model—International Futures—accounting for this pattern both predict 21st-century economic outlooks with slow growth and income convergence compared to the Shared Socioeconomic Pathways, similar to SSP4 (“Inequality”). For World Bank income groups, the differential-equation model could have produced, from 1980, consistent projections of 2100 GDP per capita, and more accurate predictions of 2010s growth rates than the International Monetary Fund’s short-term forecasts. Both forecasts were positively biased for the low-income group. SSP4 might therefore represent a best-case—not worst-case—scenario for 21st-century economic growth and income convergence. International Futures projects high poverty and population growth, and moderate energy demands and carbon dioxide emissions, within the Shared Socioeconomic Pathway range.

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Predicting 21st-century economic growth is central to anticipating a wide range of societal and environmental challenges and is a central concern to most governments¹. All else equal, a future world with higher affluence—as measured by gross domestic product (GDP) per capita—would lead to a variety of important and knowable transitions, including reduced poverty. This scenario would include improved technology, and therefore improved health, medicine, and capacity to adapt to natural disasters². It would also likely have greater demands for energy, food, and materials, and therefore possibly higher greenhouse-gas emissions and ecological footprints, unless sustainable transitions cause these environmental impacts to eventually decline with affluence, similarly to air pollution³ and agricultural land use^{4,5} historically. If past relationships persist, a richer world might also have lower birth rates and fewer people^{6,7}, more democracy^{8,9}, greater gender equality¹⁰ and other social and political rights¹¹, greater life satisfaction¹², and enhanced social trust^{13,14}. Cross-country patterns of 21st-century economic growth may also change the balance of geopolitical power^{6,15}. Because of the importance of economic affluence and growth as drivers and correlates of key social and environmental factors, scholars and activists sometimes argue for increasing¹¹, maintaining¹⁶, or decreasing¹⁷ economic growth or affluence (the latter for environmental reasons).

Projections of 21st-century global and regional GDP per capita span a wide range, and long-term economic forecasting has consequently been identified as a key priority by the Intergovernmental Panel on Climate Change (IPCC)¹⁸ and the US National Academies of Sciences, Engineering and Medicine (NASEM)¹⁹. Previous statistical forecasts^{20–23}, expert surveys^{20,23}, and socioeconomic scenarios¹⁵ have identified, as plausible, ranges of 21st-century growth rates leading to ranges of 2100 world GDP per capita spanning an order of magnitude (Fig. 1b; Supplementary Information, Supplementary Fig. 1), and even wider ranges for today's developing regions. Scenarios and expert outlooks having relatively slow growth are characterized by relatively low trade and international cooperation, less convergence between poor and rich regions, and less innovation; and vice versa (e.g., ref. 15). Damages from climate change, and other possible large-scale disruptions such as future pandemics, are not directly included in most scenarios and forecasts^{15,20–22}.

The Shared Socioeconomic Pathway (SSP) scenarios^{6,15} vividly illustrate the magnitude of future economic uncertainty. The SSPs are central to the IPCC's Sixth Assessment Report²⁴, and are widely used by researchers. The highest-growth SSP scenario, SSP5 (“Fossil-fueled Development”), projects rapid growth and extreme inter-country income convergence. It projects that GDP per capita exceeds 100,000 2005 USD PPP in all income groups by 2100, with the United States's GDP per capita being only ~50% larger than Tanzania's (see fig. 4 in ref. 15). In 2021, the United States's GDP per capita was ~51,000 2005 USD PPP, ~25× larger than Tanzania's (~2000 2005 USD PPP)²⁵. The slowest-growth SSP scenario, SSP3 (“Regional Rivalry”), projects world GDP per capita in 2100 to reach ~25,000 2005 USD PPP, roughly double its 2019 value²⁵. Between-country inequality decreases slightly but remains high, with Tanzania and the United States reaching ~10,000 and ~80,000 2005 USD PPP, respectively¹⁵. The economic differences between these two scenarios, alone, result in an extra ~1 °C of global warming by 2100 (under SSP5) if no climate policies are enacted^{16,26}. These two scenarios thus represent dramatically different futures for climate change, society, and society's capacity to adapt to climate change^{2,6}. Yet, the scientific community currently uses them as research inputs with little guidance regarding their plausibilities²⁷.

Although long-run economic growth is subject to deep uncertainty, here we show that scenarios with fast growth and income convergence, such as SSP5 and SSP1, would require sizeable and immediate deviations from decades-long, ubiquitous historical economic dynamics (Fig. 1a, Supplementary Fig. 2). We show that a simple empirically fitted differential-equation model (DEM) and a complex integrated assessment model (International Futures, IFs^{28,29}), which account for these dynamics, both predict similar economic outlooks to 2100, each resembling the SSP4 (“Inequality”) scenario^{6,15} at the level of World Bank income groups³⁰. We show that the DEM could have, since 1980, made remarkably consistent GDP per capita projections to 2100 (Fig. 1b). The DEM would also have better-predicted income groups' GDP per capita growth rates observed in the 2010s than the International Monetary Fund's (IMF) near-term forecasts predicted (Fig. 2). This suggests that the merits of simple economic forecasting approaches deserve greater attention. In the low-income group of countries,

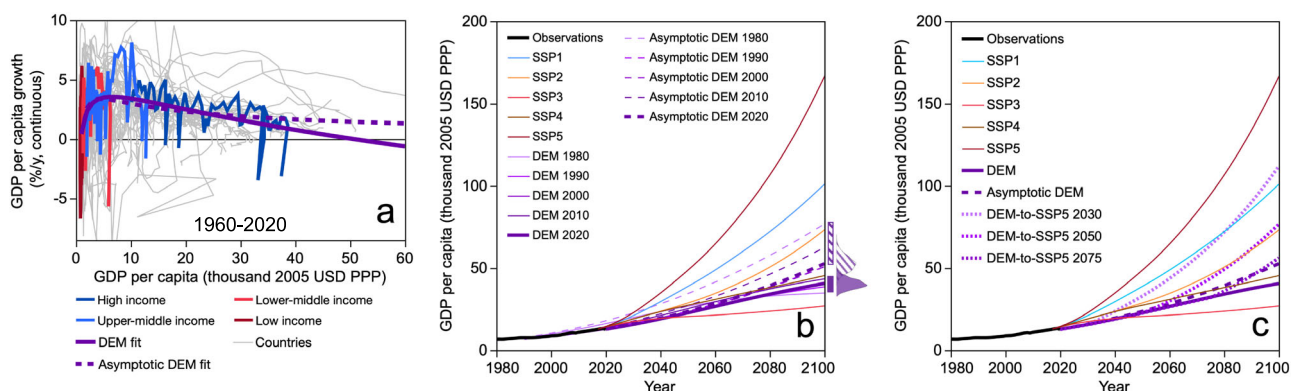


Fig. 1 Differential-equation model (DEM). **a** shows gross domestic product (GDP) per capita (in inflation-adjusted purchasing-power-parity (PPP) units) compared to GDP per capita growth (purple lines show DEM fits)^{25,31,67}. Country-level data come from the 95 large countries used by Tilman et al.³⁵ (accounting for ~90% of the world's population; see Methods and Supplementary Table 1), and country-level GDP per capita growth rates are 11-y moving averages, to reduce noise. **b** shows world GDP per capita projections that the fitted DEMs could have made starting in 1980, 1990, 2000, 2010, and 2020, compared to Shared Socioeconomic Pathway (SSP)¹⁵ projections to 2100 (calculated from regional projections, weighting by population; see Methods). Global DEM projections are aggregated from income-group-level projections assuming the United Nations Medium population scenario⁵⁶. Bars at right show ranges of 2100 GDP per capita projections from the DEM (purple, solid) and asymptotic DEM (purple, dashed) projecting forward from different years (1980–2020). Distributions at right show the ranges of 2100 GDP per capita projections of 1000 bootstrap runs (see Methods) of the DEM (purple, solid) and asymptotic DEM (purple, dashed) fits, each starting in 2020. **c** shows projections (purple, dotted) that switch from DEM-projected GDP per capita growth rates to SSP5-projected growth rates in the years indicated.

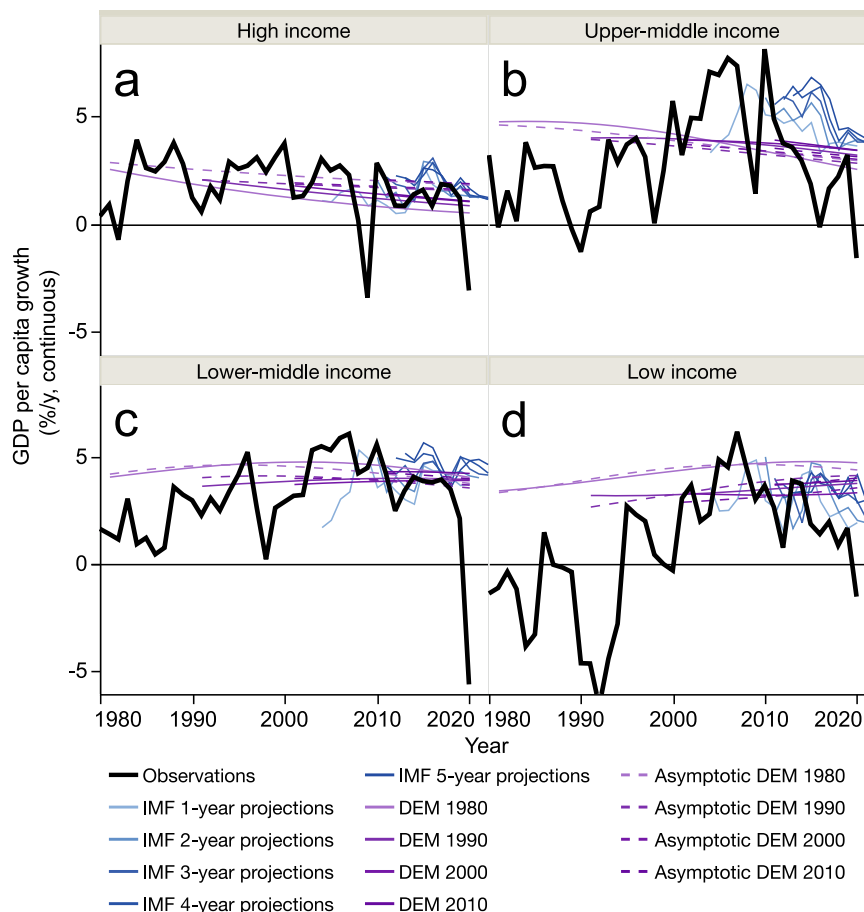


Fig. 2 DEM and IMF forecast comparison. Comparison of observed gross domestic product (GDP) per capita growth rates to historical predictions from the International Monetary Fund (IMF) (obtained from refs. 38,39) and predictions that could have been made by the differential-equation models (DEMs) in 1980, 1990, 2000, and 2010 (see Methods), at the scale of World Bank income groups³⁰ (a–d each focus on a different income group).

however, both the IMF and our DEM over-projected economic growth (Fig. 2). This may suggest that our models' projections to 2100 represent a best-case scenario for the low-income group, as may the SSP4 scenario, rather than being a most-likely scenario. Nonetheless, our analyses should be interpreted as exploratory; they cannot account for the deep uncertainty in future GDP per capita, and they accordingly do not reveal the full possible range of economic outcomes. We also explore the implications of our 21st-century economic projections, for poverty, population growth, energy demands, and carbon dioxide (CO₂) emissions, using the IFs model.

Results

Past dynamics define a clear hump-shaped relationship between GDP per capita (G) and its growth rate (dG/Gdt)³¹, which has been evident for decades^{32,33}. GDP per capita growth rates have peaked at GDP per capita between ~5000 and 15,000 2005 USD PPP (Fig. 1a). Beyond this peak, GDP per capita growth has declined with increased affluence, which developed countries have experienced during the past 50 years (Fig. 1a)⁹. This empirical relationship is the historical net effect of well-understood economic, political, cultural, and other forces on GDP per capita growth rates, as we explain below.

Fitting a curve to this empirical pattern defines a differential equation (i.e., a relationship between G and its derivative, dG/dt). The integral of this differential-equation forecasts future values of GDP per capita given a particular starting point for a group of economically similar countries. Tilman and colleagues

have used this DEM approach to forecast GDP per capita (using Selden and Song's³ Kuznets-inspired³⁴ functional form; see Methods) in several high-profile papers forecasting global food demands^{35–37} (Fig. 1a).

In Fig. 1b, we show that, as far back as 1980 (in each case using just observed G and dG/Gdt values starting in 1960), this DEM approach (using World Bank income groupings³⁰) would have consistently projected a 21st-century world GDP per capita outlook similar to the SSP4 (“Inequality”) scenario^{6,15}, reaching ~35,000–45,000 2005 USD PPP by 2100. The DEM projects slightly faster 21st-century economic growth than SSP4 in the low-income group (reaching ~25,000–35,000 2005 USD PPP by 2100), slower growth than SSP4 in the high-income group (reaching ~35,000–55,000 2005 USD PPP by 2100) and in the upper-middle-income group (reaching ~35,000–50,000 2005 USD PPP by 2100), and similar growth as SSP4 in the lower-middle-income group (reaching ~30,000–45,000 2005 USD PPP by 2100) (Fig. 3, Supplementary Figs. 3 and 4).

Our DEM projects an upper limit to income-group GDP per capita of ~55,000 2005 USD PPP, where GDP per capita growth reaches zero, due to its functional form. Since this projection is out of sample, we also include an alternate, asymptotic DEM, which assumes that GDP per capita growth will instead asymptotically approach zero as GDP per capita approaches infinity (see Methods). The asymptotic DEM projects a qualitatively similar 21st-century outlook as the simpler DEM, except that it projects faster growth (similar to SSP1, SSP2, and SSP4) in the high-income group, reaching ~100,000 2005 USD PPP by 2100

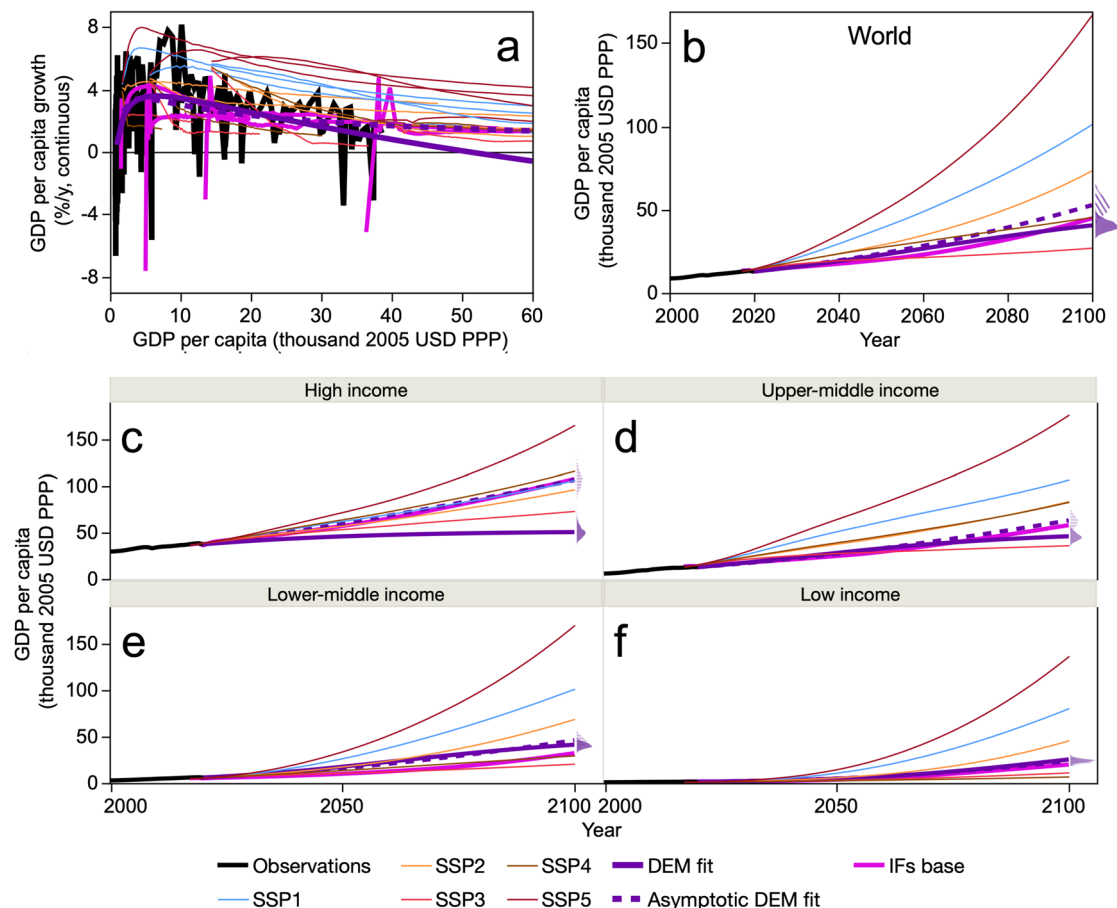


Fig. 3 Model and scenario comparisons. Comparison of gross domestic product (GDP) per capita and GDP per capita growth observations (at the level of World Bank income groups³⁰ in **a, c-f**; at the global level in **b**) to Shared Socioeconomic Pathway (SSP) projections (run in the International Futures (IFs) model^{28,29} based on SSP assumptions^{6,15}), IFs base model projections, and differential-equation model (DEM) projections. Global DEM projections in **b** are aggregated from income-group level projections assuming the United Nations Medium population scenario⁵⁶. Distributions at right in **b-f** show the ranges of 2100 GDP per capita projections of 1000 bootstrap runs (see Methods) of the DEM (purple, solid) and asymptotic DEM (purple, dashed) fits, starting in 2020.

(Figs. 1b, 3, Supplementary Figs. 3 and 4). The asymptotic DEM's projections from 1980 and 1990 would have suggested higher world GDP per capita outlooks to 2100 (similar to SSP2), but only because they over-projected pre-2020 growth (Fig. 2, Supplementary Fig. 4). Projections from both DEMs are qualitatively robust to bootstrapping the model fits (see Figs. 1b and 3, Methods, and Supplementary Figs. 5 and 6).

In Fig. 1c, we compare the DEMs' and SSPs' projections of world GDP per capita to illustrative hypothetical scenarios, in which we assume that the world experiences (non-asymptotic) DEM GDP per capita growth rates until 2030, 2050, or 2075, and then instantly switches to having SSP5 growth rates thereafter. Switching to SSP5 growth rates in 2030 results in 33% less GDP per capita in 2100 compared to SSP5 (~110,000 2005 USD PPP), similar to SSP1. Switching to SSP5 growth rates in 2050 results in 54% less GDP per capita in 2100 compared to SSP5 (~75,000 2005 USD PPP), similar to SSP2. Switching to SSP5 growth rates in 2075 results in GDP per capita in 2100 similar to the asymptotic DEM and SSP4. These unrealistic scenarios are intended to illustrate that the world would need to either reach SSP5 GDP per capita growth rates almost immediately, or it would need to sustain growth rates substantially exceeding SSP5's rates, to realize SSP5's 2100 GDP per capita projections.

In Fig. 2 and Supplementary Figs. 7 and 8 (see Methods), we compare our DEMs' GDP per capita growth projections, from

1960 to 1980 onwards, to 1980–2020 observations and to 1–5-year forecasts from the International Monetary Fund's (IMF) World Economic Outlooks (WEOs) for the years 2004–2020³⁸. (Earlier WEOs have too sparse coverage to aggregate meaningfully to income groups³⁹.) In the high-income group, the DEM projecting from 1980 would have had an average error of -0.37% per year GDP per capita growth, resulting in a GDP per capita projection error of only -14% in 2020 (40 years later). The asymptotic DEM projecting from 1980 would have had positive bias of about twice this magnitude (mean 0.6% per year growth projection error). In contrast, the IMF had a median projection error of 0.76% per year in its 3-year forecasts during the 2010s. Both DEMs would have had a positive bias in projecting GDP per capita, but less than IMF's, in the upper-middle-income (mean 1% per year growth projection error with the simple DEM projecting from 1980) and lower-middle-income (mean 1.5% per year growth projection error with the simple DEM projecting from 1980) groups. In the low-income group, both DEMs have substantial positive bias (mean 3.5% per year and 2% per year growth projection error with the simple DEM projecting from 1980 and 1990, respectively), slightly larger in magnitude to the IMF's from 2004–2020 (mean 1.9% per year projection error in 2-year forecasts).

Why does the hump-shaped empirical relationship between GDP per capita and GDP per capita growth (Fig. 1a) exist? At the

low-income end, challenges such as conflict traps, poor governance, extractive institutions, lack of infrastructure, poorly developed capital, and market access constrain growth^{40,41}. At the high-income end, increasing affluence is accompanied by populations aging (Supplementary Fig. 2a, b), which increases the non-working-age fraction of the population (age dependency); and shifts from manufacturing towards more service-oriented economies⁴² (Supplementary Fig. 2c–f). Service industries have slower labor productivity growth than manufacturing industries, because labor is less substitutable⁴². Some argue that declining innovation has also played a role in slowing growth in rich countries⁴³ (but see also refs. 44,45). Middle-income countries have the highest GDP per capita growth, likely because of a comparative advantage in labor-intensive manufacturing (Supplementary Fig. 2e, f), sufficient capital and governance to support it, and an emerging middle class contributing to aggregate demand^{46,47}. Some middle-income countries, such as China, also have very high investment⁴⁸. However, eventually middle-income countries' growth, too, begins to slow (the “middle-income trap”^{46,47}), partly due to effects of aging and shifts to services, similarly to richer countries^{47,48}. Additional factors contributing to the middle-income trap include: lack of human capital constraining shifts to high-tech manufacturing, unsustainability of high investment, currency undervaluation, and mean reversion^{46–48}.

So long as rising affluence comes with population aging and shifts to service-based economies, it is probably unavoidable that these changes slow GDP per capita growth. Indeed, Vollrath⁴² estimates that these two factors account for most of the United States's decline in GDP per capita growth in recent decades. That increasing affluence leads countries to shift to service-dominated economies has been historically ubiquitous (Supplementary Fig. 2c), and may be theoretically inevitable, as it largely stems from material needs being met⁴². That increasing affluence coincides with falling birth rates may not be theoretically inevitable, but this pattern, too, has been historically ubiquitous (Supplementary Fig. 2a), and it may be accelerating^{49,50}. The contribution of manufacturing to GDP is highest in middle-income countries. Supplementary Fig. 2e shows this in terms of the employment share in industry, which has better global data coverage than manufacturing value added²⁵.

In Fig. 3 and Supplementary Fig. 2, we evaluate the SSP scenarios^{6,15} in light of these historical dynamics. The SSPs span a similar range of economic futures as expert projections^{20,23} and statistical forecasts^{20–22} (Fig. 1). We compare SSP projections to: (i) historical dynamics shown in Fig. 1a, (ii) projections to 2100 from both DEMs (see Methods and Fig. 3), and (iii) the “base” projection from the IFs model^{28,29} (IFs version 7.81).

In contrast to the simple DEM approach, IFs is a highly complex integrated assessment model, which builds country-level projections from hundreds of fitted empirical relationships among drivers of economic growth. Key economic features of IFs include: (i) a production function with attention to drivers of multifactor productivity; (ii) a social accounting matrix structure tracking financial flows among households, firms, and governments, within and across countries; and (iii) an equilibration process across time that does not require exogenous closure rules (see Methods and Supplementary Methods for summary and refs. 28,29 for full description). The IFs model has been developed over the past four decades and used in many peer-reviewed studies of international development (e.g., recently in refs. 51–54). We run both the IFs base and the SSP projections in the IFs modeling platform for internal consistency, and also to allow tracking of variables such as services and industry employment which are not available in the public SSP database⁵⁵ (see Methods).

The IFs base model's projections—of both GDP per capita to 2100 and the relationship between GDP per capita and GDP per

capita growth—are remarkably similar to both DEMs' projections for the low-, lower-middle, and upper-middle-income groups (Fig. 3a, b, d–f), and similar to the asymptotic DEM's projections for the high-income group (Fig. 3a, c). It is not surprising that there is disagreement between the models' high-income projections, as these projections extrapolate trends outside the ranges of historical observations that the models are fit to (Fig. 1a).

In contrast to the DEMs and IFs base projections, high-growth SSP scenarios (SSP1 and SSP5) project large increases in GDP per capita growth (caused by increases in productivity growth^{6,15,29}) (Supplementary Fig. 9), requiring growth in low- and middle-income countries to quickly reach rates approximately double the rates seen in recent decades in those regions (Supplementary Fig. 9d–f; see also Fig. 1c) and the rates seen previously in now-richer regions when they had the same GDP per capita levels (Fig. 3a, Supplementary Fig. 9a). These high-growth scenarios project substantially slower shifts to service-oriented economies than have been seen historically (Supplementary Fig. 2d).

Fig. 4 compares the IFs base and SSP scenarios on four GDP per capita-related quantities of interest regarding development and the environment (see Methods and Supplementary Methods). The IFs base model projects a global population trajectory intermediate to SSP3's and SSP4's—similar to the 2019 UN Medium projection⁵⁶, and higher than the high-economic growth SSP scenarios (SSPs 1, 2, 5) (Fig. 4a). This is due to the well-known historical negative relationship between affluence and population growth (Supplementary Fig. 2a), which IFs preserves (Supplementary Fig. 2b). Relative to higher-growth SSP scenarios, the IFs base model projects greater poverty and economic inequality between countries, similar to SSP4 (with the IFs base model projecting somewhat more poverty early in the century and less later in the century) (Fig. 4b).

The IFs base model projects energy demand (Fig. 4c) and CO₂ emissions (Fig. 4d) in the mid-range of the seven SSP marker scenarios (i.e., the main scenarios used by the IPCC²⁴), which combine socioeconomic and climate mitigation projections⁶. All else equal, more GDP per capita results in higher energy demands and emissions (as is the case in SSP5; Fig. 4c, d), but the SSP1 and SSP2 marker scenarios assume sufficient progress in energy efficiency and decarbonization to more than offset their higher GDP per capita growth, compared to the IFs base model (Fig. 4c, d). The IFs base model projects a CO₂ emissions trajectory similar to SSP2-4.5, which is consistent with several other recent scenario analyses that use a variety of methodologies^{27,57–59}, and would result in 2–3.5 °C of warming by 2100 above pre-industrial levels²⁶.

Discussion

Our results show that a long-standing historical relationship between GDP per capita growth and GDP per capita—whose drivers are well-understood^{40–42,46–48}—projects a 21st-century economic outlook with slow growth and slow income convergence compared to the range of SSP scenarios, similar to SSP4 (“Inequality”)^{6,15}. We show this using two modeling approaches on opposite extremes of the complexity spectrum—the DEMs very simple, and the IFs model very complex. Our DEM forecasts, based on this relationship, would have been consistent since 1980 and would have outperformed recent IMF forecasts, but they would still have been positively biased in low- and middle-income groups historically (Fig. 2, Supplementary Fig. 8). These results have two important sets of implications.

First, they suggest that slow-growth, slow-convergence economic scenarios deserve greater attention in research and policy, and that the range of economic scenarios treated as plausible in research may need to be revised in this direction. SSP4 is currently seen as a worst-case scenario for global income convergence and a relatively

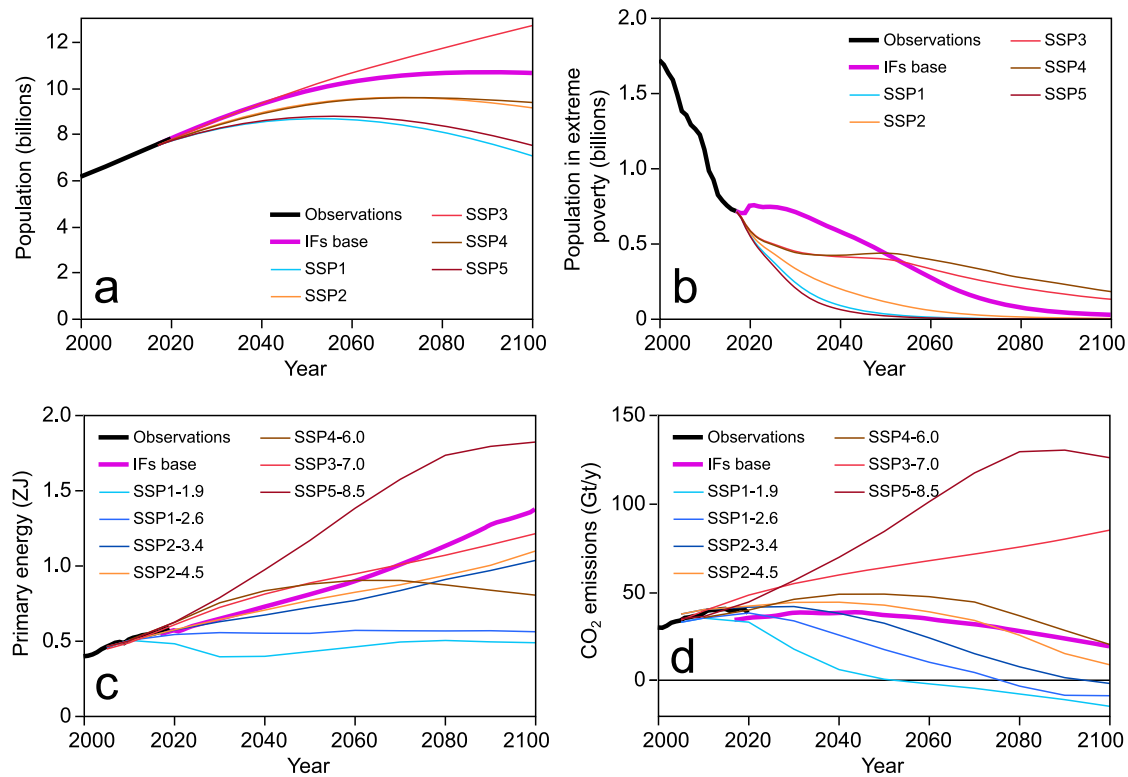


Fig. 4 Population, extreme poverty, energy demand, and CO₂ emissions. Comparison of the International Futures (IFs)^{28,29} base scenario and Shared Socioeconomic Pathway (SSP)^{6,55} scenario projections of: **a** population, **b** extreme poverty, **c** primary energy, and **d** CO₂ emissions. Extreme poverty is defined in the IFs model as living on <\$1.90 per day (in 2011 USD PPP). SSP projections of population and poverty in **a**, **b** are generated from the IFs model. SSP marker scenario projections of primary energy and emissions in **c**, **d** come from the 2018 SSP database⁵⁵. Observations come from refs. ^{67,77,79,82,83}.

slow-growth scenario¹⁵. In contrast, SSP4 is modal compared to our projections, which would have over-projected economic growth and income convergence historically. This suggests that SSP4 might actually be a more realistic best-case scenario for growth and convergence.

Indeed, the past 15 years of economic growth have followed a slower trajectory than any of the SSPs envisioned⁹. In contrast, high-growth, high-convergence SSP scenarios would require both substantial and immediate upward deviations from the historical relationship between GDP per capita growth and GDP per capita (Figs. 1c, 3a).

Long-run economic growth is subject to deep uncertainty—as the recent pandemic vividly illustrates—and it is, of course, theoretically possible for future development trajectories to have faster growth than past trajectories. For instance, low- and middle-income regions might shift more slowly to services if they retain comparative advantage in manufacturing; and unforeseen technological breakthroughs such as in artificial intelligence (AI) or nuclear fusion (or unforeseen transformative uses of existing breakthroughs⁴⁵) could sharply increase productivity growth. Nonetheless, such developments would need to be substantial enough to sizably deviate from long-standing historical trends that already include the impacts of numerous, major historical technological breakthroughs⁴³ (Fig. 1a).

Other recent empirical studies also add weight to the possibility of a slower growth, slower-convergence future than previously expected. These include studies suggesting linear—rather than exponential—total-factor-productivity growth⁶⁰, studies suggesting that dictatorships exaggerate their economic growth reports⁶¹, and studies finding relatively little income convergence over the past fifty years (reviewed by Johnson and Papageorgiou³³).

Our DEM and IFs GDP per capita projections are on the low end of the range of median projections of recent studies based on

expert elicitation²⁰, statistical forecasts^{21,22}, or a combination of these²³. These other approaches also produce much wider uncertainty ranges than the DEMs, which is not surprising, given that the DEMs are not designed to quantify deep structural uncertainties (and therefore the bootstrap distributions in Figs. 1b and 3 should not be interpreted as probabilities). Christensen et al.²⁰ surveyed experts and also projected a low-frequency statistical model (based on ref. ⁶²). The median 2100 world GDP per capita from their statistical and expert forecasts were slightly above and slightly below SSP2 (between SSP4 and SSP2; Supplementary Fig. 1), respectively. Startz²² used a Bayesian econometric model that estimates and projects growth rates in the global frontier and country-specific convergence states and rates. He projected higher 2100 world GDP per capita, similar to SSP5, driven especially by convergence of populous countries²². Müller et al.²¹ used a Bayesian latent factor model that estimates and projects a common global growth factor and jointly estimates and projects countries' convergence (or divergence) rates. They projected a median 21st-century world GDP per capita growth rate (2.04% per year) similar to Christensen et al.'s²⁰ median expert projection (2.03%), implying a world GDP per capita outlook between SSP4 and SSP2. Rennert et al.²³ combined an expert survey and a statistical forecast using Müller et al.'s²¹ method. They projected a median 21st-century world GDP per capita growth rate of ~1.5% per year (see their Fig. 1b), which implies an outlook similar to the DEMs, IFs, and SSP4. Drivers of the differences and similarities between these models' projections merit further study.

The second important implication of our results, which also merits further study, is that the consistency (in forecast) and accuracy (in hindcast) of our DEM projections suggest that simple empirically-based economic forecasting approaches may

have under-explored potential. Our DEM approach works because there is a strong dependency of GDP per capita's growth rate on its magnitude (Fig. 1a). There are many analogous patterns in nature (as noted by Smil⁶³). For example, animal population sizes often strongly influence their growth rates, with growth typically decreasing at high populations. Population models that can capture this relationship, such as the logistic model⁶⁴, can sometimes provide accurate population forecasts, even if they do not explicitly describe the processes causing population growth's dependency on population size. More generally, it is impossible to perfectly describe the processes of complex, chaotic systems, but empirically describing their attractors can yield powerful forecasting methods⁶⁵.

Simple approaches may be especially useful for forecasting economic growth at large spatial scales (groups of countries) and time scales, reducing effects of noise and idiosyncrasies. However, our DEM approach should be used cautiously at smaller scales. Our approach's simplicity should make it accessible to researchers across wide-ranging disciplines who make economic growth-dependent projections, such as Tilman and colleagues' projections of food demand^{35–37}. Our results also underscore the need for improved economic forecasting approaches for low-income regions. Our approaches were not able to overcome the challenges that have led to a positive bias in economic forecasts in these regions^{39,66}.

Our IFs projections suggest that a slow-growth, slow-convergence economic pathway would be associated with relatively high poverty and population growth, and moderate energy demands and CO₂ emissions (Fig. 4). These projections are consistent with other research using different methodologies^{27,57–59}. A slow-growth world could also be a world with comparatively less innovation—including in clean energy and carbon removal—and less capacity to adapt to climate change and other challenges². Despite these potential challenges, we note that the world envisioned by the IFs base model and DEMs is nonetheless substantially richer than the world today—with many regions reaching affluence greater than today's affluence in high-income regions, and with lower-income regions having the most rapid increases in affluence (Fig. 3a, Supplementary Fig. 9).

Methods

Differential-equation model (DEM). We fit a quadratic logarithmic function^{3,35} to the empirically observed relationship between GDP per capita [denoted $G(t)$ at time t] and the GDP per capita growth rate (denoted $\dot{G}(t)$ at time t):

$$\dot{G}(t) = a + b \ln[G(t)] + c [\ln[G(t)]]^2 \quad (1)$$

We estimate the parameters a , b , and c using least squares. The curve in Fig. 1a (solid purple) is fit to 1960–2020 data^{25,31,67} at the level of World Bank income groups³⁰. We convert to 2005 USD PPP (to be consistent with SSP and IPCC units) using World Bank conversions²⁵. Tilman et al.³⁵ fit the same model to 1961–2009 data from seven income groupings from 95 large countries and aggregates (Supplementary Table 1). In Supplementary Fig. 5, we fit the model to 1960–2020 data from these same groupings, and show that these produce very similar fits as in Fig. 1a. We measure $\dot{G}(t)$ as:

$$\dot{G}(t) = 100[\ln[G(t)] - \ln[G(t-1)]] \quad (2)$$

The asymptotic DEM (dashed purple in Fig. 1a) involves fitting the following equation, instead of Eq. (1):

$$\dot{G}(t) = [1/G(t)](a + b \ln[G(t)] + c [\ln[G(t)]]^2) \quad (3)$$

To project the DEMs forward, we set $\dot{G}(t) = 100dG/Gdt$, which makes Eqs. (1) and (3) differential equations that can be solved numerically, using observed 2020 GDP per capita of World Bank income groups as initial conditions (these projections are insensitive to the starting year, even despite the COVID-19 pandemic; see Supplementary Fig. 3).

However, when projecting forward using the DEMs, we must also account for variance and heteroskedasticity, because increasing variance in a random exponential growth rate increases the mean growth (see Garnett and Anderson⁶⁸, who noted the importance of this issue to the dynamics of sexually transmitted diseases). Specifically, if the GDP per capita growth rate in a particular year is $r(t) = 0.01\dot{G}(t) = dG(t)/G(t)dt$ is a normally distributed random variable, then $G(t+1) = G(t)e^{r(t)}$ is lognormally distributed. The expected value of $e^{r(t)}$ where

$r(t) \sim \mathcal{N}[\mu(t), \sigma(t)]$ is $e^{[\mu(t) + \frac{\sigma^2(t)}{2}]}$. Therefore, to correct for variance we need only to add $\sigma^2(t)/2$ to each projection of $r(t)$. To do this, we must estimate the variance in GDP per capita growth, $\sigma^2(t)$, and allow it to be a function of GDP per capita ($\sigma(G)$) to account for heteroskedasticity.

To estimate $\sigma(G)$, we use a weighting function common to Empirical Dynamic Modeling (EDM)^{69,70}. This works as follows: For a given observation G_i , we calculate the difference between it and every other observation G_j . These distances d_i are converted to weights by the equation $w_i = e^{-\theta_i d_i/d}$. This nonlinearly gives more weight to more similar observations. The degree of nonlinearity is determined by θ_i , where larger values increasingly put more of the weight on more similar observations. Note that $\theta_i = 0$ for all i produces an unweighted estimate. EDM usually treats θ_i as constant across observations, but here we use a unique θ_i for each observation to better handle non-normally distributed growth distributions. We define θ_i as the value that maximizes $\text{Var}(w_i)$. This maximizes the resolution of the weighting distribution by ensuring the data are maximally distinguished. Then, with these weights, we calculate a weighted standard deviation according to the well-known equation:

$$\theta_i(G_i) = \sqrt{(\sum_{j=1}^N w_j(x_j - \bar{x}_w)^2) / (\sum_{j=1}^N w_j - 1)} \quad (4)$$

Here, \bar{x}_w is the weighted mean of the observations x . We calculate the weighted variance using the Hmisc R package⁷¹.

In the process of projecting growth, we have to estimate $\theta(G_i)$ for values of G not actually observed. We estimate these using a spline created with each observation serving as a knot. For values of G greater than the maximum observed we use the estimated $\theta(G_{\max})$ rather than attempting to estimate out of sample.

In Supplementary Figs. 5 and 6, we bootstrap the asymptotic and non-asymptotic DEMs in the following way. We sample with replacement from each World Bank³⁰ income group one at a time the number of observations in each group. Then we fit the simple and asymptotic DEMs to the resulting combined bootstrapped groups, creating a single bootstrap replicate. We repeat this procedure 1000 times producing 1000 equations per model (i.e., for each of the asymptotic and simple DEMs). From this, we calculate the 5th and 95th percentile projections of GDP per capita growth rate (relative to GDP per capita) in Supplementary Fig. 5, and GDP per capita (relative to year) in Supplementary Fig. 6. In Supplementary Fig. 5, we repeat this procedure using Tilman et al.'s³⁵ economic groupings (Supplementary Table 1) instead of the World Bank income groups³⁰ (Supplementary Table 2). The fits and bootstrap ranges are nearly identical.

DEM comparison to IMF projections. Burgess et al.³⁹ compile IMF projections of population and GDP per capita at the country level from 2003 to 2019 (ranging from one year ahead to five years ahead, depending on the projection year; IMF projections are too sparse at the country level before 2003 to be useful for this exercise³⁹). We aggregate these projections to the level of World Bank income groups by calculating IMF's projected growth rates in GDP and population (in continuous units), and calculating their projected GDP per capita growth rate as the difference of these (Burgess et al.³⁹ use a similar procedure to calculate IMF projections of GDP per capita growth in IPCC regions).

To generate hypothetical DEM projections for comparison (Fig. 2, Supplementary Fig. 7), we fit the DEM from Eq. (1), using data from 1960 to the hypothetical starting projection year (2003, 2004, ..., 2020), and then project it forward (with the variance correction described above). We also repeat this exercise stopping each year all the way back to 1980 (Fig. 2, Supplementary Figs. 3, 4, 8), to illustrate how consistent the GDP per capita vs. GDP per capita growth pattern has been in recent decades.

International Futures (IFs) model. We describe the IFs economic model in detail in Supplementary Methods. IFs is a dynamic, recursive system with annual time-steps from its base year of 2015 through horizons as distant as 2100, thereby including 2030 (and 2050) for the UN Sustainable Development Goals (SDGs)^{28,29}. It is hybrid in structure, including conscious use of stock-and-flow and equilibrating feedback representations across time common in systems dynamics models. Yet, the system is strongly data-based (>5500 series integrated with it) and theoretically founded. It draws upon standard issue-based approaches for most component models, including demographics (cohort-component structure augmented by endogenous fertility and mortality representations), economics (general equilibrium structure), and energy and agriculture (partial-equilibrium systems linked into the general equilibrium economic model). Collectively, the models of the IFs system project more than 700 variables of which more than 100 represent goals and targets of the SDGs.

At the core of the International Futures (IFs) system's economic representation is a global, annually recursive dynamic general equilibrium model, integrated extensively with all other models of IFs. IFs combines country-specific and globally linked social accounting matrices (SAM) with structures that generate their dynamics. Three important features differentiate IFs from most other models with these characteristics. First, the representation in IFs of economic growth is responsive to an unusually extensive set of productivity drivers, as well as to capital and labor. Second, the social accounting system of IFs has an especially extensive

representation of government revenues and expenditures. Third, IFs elaborates general equilibrium treatment of the economy with extended partial-equilibrium representations of agriculture and energy, with representation of the informal economy, and with elaborated formulations of income inequality and poverty. See ref. 29 for a full description of the economic assumptions of IFs.

As with observations, we convert GDP per capita output from IFs to 2005 USD PPP using World Bank conversions²⁵.

IFs projections in Fig. 4. Population projections in IFs^{28,29} are made using an age-sex cohort-component model with endogenous relationships with both fertility and mortality initialized using UN Population Division (UNPD) data measuring population by age and sex (Section 5.1.4 in ref. 28). Fertility rates are driven by GDP per capita (at PPP), contraception access, infant mortality, and educational attainment (Section 3.2 in ref. 72). The mortality model relies upon both distal and proximate drivers of 21 causes of mortality by age and sex^{73,74}.

Poverty in IFs rely upon (a) economic production/consumption models; (b) resource distribution; and (c) demographic dynamics^{53,75,76}. Economic production is driven by a dynamic-recursive computable general equilibrium model with Cobb-Douglas production function and Solow residual (Section 6.1 in ref. 28). The model assumes a log-normal income distribution and uses a measure of Gini-coefficient for income inequality to drive changes in distribution across time. Poverty values are initialized from PovCalNet at the World Bank⁷⁷.

Carbon emissions are computed annually in IFs driven by fossil fuel production of oil, gas, and coal (Section 7.4 in ref. 28; ref. 78). Carbon emission dynamics are driven by logic in the IFs partial-equilibrium energy module which represents the investment for energy production, which changes as technology develops and fossil fuel resources are used (section 7.2.4 in ref. 28, and Section 3.1 in ref. 79). IFs represents distinct levels of carbon content for different fuel types that are global (Section 7.5.4 in ref. 28).

The energy model in IFs is partial-equilibrium and represents the production of energy (oil, gas, coal, hydro, nuclear, and other renewable sources) driven by the logic that is connected to overall resources and accessible resources that connect to patterns of demand, driven by both energy dynamics and broader economic factors (Section 7.2 in ref. 28). Energy demand responds to changes in energy efficiency per unit of GDP and a moving average on overall energy prices (Section 7.2.4 in ref. 28; section 3.1 in ref. 79). As countries improve their development (as measured by GDP per capita at PPP), their energy intensity converges downward. Energy price in IFs is global and includes all energy types and is responsive to changing patterns of demand and inventories (which are responsive to changes in investment).

Data availability

All data used in this study, besides those used by the IFs model, are publicly available in our Zenodo repository⁸⁰. The IFs model, and all data used therein, are publicly available from the Josef Korbel School of International Studies at the University of Denver⁸¹.

Code availability

All code used in this study, besides the IFs model, is publicly available in our Zenodo repository⁸⁰. The IFs model is publicly available from the Josef Korbel School of International Studies at the University of Denver⁸¹. Assistance with code is available on request from the corresponding authors.

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Author contributions

M.G.B.: conceptualization, project administration, resources, data collection, coding, data analysis, visualization, writing—original draft, writing—review, and editing. R.E.L.: conceptualization, coding, data analysis, visualization, writing—original draft, writing—review and editing. J.D.M.: conceptualization, coding, data analysis, writing—original draft, writing—review and editing. A.D.: conceptualization, writing—original draft, writing—review and editing. B.B.H.: conceptualization, coding, data analysis, writing—original draft. D.T.: conceptualization, writing—review, and editing.

Competing interests

The authors declare no competing interests.

Additional information

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