# Rethinking S-curves for policy-driven energy technologies



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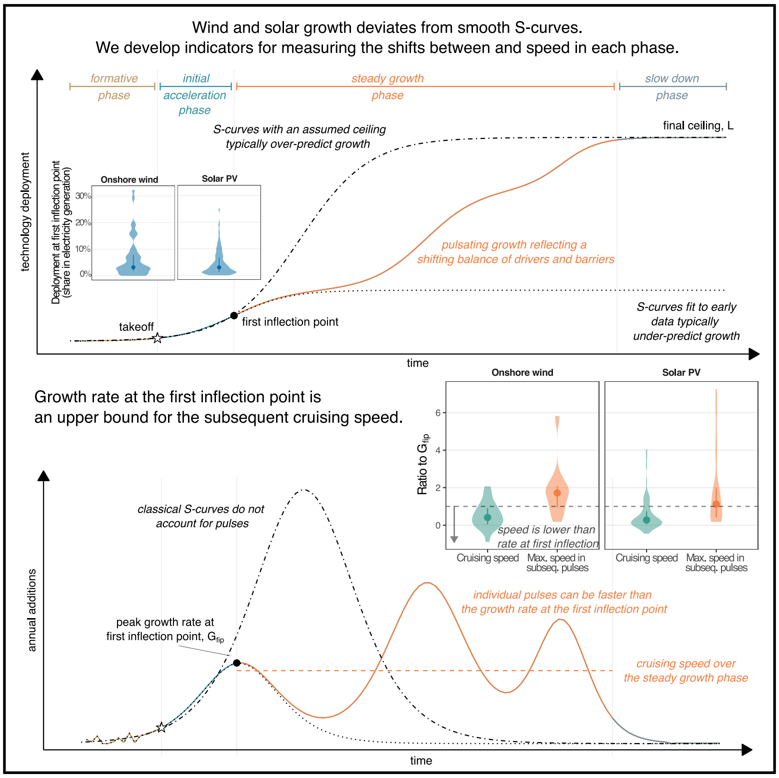
## Graphical abstract




## Highlights

- Existing metrics and models fail to predict growth of wind and solar power
- We develop diagnostics and metrics for takeoff, inflection points, and cruising speed
- Initial acceleration ends at only ∼3% of national electricity generation
- Post-inflection growth pulsates around a cruising speed slower than the first peak

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## In brief

The adoption of new technologies typically follows an S-curve of acceleration followed by a slowdown, but wind and solar in most countries deviate from this pattern. After a formative phase of erratic growth, renewables undergo initial acceleration that peaks at low market penetration. Growth then alternates between pulses of slower and faster expansion, with average rates below the first peak. Growth rates in front-runner countries therefore provide a benchmark for the likely speed of future global deployment.

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# Rethinking S-curves for policy-driven energy technologies

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**CONTEXT & SCALE** Understanding how fast wind and solar power can expand is central to global climate scenarios and national energy planning. Debates about how fast these technologies can grow are often framed around a false binary: either they will continue accelerating or they are already losing momentum. Both views assume that renewables follow an S-curve with near-exponential expansion followed by a slowdown. Here, we show that this framing is too simple. Instead, wind and solar follow a sequence of distinct phases: (1) a formative phase of uncertain, slow growth; (2) takeoff followed by a brief initial acceleration; and (3) prolonged steady growth punctuated by pulses of faster and slower expansion. To measure these dynamics, we introduce model-agnostic diagnostics for detecting takeoff, inflection points, pulses, and measuring cruising speeds. Through hindcasting, we show that our metrics outperform year-on-year growth rates or fitted S-curve parameters.

We find that in contrast to classic S-curve expectations, initial acceleration typically ends when wind or solar reach only ~3% of national electricity generation but growth does not slow thereafter. Instead, it proceeds at an average cruising speed somewhat below the first peak (~0.7 percentage points [p.p.] year$^{-1}$, interquartile range [IQR]: 0.4–1.5 for wind and 0.3–1.9 for solar), with pulses of acceleration and deceleration. These patterns emerge consistently across countries and appear typical of policy-driven technologies, where growth is shaped not only by technological learning and market dynamics but also by evolving policy support. We further demonstrate that peak national growth rates set a ceiling on the speed of global expansion since later adopters do not systematically grow faster than front-runners. By identifying recurring growth patterns across technologies and countries, this work provides an empirical foundation for near- to medium-term renewable energy projections and may inform the upscaling of other policy-dependent technologies.

## SUMMARY

Debates about the future of wind and solar power are often framed around a false binary: either these technologies will continue accelerating or they are already losing momentum. Both views assume that renewables follow an S-curve with near-exponential expansion followed by slowdown. Using national deployment data, we show that renewables' growth departs from ideal S-curves. Instead, it proceeds through a formative phase of erratic growth, followed by takeoff and brief acceleration that ends at low levels of market penetration (≈3% of electricity generation). Renewables then enter a prolonged steady growth phase punctuated by pulses of acceleration and deceleration, with an overall cruising speed that is slower than the first growth peak (≈0.7 percentage points [p.p.] year$^{-1}$; interquartile range [IQR]: 0.4–1.5 for wind and 0.3–1.9 for solar). We develop diagnostic tools and metrics for these phases. Hindcasting shows that these outperform year-on-year trends and fitted S-curve parameters. Peak growth in front-runner countries provides a reliable upper bound for global expansion.

## INTRODUCTION

Rapid growth of renewables, especially solar photovoltaic (PV), regularly makes headlines, yet the pace still remains too slow to meet climate goals and government targets.[1,2] Achieving the COP28 Global Pledge to triple renewable capacity by 2030 would require annually adding well over twice the record capacity installed in 2024 (≈1,180 GW), and nearly four times the generation.[3] Over the longer term, the International Energy Agency (IEA) Net-Zero scenario requires increasing the share of wind and solar in global electricity by roughly 54 percentage points (p.p.) between 2025 and 2040 (≈3.4 p.p. year$^{-1}$) versus the 1.6 p.p. added in 2024.[2]

Optimism that such acceleration is feasible often draws on the canonical S-curve of technology diffusion,[4–8] where new technologies initially experience a period of quasi-exponential growth driven by cost reductions, technological improvements, and increasing acceptance[9,10] before eventually slowing as they approach market limits. The recent 20%–30% annual growth rates of renewables seem consistent with this quasi-exponential stage, reinforcing expectations that such growth will continue. This looks especially plausible since they appear to be relatively early in their growth trajectories, with current market shares still far below their potential to supply most of global electricity.[11,12]

However, empirical evidence does not fully align with these expectations. In many countries, wind and solar no longer show consistently accelerating growth,[13] and global year-on-year growth rates are declining. Scholars interpret these patterns differently. Some view declining growth rates as evidence that deployment has already reached the "inflection point" of the S-curve, signaling imminent slowdown and saturation.[14,15] Others dismiss such slowdowns as temporary fluctuations irrelevant to underlying quasi-exponential growth trends.[16–18] A third position argues that while global growth need not slow down, solar and wind deployment rates are unlikely to exceed the peak values already observed in front-runner countries.[13] So far, this debate has focused on statistically interpreting data to infer "where renewables sit on their S-curves," i.e., whether the inflection point is distant, imminent, or has already passed.[14,18]

We advance this debate beyond statistical analysis by questioning the central assumption that single inflection S-curves adequately represent renewable energy diffusion. Although S-curve theory successfully explained the growth of historical technologies,[4–8] its usefulness for projecting future growth has been extensively questioned.[13,19,20] These limitations become more acute for wind and solar, which unlike most historical technologies have a strong dependence on policy support and may thus follow trajectories that substantially deviate from ideal S-curves. Given these divergent empirical signals, contrasting interpretations, limitations of classic models, and the specificity of policy-driven technologies, how can the growth of renewables be explained and anticipated?

We address this challenge by developing a model-agnostic approach that does not rely on assumptions about the shape of deployment trajectories or eventual saturation levels. Building on conceptual work on the four phases of technological transitions,[13,21,22] we apply new methods to identify and characterize the three distinct phases of wind and solar growth where the bulk of a technology's expansion occurs. We validate our methods using hindcasting for solar and wind as well as a set of four technologies whose deployment curves are more complete.

We show that in most countries, renewables move from their formative phase, characterized by erratic growth, to takeoff once they reach roughly 1% of electricity generation. Takeoff is followed by a few years of consistently accelerating growth that reaches peak speed when renewables achieve market shares around 3% of electricity generation—much earlier than standard S-curve expectations would suggest. Thereafter, growth does not enter the monotonic slowdown characteristic of an ideal S-curve but instead settles into a cruising speed somewhat slower than the peak speed (≈0.7 p.p. year$^{-1}$, interquartile range [IQR]: 0.4–1.5 for wind and 0.3–1.9 for solar), punctuated by pulses of acceleration and deceleration.

Growth metrics derived from standard S-curve models such as year-on-year growth rates,[16–18,23,24] "duration of transition,"[6,8,25–28] and the inflection point timing[14,15,29] prove unreliable for such trajectories. Instead, we demonstrate the salience of the growth rate at the first inflection point (FIP) and the subsequent average rate of annual additions (cruising speed). We further show how cruising speeds in front-runner countries constrain global expansion, challenging expectations of prolonged exponential growth. Taken together, these findings provide a transparent, empirically grounded basis for assessing the future growth of renewables and potentially for other policy-driven energy technologies, and our analytical approach provides the foundation for formally testing what drives the pulsating growth pattern.

## RESULTS

### Phases and patterns of growth

Growth of new technologies is driven and constrained by many different mechanisms,[22,30,31] such as technological innovation, availability of land with suitable geophysical conditions, raw materials and manufacturing capacity, cost and market dynamics, integration with existing infrastructure, and social acceptance. In contrast to most historical technologies that were primarily driven by their cost advantage,[32] wind and solar power have also depended on government policies such as subsidies and electricity market regulations.[33–39] These policies in turn depend on political and institutional factors. Techno-economic, sociotechnical, and political mechanisms shift in importance as technologies scale from pilot and niche applications to deployment on national and global scales. As the balance of these mechanisms shifts, technology diffusion goes through distinct phases of growth[13,21,22,36] (Figure 1).

In the first, formative phase, deployment remains small and limited to protected niches. Growth is erratic and shaped by experimentation, radical innovation, frequent failures, high costs, and uncertainty.[40–43] The formative phase ends at takeoff, after which growth becomes more consistent. Takeoff has been documented both globally[42,43] and nationally,[13,44,45] and scholars have suggested various thresholds at which it occurs (absolute deployment,[45,46] share of the eventual market,[4,42,43] share of electricity generation[13]). Using the formative phase Bayesian point change indicator (FOBI),[47] we diagnose takeoff

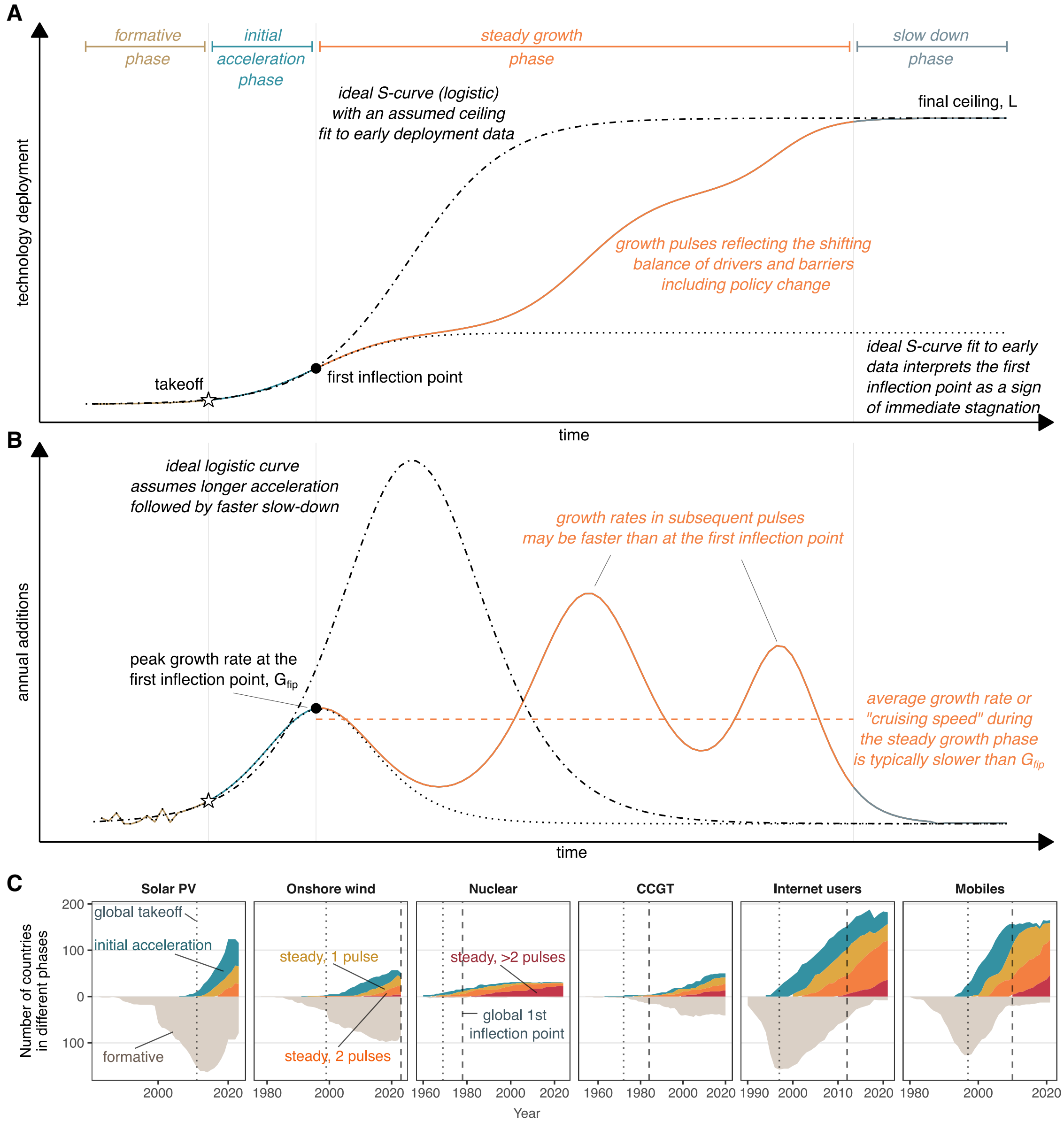


**Figure 1. Ideal S-curves and the four phases of growth of policy-driven technologies**

(A) A technology growth trajectory; (B) annual additions along the same trajectory; (C) number of countries in different phases of growth. Unlike ideal S-curves such as the logistic function, policy-driven technologies experience an erratic formative phase; a relatively brief initial acceleration after takeoff; prolonged steady growth, which may include distinct growth pulses; and eventual slowdown (B). Over time, an increasing number of countries progress through these phases (C).

as the moment when erratic early growth begins to consistently accelerate. We show that nationally, solar and onshore wind typically take off at electricity generation shares of around 0.7%–0.8% (Table S1) and globally at around 0.15%, with higher thresholds in smaller countries (Figure S1).

After takeoff, growth enters initial acceleration, as manufacturing economies of scale, technology and institutional learning, network effects, and positive feedbacks between policy and politics reinforce one another.[44,48,49] Eventually, this expansion encounters countervailing forces from grid integration constraints, resource and land competition, manufacturing and supply bottlenecks, permitting delays, and mounting social and political resistance often leading to reduced policy support.[22,35,50] As a result, acceleration slows and eventually ends at the FIP, when the growth speed reaches its first peak. Classic S-curve theory suggests that the inflection point is followed by monotonic deceleration. However, we find that after the FIP, growth in most countries slows down only temporarily, subsequently experiencing secondary growth pulses (Figure 2A). We introduce a model-agnostic method for detecting the FIP and subsequent pulses: the deceleration and acceleration dynamics for inflection point and pulse detection (DAIP). DAIP identifies the

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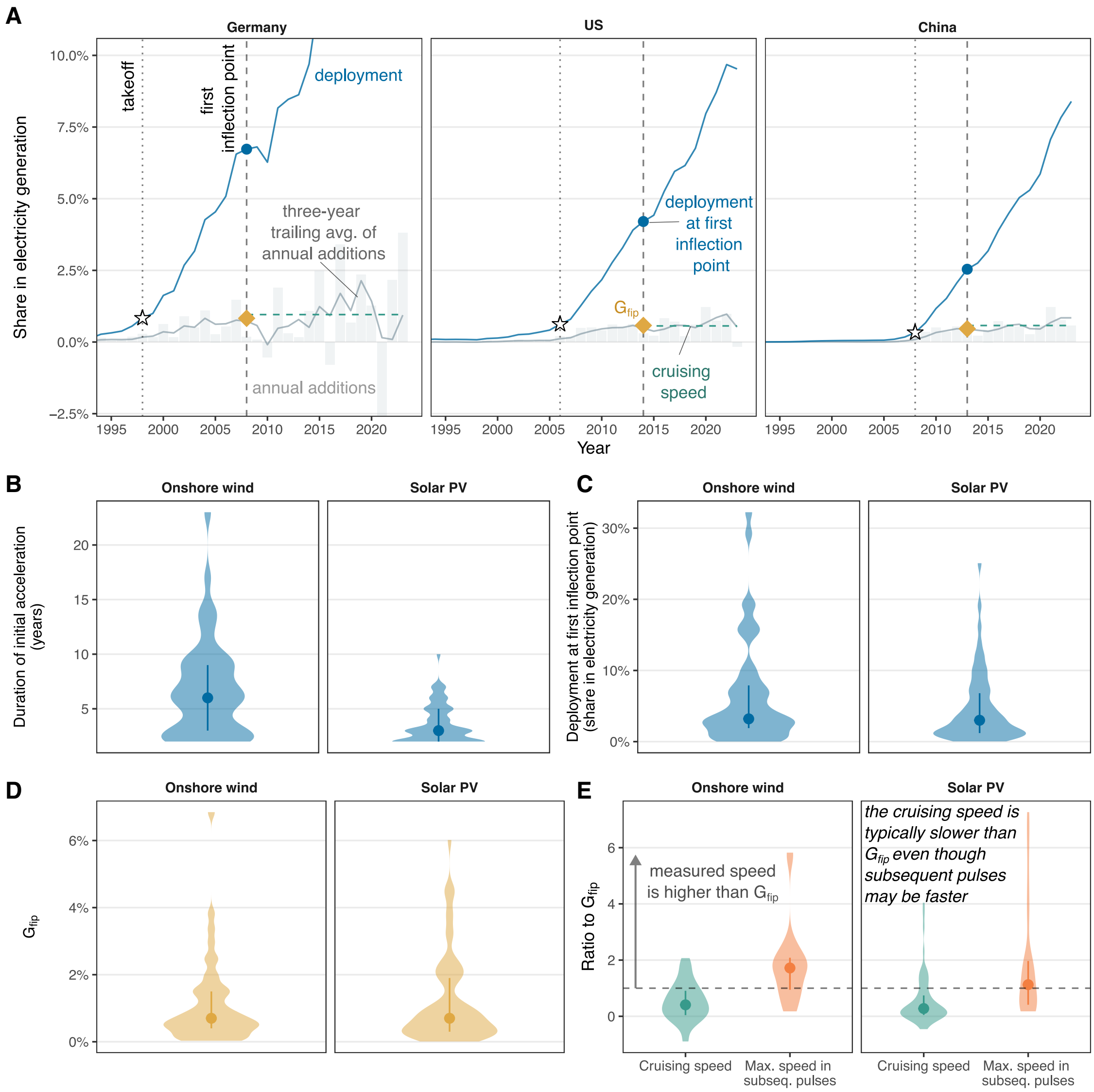


**Figure 2. Metrics and parameters of technology growth in the steady growth phase**

(A) Empirical deployment trajectories (blue lines) and annual additions (gray bars, 3-year trailing average as gray line) for onshore wind in three illustrative countries, with three key DAIP outputs marked: the FIP; the maximum growth rate at the FIP ($G_{fip}$, yellow dot); and the cruising speed, the average annual growth rate after the FIP (green dashed line).

(B) Distribution of initial acceleration phase durations across countries.

(C) Distribution of deployment levels at the FIP across countries.

(D) Distribution of $G_{fip}$ across countries.

(E) Cruising speed (green) and the maximum speed in subsequent pulses (orange) expressed as a ratio to $G_{fip}$. Violins show the cross-country distribution; dots and lines indicate medians and IQRs, respectively (B–E).

FIP when the first discrete derivative of 3-year trailing averages for annual additions becomes negative for $\geq$ 2 years; subsequent pulses are detected when growth re-accelerates and this derivative becomes positive again (methods).

We find that the FIP occurs about 6 years after takeoff for onshore wind (IQR 3–9 years) and 3 years after takeoff for solar (IQR: 2–5 years) (Figure 2B; Table S1). At this point, both technologies have reached around 3% of electricity (IQR: 2%–8% for wind and 1%–7% for solar), and their annual growth rates peak at ≈0.7 p.p.year$^{-1}$ (IQR: 0.4–1.5 for wind and 0.3–1.9 for solar). Both the market penetration levels and the peak annual growth rates at the FIP decline with country size (Figures S2 and S3). Remarkably, initial acceleration ends at deployment levels far below those predicted by a standard logistic growth model, which reaches peak growth at $\frac{1}{2}$ of its eventual ceiling (i.e., at 15%–25% of electricity generation assuming a long-term ceiling of 30%–50% for wind or solar). By comparison, the FIPs for mobile telephones and internet use occur at a median of 79% and

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38% of per-capita penetration, respectively (Table S1). The much earlier inflection observed for wind and solar supports the hypothesis that policy dynamics cannot sustain the initial acceleration of these technologies beyond relatively low deployment levels, almost an order of magnitude below those observed in market-driven technologies (Figure 2C; Table S1). We also find that peak growth rates during secondary pulses sometimes exceed those at the FIP (Figure 2D). However, these pulses are separated by periods of slower growth and occur primarily in countries with slower initial peak growth levels (Figure S4). As a result, the average post-FIP growth rate—which we refer to as the cruising speed—remains below the growth rate at the FIP ($G_{fip}$) in most countries (Figures 2C and S5). At the same time, the average deceleration after the FIP is slower for wind and solar than for other technologies, which tend to experience more pronounced slowdowns after the FIP (Figure S6). These findings are robust to a reasonable variation in DAIP's smoothing window and persistence criterion, although the number of pulses we detect tends to be more sensitive than the distributions of cruising speeds or $G_{\text{fip}}$ and the relationships between them (methods; Table S2; Note S3). Taken together, these observations support the existence of a steady growth phase for policy-driven technologies, characterized by oscillations around the cruising speed rather than monotonic acceleration or deceleration.[13,22,47,51]

## Measuring and modeling growth

Having identified these patterns, we now assess whether existing metrics and models can reliably capture them. We begin by reviewing established approaches, including recent efforts to extrapolate logistic and other S-curve models, as well as tools for diagnosing growth phases and estimating cruising speeds.

A widely used metric is the year-on-year growth rate derived from historical time series of solar and wind deployment.[9,17,18] This measure is intuitive and facilitates straightforward comparisons across technologies and countries. It captures the effects of "increasing returns" and other positive feedback mechanisms that drive accelerating growth in the early stages of technology deployment. Mathematically, the year-on-year growth rate remains nearly constant early in an S-curve described by the logistic function (Figure 3). This expectation is seemingly confirmed by near-linear trends on semi-logarithmic plots of deployment over time (Figure 3B).

Yet under closer examination, this metric proves far from robust. Mathematically, stable year-on-year growth rates can only be expected if deployment follows an ideal logistic curve and remains far from the inflection point—neither of which is necessarily true. Under other functional forms (e.g., the Gompertz model[58]), which often fit historical deployment time series at least as well as the logistic,[13,20,59] the year-on-year growth rate steadily declines rather than staying constant (Figure 3C). The metric also conflates the effects of fundamentally different processes: radical innovations in the formative phase, increasing returns during initial acceleration, and shifts in the balance of barriers and drivers during steady growth.

On a log scale, the eye is drawn to early years where small absolute deployments grow rapidly, while the systematic deceleration at higher deployment levels is rendered nearly invisible (Figure 3). In reality, technologies show rapid and erratic growth in their formative phase, followed by accelerating absolute deployment after takeoff, even as year-on-year rates steadily decline, before eventually entering a steady growth phase (Figure 3). Treating this entire trajectory as a single exponential process obscures these shifts and leads to large forecasting errors for all technologies, but especially for wind and solar where initial acceleration ends at relatively low deployment levels (Figure S6). The departure from a purely expential trend is highly statistically significant across all six technologies ($p < 10^{-8}$ in all cases; Table S3).

Scholars have dealt with the variability of year-on-year growth rates by measuring growth over specific periods or phases of the technology life cycle.[26,28,60,61] One approach has been to measure the average year-on-year growth rate, $R_a$, over the time it takes for a technology to grow from 10% to 90% of its final ceiling—the period when most growth occurs—excluding both the erratic initial growth in the formative phase and the slow growth near saturation.[28] This rate is directly derived from another widely used metric, the "duration of transition" or $\Delta t$,[26,62] which measures the time (in years) it takes for a technology to grow from 10% to 90% of the eventual ceiling: $R_a = 219.7/\Delta t$. $\Delta t$ has the advantage of being comparable across technologies, making it possible to use historical technologies as "reference cases"[21,63] even before long enough time series were available for renewables themselves.[26,28,64,65] Iyer et al.[28] used this metric to classify technologies into fast-growing ($R_a > 15\%$, $\Delta t < 15$ years) and slow-growing ($R_a < 5\%$, $\Delta t > 40$ years). Other scholars proposed dividing the S-curve into phases or segments rather than characterizing the entire trajectory with one metric, distinguishing an earlier period of faster growth from a later period of slower growth.[60,61]

Baumgärtner et al.[18] criticized these methods for "selection bias," for relying on small samples of technologies and thus underestimating feasible rates of wind and solar growth. However, this criticism overlooks the specific phases these studies focused on. When phases are properly accounted for, this literature provides largely correct—albeit occasionally too broad—estimates for the speed of renewables growth, with some forecasts that have proven accurate over horizons of up to 15 years (Note S1). However, these methods do suffer from a critical limitation that is conceptual rather than statistical in nature. Their application depends on diagnosing the position of renewables on the S-curve, which is not possible with available data.[19,20,59] Furthermore, even if the range of growth rates derived from historical technologies is statistically valid, it remains too wide for accurate projections because even small differences in estimated year-on-year growth rates quickly compound to large differences in deployment levels.

In response to these limitations and as renewable deployment has increased, scholars have shifted their focus to analyzing actual time series of wind and solar deployment rather than historical analogs, searching for reliable metrics and methods of extrapolation. They typically used the same logistic model previously applied to historical technologies[14,15,23,66] (methods). However, while historical analyses dealt with nearly completed S-curves, applying the same method to early phases of deployment has proved challenging, if not impossible. Although slightly

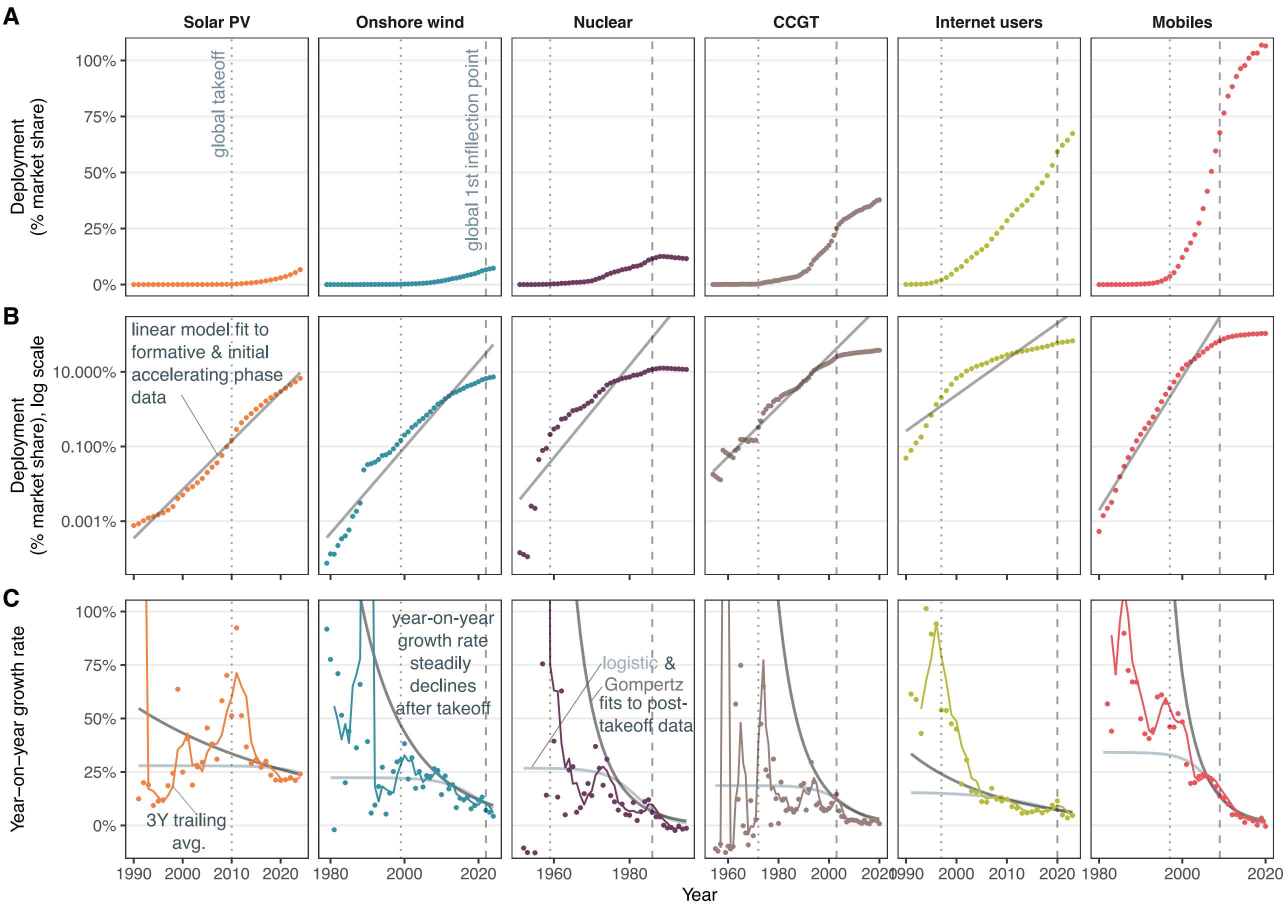


**Figure 3. Empirical evolution of year-on-year growth rates**

Global deployment of solar PV, onshore wind,[52,53] and nuclear power[53,54] measured as percentage share in electricity generation; CCGTs[55] measured as percentage share in installed gas power plant capacity; and internet users[56] and mobile phone subscriptions[57] measured per capita. Vertical dotted line shows year of global takeoff. Vertical dashed line shows year of global FIP.

(A) Cumulative deployment graphed on a linear scale.

(B) Same data but with a log-scaled vertical axis. Gray line shows a linear model fit to data up to the FIP.

(C) Year-on-year growth rates (dots) and their 3-year trailing average (solid lines). Gray lines show year-on-year rates for logistic (light) and Gompertz (dark) functions fit to the deployment time series. The seemingly straight lines (B) are dominated by data from tiny deployment levels (A) and conceal the declining trends in year-on-year rates (C). The departure from the exponential trend (B) is highly statistically significant ($p < 10^{-8}$ in all cases, Table S3).

more accurate than exponential models, extrapolating S-curves from existing data systematically underpredicts growth for wind, solar, and past technologies (Figure S7).

The problem is not only statistical and mathematical (documented for the logistic model since the 1980s[13,18–20,59]) but also conceptual; logistic functions collapse acceleration, steady growth, and slowdown into the same parameters, even though these phases are governed by different combinations of drivers and barriers. In reality, the rate of slowdown and the eventual asymptote of an S-curve cannot be estimated from observing the acceleration phase. The problem is aggravated by the prominence of the steady growth phase for policy-dependent wind and solar power. Fitting logistic curves may misread the start of the steady growth phase as a sign of imminent slowdown, yielding ceilings that are too low and transition durations that are too short. As new data come in, these parameters change (Figures 4A and 4B), demonstrating their lack of robustness.[18]

One approach to tackle these challenges has been to set the logistic ceiling exogenously using normative targets or scenarios[23,24] rather than estimating it from historical data. Although this method avoids unrealistically low ceilings, its hindcasting performance is almost as poor as that of exponential models and does not match the empirical reality of the steady growth phase and underlying growth pulses (Figures 4 and S7). As Figure 4 shows, fixed-L models may first underpredict early deployment and then project unrealistically fast growth. More sophisticated data-driven approaches,[69,70] including weighted ensembles of multiple growth functions, offer technical improvements but face the same deeper uncertainty, i.e., early-phase data provide no insight into later phases because the underlying dynamics change.

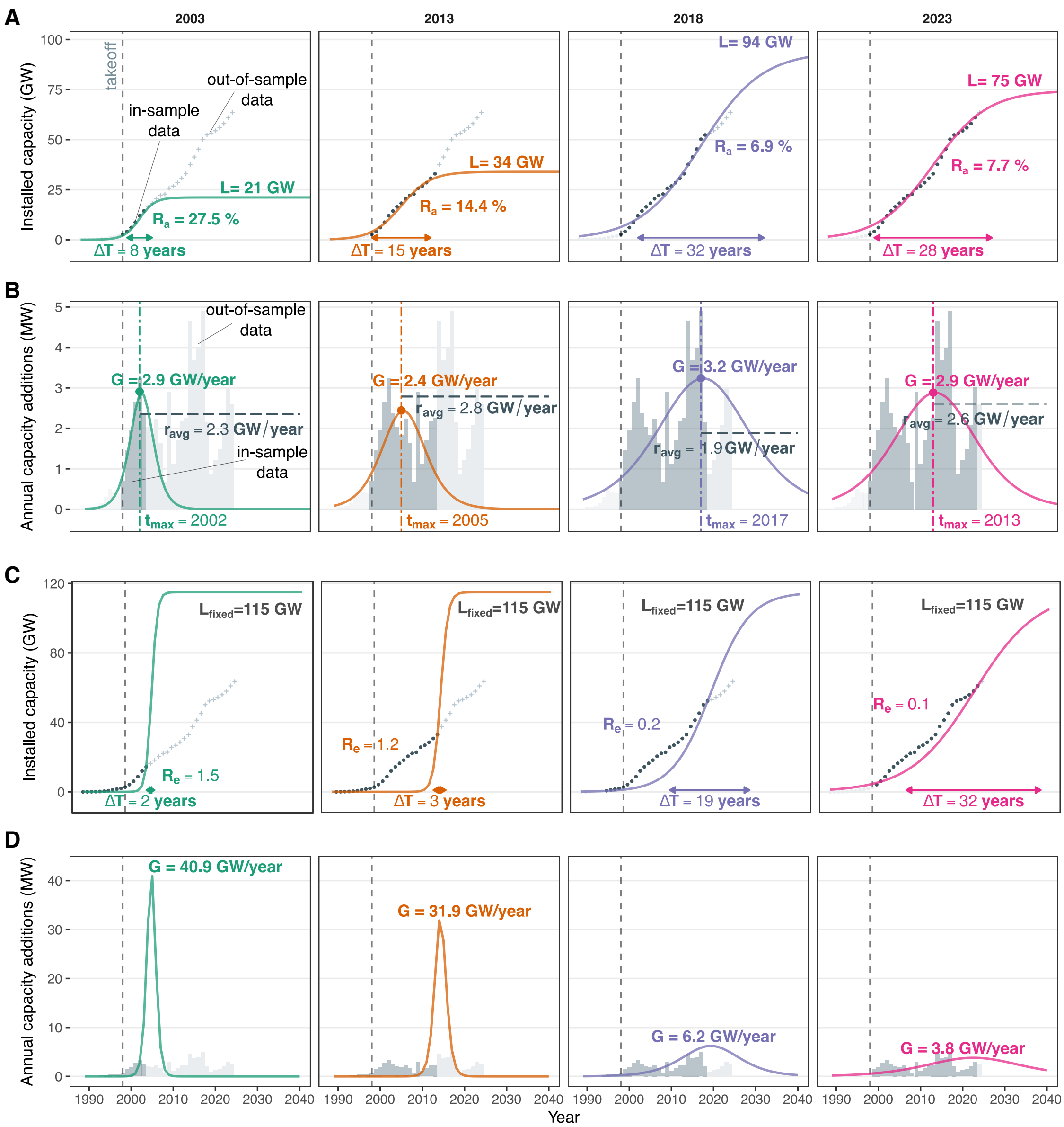


**Figure 4. The limitations of logistic models in projecting future growth at the steady growth phase with growth pulses**

Data on onshore wind capacity in Germany.[53] Dots (A and C) show cumulative deployment, and bars (B and D) show annual additions. Dark dots/bars show in-sample data, truncated at different years (2003, 2013, 2018, 2023) and used to parametrize the models. Faint dots/bars show out-of-sample data. Vertical dashed line marks the takeoff year (1999). (A and B) Solid lines show deployment and annual additions in logistic functions[67] fit to in-sample data[13] and extrapolated forward in time. $L$ refers to the estimated growth asymptote, $\Delta t$ to the duration of transition (the time it takes to grow from 10% to 90% of the estimated $L$),[68] and $R_a$ to the average annual growth rate during this period.[28] Vertical dot-dash line in (B) shows $T_{max}$ (the fitted curve's inflection point), $G$ is the maximum annual growth rate,[13] and $r_{avg}$ is the average annual additions after $T_{max}$.

(C and D) Solid lines show deployment and annual additions in logistic functions, with the asymptote $L$ exogenously fixed at Germany's current political target and the emergence rates ($R_e$) empirically estimated from the latest 25 years of in-sample data as in Grubb et al.[23] The logistic function based on empirical data has unstable $L$ and $\Delta T$ (A) but a relatively stable $G$ providing a ceiling for $r_{avg}$ (B). The logistic function with exogenous $L$ projects unrealistically fast growth based on early data (C and D).

Cherp et al.[13] proposed an approach to anticipate wind and solar growth without extrapolating trends from early to later phases. They fit logistic functions to post-takeoff data to identify inflection points and then calculated the maximum growth rate $G$ for countries past their inflection points as $G = kL/4 \approx 1.1L/\Delta t$, where $L$ is the asymptote, $k$ is the growth constant, and $\Delta t$ is the duration of the transition, all estimated from fitted functions. They showed that $G$ is less sensitive to data noise and to the choice of S-curve specification than other parameters (Figure 4) and documented the statistical range of $G$ for those countries where it could be estimated. The resulting metric was relatively consistent across countries with medians of 0.8 (IQR: 0.6–1.1) p.p. $year^{-1}$ for wind and 0.6 (IQR: 0.4–0.9) p.p. $year^{-1}$ for solar—much lower than global rates in 1.5°C- and 2°C-compatible Intergovernmental Panel on Climate Change (IPCC) scenarios. The aim of this estimate was not to project the future of renewables but to signal feasibility constraints for future global growth; Cherp et al.[13] proposed setting these constraints at the upper end of national $G$ values.[71,72]

Our model-agnostic estimates of growth at the FIP ($G_{fip}$) and the cruising speeds from the previous section strongly overlap with estimates of $G$ from this method (Table S1; Figure S8). This confirms the hypothesis that for policy-dependent technologies, the growth rate at the FIP is close to the subsequent cruising speed (Figures 2C and S9).

At the same time, the identification of the FIP in Cherp et al.[13] differs from our model-agnostic estimate in roughly one-quarter to one-third of cases (Figure S10; Note S2). Baumgärtner et al.[18] attribute this mismatch to statistical "overfitting." Although overfitting does play a role, the deeper issue is that single-inflection S-curves cannot capture the real-world dynamics of the steady growth phase punctuated by growth pulses. S-curve models sometimes fail to detect the FIP if it is followed by pulses. As Baumgärtner et al.[18] note, this can create the appearance that a technology drifts in and out of the accelerating growth phase, raising doubts about the robustness of the curve-fitting method. In fact, this pattern shows that single-inflection S-curves are ill-suited for detecting ongoing steady growth phases, even though $G$, where it can be estimated, is reliable. The model-agnostic approach we propose here is more robust; the FIP marks the onset of the steady growth phase, and the phase classification does not change thereafter (Figure S11).

In summary, our findings confirm the hypothesis formulated by Cherp et al.[13] that potentially emerging growth pulses may affect the accuracy of $L$ and $\Delta t$ estimates (determined by the location of inflection points) but do not significantly change the estimates of $G$ (Figures 4 and 5), which serves as a proxy for the cruising speed in the steady growth phase (Note S2).

## The relationship between national and global growth

So far, our analysis has focused on the national level. However, debates on the feasibility of rapid renewable energy expansion are largely global. How can national deployment patterns inform such assessments? Cherp et al.[13] argue that the observed range of maximum national growth rates for wind and solar power can serve as a proxy for feasible global growth rates. The logic is straightforward; global growth aggregates national trajectories, and the countries that have already passed their FIPs provide a statistically meaningful sample of peak—and thus cruising—speeds. These speeds are assumed to apply not only to early front-runners but also to later adopters once they reach similar phases (Figure S3).

Our results substantiate and extend this reasoning through two empirical regularities. First, growth at the FIP ($G_{fip}$) is a reliable predictor of subsequent steady-phase growth (Figure 2E). At the national level, the post-FIP cruising speed typically does not exceed $G_{fip}$, a pattern confirmed by comparing the cross-country distribution of $G_{fip}$ and cruising speeds (Table S1). Second, solar power and wind power typically do not grow faster in latecomers than in front-runners.[13,47,71] As a result, the distribution of $G_{fip}$ values observed in countries that have already passed their FIPs provides a prospective benchmark for those that have not yet reached this phase. Together, these two properties imply that the cross-country $G_{fip}$ distribution defines a reliable range for plausible global growth rates.

Figure 5 illustrates how the representativeness of this sample is improving. As an increasing share of the global market consists of countries in the steady growth phase (Figures 5A and 5C), coverage of $G_{fip}$ correspondingly expands and becomes more reliable (Figures 5B and 5D). For onshore wind, nuclear, combined cycle gas turbines (CCGTs), internet users, and mobile telephones—once this coverage becomes sufficiently broad—the median $G_{fip}$ serves as a robust upper bound for the global growth rate; in each case, the median national $G_{fip}$ consistently exceeds the observed global rate, while the upper quartile (Q3) of its distribution provides a more optimistic ceiling (Figures 5B and 5D).

Solar PV, however, is less mature, with many countries yet to reach their FIPs. Consequently, observed global solar growth currently tracks the upper quartile (Q3) of the existing $G_{fip}$ distribution rather than its median (Figure 5B). We attribute this primarily to the dominant role of China, whose rapid recent acceleration stems from the dramatic expansion of cheap solar PV manufacturing. China accounts for the majority of global solar additions while growing faster than the current cross-country median. As growth in China and other large accelerating economies stabilizes (as forecasted by the IEA and Cheung[52,74]), the relationship between the national cruising speeds and global growth is expected to stabilize—much as it already has for wind and the other technologies.

Baumgärtner et al.[18] appear to challenge this conclusion, noting that the median peak growth rate for mobile telephones (estimated from logistic curve fitting) increased 10-fold between 1990 and 2000, suggesting that a similar jump could occur for renewables. However, this apparent increase is largely an artifact of sampling too few countries too early (Note S1). A reliable estimate of the statistical range of peak national rates requires (1) at least five countries already past their FIP and (2) the technology having reached its global takeoff. Mobile telephones met both criteria only in 2001 (Table S4). From that point onward (and even a few years before), the statistical range of $G_{fip}$ is remarkably stable (Figure 5), and the median national $G_{fip}$ provides a consistent prospective ceiling for global growth speeds. By contrast, Baumgärtner et al.[18] rely on years as early as 1990, when mobile telephones remained in their formative phase (with takeoff in 1997), and only 2 out of approximately 150 countries had passed their FIPs. For comparison, by 2019, wind and solar were already 20 and 9 years past their global takeoff, respectively, with at least 29 countries in the steady growth phase for wind and 38 for solar. Other technologies—nuclear, CCGTs, and internet users—show the same pattern; once a sufficient number of countries reach the steady growth phase, the median of national peak growth rates becomes a reliable upper bound on the speed of global growth (Figure 5).

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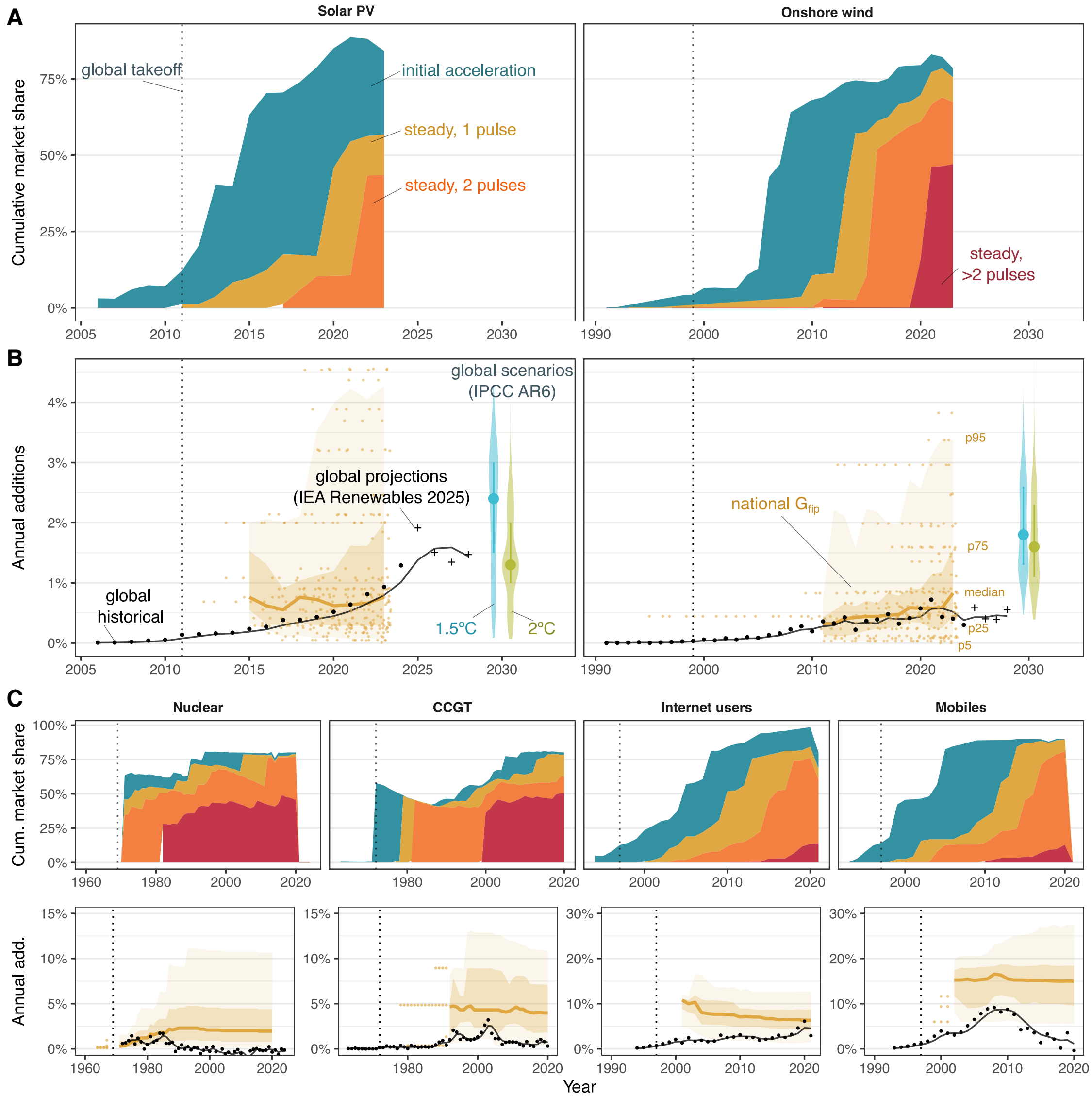


**Figure 5. The relationship between national $G_{fip}$ and global growth rates**

(A) Colored areas show the cumulative market share of the countries in different phases of growth. Vertical lines show years of global takeoff.

(B) Black dots show historical global annual additions, black crosses show projections from the IEA,[52] and black solid lines show their 3-year trailing average. Shaded regions show the statistical distribution of national $G_{fip}$, and solid lines show their median. Violins show distribution of maximum annual global additions in 1.5°C (C1 and C2) and 2°C (C3 and C4) pathways from the IPCC AR6[73]; dots and lines represent their medians and IQRs.

(C) Same as (A) and (B).

## DISCUSSION

Debates about the future of renewables often hinge on a question: where are wind and solar on the S-curve? Conventional wisdom suggests that technologies still early on their S-curves will continue accelerating, whereas those further along will slow down. Yet, this question cannot be answered with current knowledge. A simple S-curve can only be fitted once the endpoint of a technology's expansion is known. For wind and solar, this endpoint depends on future policies, technological change, and market dynamics, which cannot be inferred from past data. Future historians may one day reconstruct simple S-curves for 21st-century energy transition, but they will rely on information not available to us today.

Given this limitation, what can be said about global renewable growth in the near to medium term? We argue that meaningful, empirically grounded judgments are possible if attention shifts from the final destination of the S-curve to the early and middle phases of growth. Over this horizon, the global trajectory will be shaped not by a few countries approaching the endpoint of wind and solar expansion but by the many where deployment continues through initial acceleration and—more importantly—the steady growth phase. For these phases, we have rich evidence from front-runners, sufficient to characterize recurring growth patterns and the constraints they impose on future growth.

To this end, we evaluate and advance metrics and diagnostic tools appropriate for measuring and modeling renewables growth. First, FOBI, a Bayesian method for detecting the end of the formative phase,[47] yields country-specific takeoff estimates rather than generic thresholds.[13,42,45,46] Second, DAIP reliably detects the FIP and subsequent pulses, outperforming curve-fitting approaches that assume smooth trajectories. Third, the growth rate $G_{\mathrm{fip}}$ at the FIP approximates the maximum growth rate $G$ from classic growth models[13] but is more robust to pulses and serves as a reliable proxy for the long-run cruising speed. We also highlight the limitations of widely used metrics, including year-on-year growth rates[9,18] and exogenously assumed asymptotes and durations of transitions.[23,24,26]

Consistent with earlier work, wind and solar deployment in individual countries begins with a formative phase characterized by erratic growth, which ends at takeoff at around 1% of national electricity generation.[13,43,71] This is followed by a brief period of initial acceleration, driven by reinforcing feedbacks between technology, manufacturing, costs, institutions, and policy. Remarkably, this acceleration ends much earlier than predicted by standard S-curve theory. The FIP—when initial acceleration ends—typically occurs at only 3% share of electricity generation, far below standard logistic expectations. After this point, growth does not transition into monotonic slowdown. Instead, renewables shift into a steady growth phase,[13,22,47,51] where deployment proceeds at a cruising speed slightly below the peak and is punctuated by growth pulses. In both respects, wind and solar differ from historical technologies where inflection points occur at higher penetration levels and post-inflection slowdowns are more pronounced (Figures S5 and S6; Table S1).

Insights from national growth trajectories have direct implications for global growth. Countries that are already in the steady growth phase provide a robust statistical sample of feasible cruising speeds. Wind and solar power in latecomer countries rarely grow faster than in front-runners, likely reflecting two competing effects. On the one hand, technology learning, cost reductions, and supply chain maturation favor late adopters, but on the other hand, these gains may be offset by more challenging geographic, infrastructural, economic, institutional, or political contexts in late adopters.[4,13,46,75] The net result is a cruising speed distribution that is stable over time, with the median and upper quartile of national peak speeds in front-runner countries offering stable ceilings for plausible global growth. Our results thus reinforce earlier findings that expectations of globally sustained exponential growth are inconsistent with empirical evidence. In broad terms, they align with recent IEA[52] and other forecasts[74] of near-linear rather than near-exponential growth for both wind and solar. They also underscore the need for weighted statistical approaches when large countries such as China exert disproportionate influence on global trends.

The cruising speed regularities and the relationship between national and global growth are not specific to wind and solar. The same patterns are observed across nuclear power and gas turbines to mobile telephones and internet adoption—suggesting that our findings may reflect a general feature of how technologies scale. Future work can extend this diagnostic framework by using model-agnostic national parameters such as $G_{\mathrm{fip}}$ to construct probabilistic global or regional deployment scenarios without assuming a specific functional form for the trajectory.[24,47,69,76] As deployment histories lengthen, our framework should also be tested for new technologies—such as electric vehicles, heat pumps, or green hydrogen—whose trajectories are still too short to analyze. The same approach can also inform the parameters for the eventual slowdown as front-runner countries begin to reach saturation—a phase which lies beyond the scope of this study.

The patterns we identify—inflection points, phase transitions, and growth peaks—are consistent with the broader theory of technology diffusion but challenge the common assumption that diffusion follows a smooth, single-inflection S-curve. In contrast to the monotonic deceleration predicted by simple S-curve functions, wind and solar enter a steady growth phase where deployment proceeds at an average rate close to that at the FIP while undergoing pulses of acceleration and deceleration. Although such dynamics could in principle be reproduced by more flexible parametric models—for example, bi-logistic or multi-phase formulations[47,51,69,77]—these approaches are less parsimonious, rely on additional structural assumptions, and are sensitive to choices such as the number and timing of pulses. Our model-agnostic diagnostics such as FOBI, DAIP, and $G_{fip}$ provide a more robust and transparent empirical basis for identifying growth phases and benchmarking diffusion trajectories without imposing restrictive parametric assumptions.

We hypothesize that renewables diverge from classic S-curve trajectories in part because their diffusion is shaped by public policies, which are more fluid and adaptive than techno-economic drivers. Policies governing renewables are influenced by multiple rapidly evolving and often competing forces—including state objectives, voter preferences, interest groups, and fiscal constraints.[31,34,78–83] This complexity means that policies can act both as a constraint and as a catalyst; the same volatility that can stall growth through rollbacks or bottlenecks can also re-accelerate growth through renewed political commitment, producing the pulses observed in growth trajectories.[39,51,79,82,83] Policy processes are also adaptive. Governments frequently respond to emerging barriers through deliberate adjustments aimed at sustaining deployment in line with long-term objectives.[34,51,78,84–86] Moreover, the market for renewables is partly policy-determined; for example, mandates, auction volumes, fossil fuel phase-out commitments, and electrification policies can expand it over time.[86,87] Recent work suggests that targeted policies can prevent slowdown[34,83,84] and that policy shifts frequently coincide with the FIP and secondary re-acceleration, with policy targets often aiming to simply replicate historical growth peaks.[51] However, more work needs to be done to disentangle the role of policies from other factors such as market shocks and supply chain constraints in shaping the dynamics of growth pulses. The framework developed here provides a basis for such analysis including quantitative testing of these dynamics, analogous to recent efforts linking climate policies to emissions reductions.[88,89]

The phases and patterns of solar and wind power deployment documented here have emerged across dozens of countries over the past three decades, despite substantial political, economic, and technological changes. There is no guarantee, however, that they will hold in the future. Factors that could accelerate deployment beyond historical cruising speeds include innovations in battery storage that relax grid-integration constraints, synergies between cross-sectoral decarbonization efforts, more ambitious climate policy, and even stronger energy security concerns. Factors that could slow it down include further trade fragmentation, policy rollbacks, and aggravating grid investment shortfalls. The potential effects of such factors could be explored through scenario analysis, which can use our empirically grounded metrics as transparent reference points to benchmark the effects of potential disruptions.

More generally, our results suggest that anticipating renewable energy growth requires not only statistically robust data analysis[18] but also an understanding of the dynamics of the early and middle growth phases of policy-driven technologies. Such an understanding can refine global pathways, calibrate policy expectations, and support more realistic planning for the coming decades of the energy transition.

## METHODS

### Technology sample construction

Our analysis focuses on historical deployment of onshore wind, solar PV, CCGTs, nuclear power, mobile telephones, and internet use across ≈220 countries and dependent territories. Data coverage varies by technology: onshore wind (217 countries, 1978–2023), solar PV (223 countries, 1983–2023), nuclear power (36 countries, 1960–2023), CCGTs (91 countries, 1954–2020), mobile phones (215 countries, 1960–2023), and internet users (213 countries, 1960–2023). For onshore wind, solar PV, and nuclear power, deployment is measured as share in electricity generation; CCGT deployment is measured as share in installed gas power capacity; mobile telephones and internet users are both measured in per capita terms. Since these deployment metrics differ across technology groups, cross-technology comparisons in this paper focus on whether the same qualitative patterns emerge—the phase structure, the relationship between $G_{\text{fip}}$ and cruising speed—rather than on the numerical values of different growth parameters. We exclude technology-country pairs with fewer than 10 consecutive years of non-zero deployment data from our final analysis sample.

### Takeoff detection

To identify when countries exited their formative phase and achieved sustained growth, we applied FOBI,[47] a data-driven takeoff detection method that identifies the transition from erratic early deployment to consistent growth without requiring exogenous threshold assumptions. For each country-technology combination, we required at least 10 years of deployment data and imposed a minimum market share threshold of 0.001% before FOBI could detect takeoff, preventing false positives from isolated pilot projects.

For nuclear power, we followed Brutschin et al.[45] and assigned takeoff years to the date of the start of the first or second nuclear power plant (depending on their size and the interval between their construction) rather than applying FOBI. Nuclear deployment exhibits distinctly stepwise growth patterns due to the large unit size of individual reactors, which can cause sustained multi-year gaps between capacity additions that FOBI's continuous growth detection criteria would misinterpret as failed takeoffs rather than the characteristic deployment pattern of this technology.

Countries that had not yet achieved takeoff by the end of each technology time series were classified as remaining in their formative phase and excluded from subsequent inflection point analysis.

### Model-agnostic inflection point and pulse detection

We developed DAIP to identify shifts in growth dynamics without assuming specific functional forms. This method proceeds through the following steps:

#### *Step 1: Calculate deployment metrics*

Starting with cumulative deployment (e.g., installed capacity) $D_t$ of a technology in year $t$, we calculated the annual change in deployment (deployment additions) as $\Delta D_t = D_t - D_{t-1}$. To smooth inter-annual volatility, we used a 3-year trailing average to estimate the deployment speed: $v_t = \frac{1}{3}\sum_{i=0}^{2} \Delta D_{t-i}$. This represents the average rate of change in deployment over the 3-year window.

#### *Step 2: Measure acceleration*

We computed acceleration as the first discrete derivative of deployment speed $a_t = v_t - v_{t-1}$. Positive acceleration ($a_t > 0$) indicates increasing deployment speed (accelerating growth), while negative acceleration ($a_t < 0$) indicates decreasing deployment speed (decelerating growth).

#### *Step 3: Identify the FIP*

We defined the inflection point $t_0$ as the first year after takeoff where acceleration becomes negative for at least two consecutive years: $a_t < 0$ for $t \in [t_0, t_0 + 1]$. The 2-year persistence criterion prevents misidentifying single-year slowdowns as phase transitions. This marks the end of the initial acceleration growth phase. We recorded both the timing of this inflection point and the deployment speed $G_{\text{fip}}$ representing the maximum rate of annual additions during the initial acceleration growth phase.

#### *Step 4: Detect growth pulses*

For countries that had passed their FIP, we identified subsequent growth pulses. A growth pulse is a period between the start of re-acceleration $t_p$ and the next inflection point $t_0$.[51] We estimate $t_p$ as the year where deployment was expanding and acceleration became positive for at least 2 consecutive years: $v_t > 0$ and $a_t > 0$ for all $t \in [t_p, t_p + 1]$. This identifies periods of renewed acceleration following earlier deceleration, characteristic of policy-driven deployment surges during the steady growth phase.

To identify an inflection point in year $t_0$, we require data through at least year $t_0 + 1$ to verify the persistence of deceleration. Similarly, pulse detection requires observing 2 consecutive years of positive acceleration. This backward-looking property means that model-agnostic DAIP diagnoses phase transitions only after they have occurred, unlike curve-fitting methods that project inflection points based on fitted parameters.

To assess the sensitivity of DAIP outputs to parameter choice, we repeat the full analysis under three alternative specifications, varying the rolling-average window (3 or 5 years) and the persistence criterion (2 or 3 consecutive years of sustained directional change), yielding a $2 \times 2$ grid: baseline (3 years/2 years), variant A (3 years/3 years), variant B (5 years/2 years), and variant C (5 years/3 years). For each specification, we report the FIP detection rate, median $G_{fip}$ and its IQR, and the median and IQR of the cruising speed to $G_{fip}$ ratio. Full results are presented in Table S2 and described in Note S3.

### Benchmarking against S-curve fitting methods

We compared DAIP's phase diagnostics against the approach from Cherp et al.,[13] which fits logistic and Gompertz curves to post-takeoff deployment data to identify inflection points. As logistic and Gompertz models in Cherp et al.[13] yielded similar results, we only use logistic fits in our analysis. We tested two variants of takeoff estimation: (1) the original Cherp et al.[13] method using a fixed 1% electricity supply threshold to filter formative phase data and (2) an improved version integrating FOBI for data-driven takeoff detection.

For each country-technology combination, we fit logistic functions to post-takeoff data using nonlinear least squares, extracting inflection point estimates and maximum growth rates (*G*) from fitted parameters.

We employed confusion matrix analysis to evaluate diagnostic accuracy, using DAIP-identified inflection points as ground truth. For progressive cutoff years from 2015 to 2023, we classified each country into one of four categories: true positive (TP; both DAIP and curve-fitting detect inflection point by cutoff year), FP (curve-fitting detects inflection but DAIP does not—"phantom" inflections), true negative (TN; both methods show no inflection by cutoff year—still accelerating), and false negative (FN; DAIP detects inflection but curve-fitting does not—"missed" inflections).

We calculated phantom rate as $FP/(TP+FP)$, measuring the proportion of curve-fitting inflection detections that prove incorrect; miss rate as $FN/(FN+TN)$, measuring the proportion of genuinely accelerating countries incorrectly classified as post-inflection; and overall accuracy as $(TP+TN)/total$ (Figure S10). This framework allowed us to assess both the precision (avoiding false detections) and recall (avoiding missed transitions) of parametric versus model-agnostic approaches across different data availability conditions.

### Cruising speed estimation

For each country that had passed its FIP by the end of the empirical time series, we calculated cruising speed as the mean annual additions after the FIP and before the onset of consistent slowdown—the steady growth phase.[22] Operationally, we defined the steady growth phase as all years from the FIP and until a sustained decline in a technology's market share. To identify the start year of sustained decline while accounting for inter-annual volatility, we calculated a 5-year trailing moving average of market share for each country-technology trajectory. We diagnose the start of decline as the earliest year at which this smoothed deployment metric reached its maximum value.

We compared these empirically observed cruising speeds with two measures of peak growth: (1) $G_{fip}$, the deployment speed at the FIP as identified by DAIP, and (2) *G*, the maximum growth rate extracted from curve-fitted parameters following Cherp et al.[13] (Figures 2, S7, and S8).

### Hindcasting performance evaluation

To evaluate the relative accuracy of different projection approaches, we conducted out-of-sample hindcasting tests for countries that had passed their FIP. For each country-technology combination, we fit curves to data from the start of deployment through the inflection point year and then projected forward and compared projections against actual observed deployment. We tested four projection approaches: (1) linear: constant annual additions at the rate observed at the FIP ($G_{fip}$), (2) exponential: exponential growth fit to pre-inflection data with empirically estimated parameters, (3) empirical-logistic: logistic curves fit to pre-inflection data with empirically estimated ceilings, and (4) fixed-L logistic: logistic functions with exogenously fixed ceilings at three levels for each technology (e.g., 20%, 40%, and 60% market share for wind and solar) and emergence rates derived from the compound annual growth rate (CAGR) observed for all data in time series before the inflection point. For each approach, we calculated symmetric mean percentage error (sMPE) across projection horizons from 1 to 20+ years beyond the inflection point: sMPE $= \sum\left[(V_{proj} - V_{actual})/((V_{proj}+V_{actual})/2)\right]/n$, where $V_{proj}$ is the projected market share, $V_{actual}$ is the observed market share, and $n$ is the number of country observations at that horizon. We restricted our analysis to horizons with at least five country observations to ensure statistical reliability (Figure S7).

### Scenario comparison

We compared empirically observed national deployment rates with global projections from the IPCC AR6 scenario database.[90] For each scenario and technology, we calculated annualized addition rates as changes in electricity generation normalized by total electricity system size across decadal intervals (2020–2030, 2030–2040, 2040–2050). We categorized scenarios by warming level (C1/C2 as 1.5°C pathways, C3/C4 as 2°C pathways) and identified the maximum annual addition rate within each scenario. We computed the median and IQRs of these maximum rates across all scenarios within each warming category, representing the distribution of peak deployment rates implied by climate mitigation pathways. These are then compared with the distribution of national $G_{fip}$ measured at different years in the past (Figure 5).

## RESOURCE AVAILABILITY

### Lead contact

Requests for further information and resources should be directed to and will be fulfilled by the lead contact, Aleh Cherp (cherpa@ceu.edu).

### Materials availability

This study did not generate new unique materials.

### Data and code availability

- We use historical time series data for onshore wind, solar PV, and nuclear power generation from the IEA and IRENA[52,53,54]; CCGT capacity from the S&P Global World Electric Power Plants Database[55]; internet users from the World Bank[56]; and mobile phone subscriptions from the International Telecommunication Union.[57] Projections for onshore wind and solar PV deployment are sourced from the IEA Renewables 2025 report[52] and the IPCC AR6 scenario database.[90]

- All original code has been deposited at Zenodo under the DOI https://doi.org/10.5281/zenodo.20065454 and is publicly available as of the date of publication.
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

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## AUTHOR CONTRIBUTIONS

Conceptualization, A.C., A.J., J.J., and V.V.; analysis and visualization, A.J. and V.V.; writing, A.C., A.J., and J.J.; and supervision and funding acquisition, J.J. and A.C.

## DECLARATION OF INTERESTS

The authors declare no competing interests.

## DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT version 5.2 in order to improve grammar and style. After using this tool or service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

## SUPPLEMENTAL INFORMATION

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