Institute for
New Economic Thinking
AT THE OXFORD MARTIN SCHOOL

Empirically grounded technology forecasts and the energy transition

Rupert Way, Matthew Ives, Penny Mealy and J. Doyne Farmer

Sept 14th, 2021

INET Oxford Working Paper No. 2021-01

21st Sept 2022 - A recently published version of this paper is now available here:

https://www.cell.com/joule/fulltext/S2542-4351(22)00410-X

Empirically grounded technology forecasts and the energy transition

Rupert Way[a,b], Matthew C. Ives[a,b], Penny Mealy[a,b,c] and J. Doyne Farmer[a,d,e]

[a]*Institute for New Economic Thinking at the Oxford Martin School, University of Oxford, Oxford, UK*
[b]*Smith School of Enterprise and the Environment, University of Oxford, Oxford, UK*
[c]*SoDa Labs, Monash Business School, Monash University, Australia*
[d]*Mathematical Institute, University of Oxford, Oxford, UK*
[e]*Santa Fe Institute, Santa Fe, New Mexico, USA*

September 14, 2021

Rapidly decarbonising the global energy system is critical for addressing climate change, but concerns about costs have been a barrier to implementation. Most energy-economy models have historically underestimated deployment rates for renewable energy technologies and overestimated their costs[1,2,3,4,5,6]. The problems with these models have stimulated calls for better approaches[7,8,9,10,11,12] and recent efforts have made progress in this direction[13,14,15,16]. Here we take a new approach based on probabilistic cost forecasting methods that made reliable predictions when they were empirically tested on more than 50 technologies[17,18]. We use these methods to estimate future energy system costs and find that, compared to continuing with a fossil-fuel-based system, a rapid green energy transition will likely result in overall net savings of many trillions of dollars - even without accounting for climate damages or co-benefits of climate policy. We show that if solar photovoltaics, wind, batteries and hydrogen electrolyzers continue to follow their current exponentially increasing deployment trends for another decade, we achieve a near-net-zero emissions energy system within twenty-five years. In contrast, a slower transition (which involves deployment growth trends that are lower than current rates) is more expensive and a nuclear driven transition is far more expensive. If non-energy sources of carbon emissions such as agriculture are brought under control, our analysis indicates that a rapid green energy transition would likely generate considerable economic savings while also meeting the 1.5 degrees Paris Agreement target.

Future energy system costs will be determined by a combination of technologies that produce, store and distribute energy. Their costs and deployment will change with time due to innovation, economic competition, public policy, concerns about climate change and other factors. Figure 1 provides an historical perspective for how the energy landscape has evolved over the last 140 years. Panel (a) shows the historical costs of the principal energy technologies and panel (b) gives their deployment, both on a logarithmic scale. As we approach the present in panel (a), the diagram becomes more congested, making it clear that we are in a period of unprecedented energy diversity, with many technologies with global average costs around $100/MWh competing for dominance.

The long term trends provide a clue as to how this competition may be resolved: The prices of fossil fuels such as coal, oil and gas are volatile, but after adjusting for inflation, prices now are very similar to what they were 140 years ago, and there is no obvious long range trend. In contrast, for several decades the costs of solar photovoltaics (PV), wind, and batteries have dropped (roughly) exponentially at a rate near 10% per year. The cost of solar PV has decreased by more than three orders of magnitude since its first commercial use in 1958.

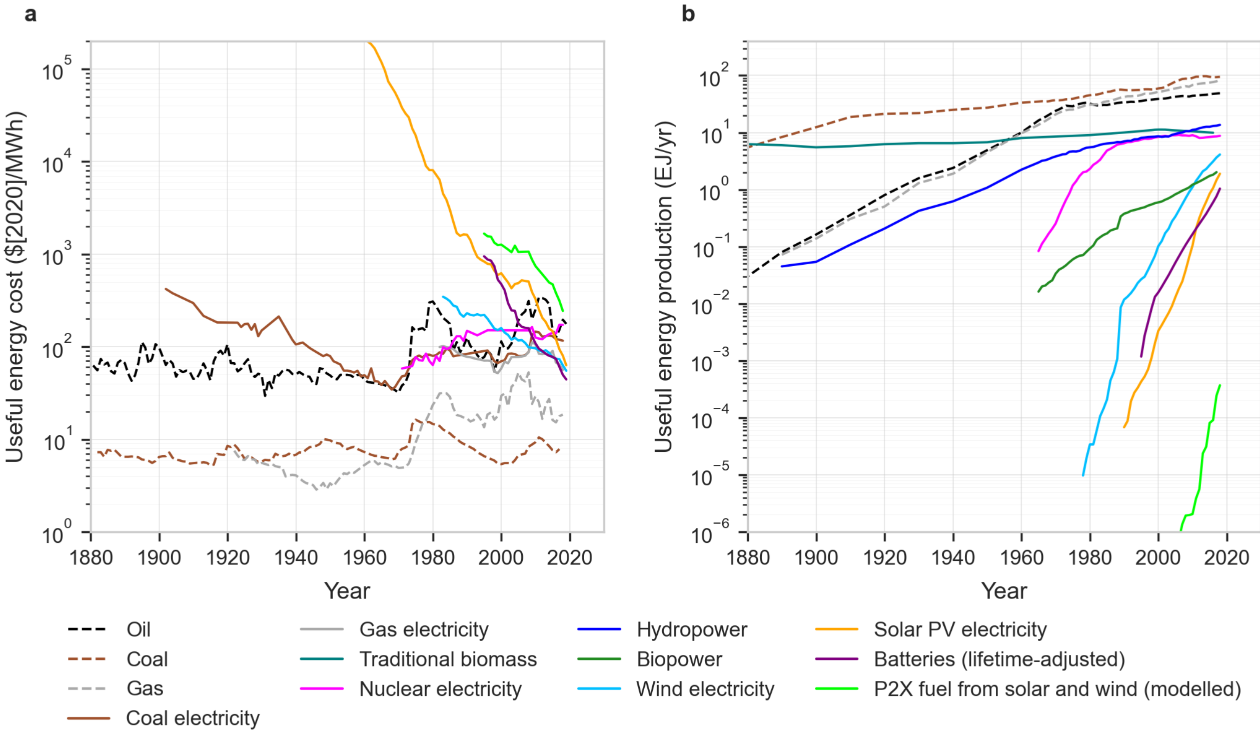

Figure 1: **Historical costs and production of key energy supply technologies**. (a) Inflation-adjusted useful energy costs (or in some cases prices) as a function of time. We show *useful energy* because it takes conversion efficiency into account (see Supplementary Note (SN) 1.7). Electricity generation technology costs are levelized costs of electricity (LCOEs). Battery series show capital cost per cycle and energy stored per year, assuming daily cycling for 10 years (these are not directly comparable with other data series here). Modelled costs of power-to-X (P2X) fuels, such as hydrogen or ammonia, assume historical electrolyzer costs and a 50-50 mix of solar and wind electricity. (b) Global useful energy consumption. The provision of energy from solar photovoltaics has, on average, increased at 44% per year for the last 30 years, while wind has increased at 23% per year. These are just a few representative time series, for a full description of data and methods see SN6.

Figure 1(b) shows how the use of technologies in the global energy landscape has evolved since 1880. It documents the slow exponential rise in the production of oil and natural gas over a century, until they eventually replaced traditional biomass and equalled coal, as well as the rapid rise and plateauing of nuclear energy. But perhaps the most remarkable feature is the dramatic exponential rise in the deployment of solar PV, wind, batteries and electrolyzers over the last decades as they transitioned from niche applications to mass markets. Their rate of increase is similar to that of nuclear energy in the 70's, but unlike nuclear energy, they have all consistently experienced exponentially decreasing costs. The combination of exponentially decreasing costs and rapid exponentially increasing deployment is different to anything observed in any other energy technologies in the past, and positions renewables to challenge the dominance of fossil fuels within a decade.

Will clean energy technology costs continue to drop at the same rates in the future? What does this imply for the overall cost of the green energy transition? Is there a path forward that can get us there cheaply and quickly? We address these questions here.

How good were past energy forecasts?

Sound energy investments require reliable forecasts. As illustrated in Figure 2(a), past projections of present renewable energy costs by influential energy-economy models have consistently been much too high. ("Projections" are forecasts conditional on scenarios, so we use the terms interchangeably.) The inset of the figure gives a histogram of 2,905 projections by integrated assessment models, which are perhaps the most widely used type of global energy-economy models[19,20,21,22], for the annual rate at which solar PV system investment costs would fall between 2010 and 2020[19]. The mean value of these projected cost reductions was 2.6%, and all were less than 6%. In stark contrast, during this period solar PV costs actually fell by 15% per year. Such models have consistently failed to produce results in line with past trends[3,23]. Considering their central role in guiding energy investment decisions and climate policy, the consequences of such systematic bias in modelling projections are alarming. Failing to appreciate cost improvement trajectories of renewables relative to fossil fuels not only leads to under-investment in critical emission reduction technologies, it also locks in higher cost energy infrastructure for decades to come. In contrast, forecasts based on trend extrapolation consistently performed much better[24,25,26,27].

Some reasons for the poor performance of energy-economy models include their seemingly arbitrary assumptions regarding the maximum deployment and maximum growth rates of renewables, plus the imposition of "floor costs", i.e. fixed levels that costs are assumed never to fall below[28]. As shown in Figure 2(b), past floor costs used in IAMs have repeatedly been violated. We know of no good empirical evidence supporting floor costs and do not impose them. (For a critique of other aspects of standard energy-economy models, see[29,8,9]).

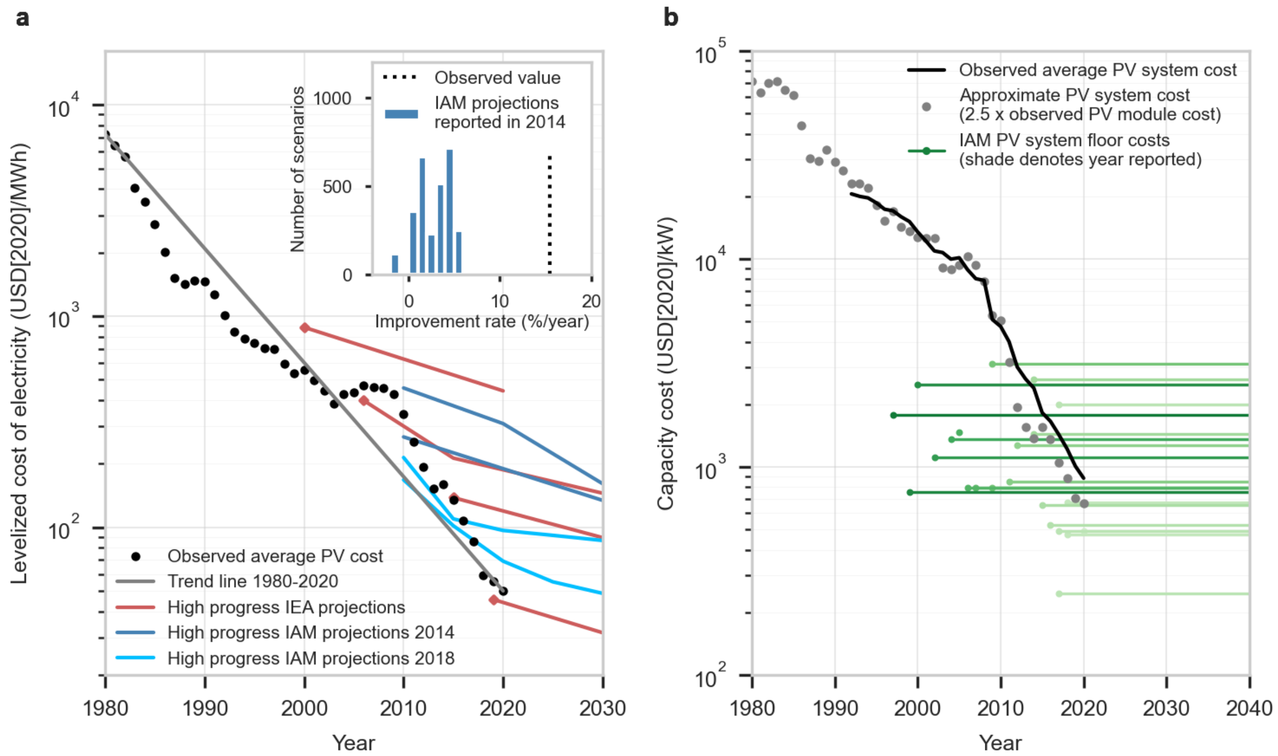

Figure 2: **Historical PV cost forecasts and floor costs.** (a) The black dots show the observed global average levelized cost of electricity (LCOE) over time. Red lines are LCOE projections reported by the International Energy Agency (IEA), dark blue lines are integrated assessment model (IAM) LCOE projections reported in 2014[19] and light blue lines are IAM projections reported in 2018[20,21]. IAM projections are rooted in 2010 despite being produced in later years. The projections shown are exclusively "high technological progress" cost trajectories drawn from the most aggressive mitigation scenarios, corresponding to the biggest projected cost reductions used in these models. Other projections made were even more pessimistic about future PV costs. The inset compares a histogram of projected compound annual reduction rates of PV system investment costs from 2010 to 2020 to what actually occurred (based on all 2,905 scenarios for which the data is available[19]). (b) PV system floor costs implemented in a wide range of IAMs. The colours denote the year the floor cost was reported, ranging from 1997 (dark green) to 2020 (light green). Observed PV system costs are also shown. The cost of PV modules scaled by a constant factor of 2.5 is provided as a reference. For further details and data sources see Extended Data Figures 6 and 7(a), and SN6.10

Predicting future technology costs

The diversity of historical cost improvement rates seen in Figure 1(a) applies to technologies in general[30,25,17,18]. For the vast majority of technologies, inflation-adjusted costs remain roughly constant through time. In contrast, for some technologies, such as optical fibers, solar PV or transistors, costs drop roughly exponentially, at rates ranging from over 50% per year to a few percent per year[31] (SN8.1). Once a track record is established, the rates of improvement tend to remain constant. While there are occasionally breaks in the trend, this is rare.

In contrast to the energy-economy models mentioned above, during the past decade simple time series models have been shown to make reliable forecasts of technology costs[32,25,33,18]. In this study we apply these methods to key energy technologies and use them to make probabilistic estimates for the cost of providing energy services under several different scenarios.

For renewable technologies we use a stochastic generalization of *Wright's law*, which predicts that costs drop as a power law of cumulative production. This relationship is also called an *experience curve* or *learning curve*, and cumulative production is also called *experience*. Experience does not directly cause costs to drop, but is believed to be correlated with other factors that do, such as level of effort and R&D, and has the essential advantage of being relatively easy to measure[34,35]. Forecasting using this model requires estimating two parameters for each technology, corresponding to a progress rate and a volatility (see Methods). In addition, there is an autocorrelation parameter that is common to all technologies. For a discussion of challenges and caveats concerning Wright's law see SN8.2.

Successful technologies tend to follow an "S-curve" for deployment, starting with a long phase of exponential growth in production that eventually tapers off due to market saturation[36]. Under Wright's law, during the exponential growth phase, costs drop exponentially in time according to a generalized form of Moore's law, which is consistent with the historical behavior of renewable energy technologies. When growth eventually slows, under Wright's law, improvement slows down. (For a discussion of causality see SN8.2.1.)

Wright's law is already widely used in energy system models[37,38,39], though to the best of our knowledge, only deterministic implementations have been used so far. Our key contribution here takes advantage of new results that extend Wright's law to provide an estimate of the *probability distribution* of future technology costs, thus providing an estimate of forecasting uncertainty. This method was carefully tested by making forecasts at reference dates in the past, using only the data available at the time, and making predictions over all time horizons up to 20 years into the future with respect to each reference date. This was done using historical data for 50 different technologies, for a total of roughly 6,000 forecasts. The forecasting accuracy closely matched *a priori* derived estimates on all time horizons[17,18].

Because fossil fuel costs have not changed in the long run, they require a different time series forecasting model. Since costs have not dropped with experience[40], the stochastic form of Wright's law that we use here reduces to a geometric random walk without drift. This is a common model for financial time series, including tradeable commodities such as oil or gas, and can be justified based on the efficient markets hypothesis. On short timescales (say ten years or less) this is a reasonable approximation, but over longer timescales it predicts too much volatility in comparison to the historical record. Fossil fuel prices show mean reversion on longer timescales and are better captured by an AR(1) autoregressive process[41].

We thus use a univariate AR(1) model to forecast coal, oil, and gas (see Methods), SN5.1 and SN6.1-6.3). While coal-fired electricity and gas-fired electricity showed significant drops in cost for some of the twentieth century, in the long run their costs are increasingly dominated by fuel costs[42], so we use the AR(1) model for these as well (SN6.4-6.5). The technologies for which we use Wright's law to generate probabilistic cost forecasts are: solar PV, wind, batteries, electrolyzers, nuclear power, biopower and hydropower. While the first four of these technologies have strong historical progress trends, the latter three have either flat or rising costs, so have less potential to play a significant role in energy transition, and hence are less important in this analysis (SN6.6-6.12).

Figure 3 shows probabilistic forecasts for seven key energy technologies under a rapid energy transition scenario that we will define in a moment. Each renewable technology initially follows its current trend of exponential decreasing costs, which slows when it becomes dominant and its rate of deployment drops. We also show a selection of cost projections reported by IAM and IEA studies. We show only their most optimistic projections, i.e. low cost projections that correspond to high technological progress scenarios. Consistent with the historical behavior of these models illustrated in Figure 2, these projections are high relative to historical trends. Although viewed as highly optimistic, they are all higher than our median forecasts, and except for wind, substantially higher.

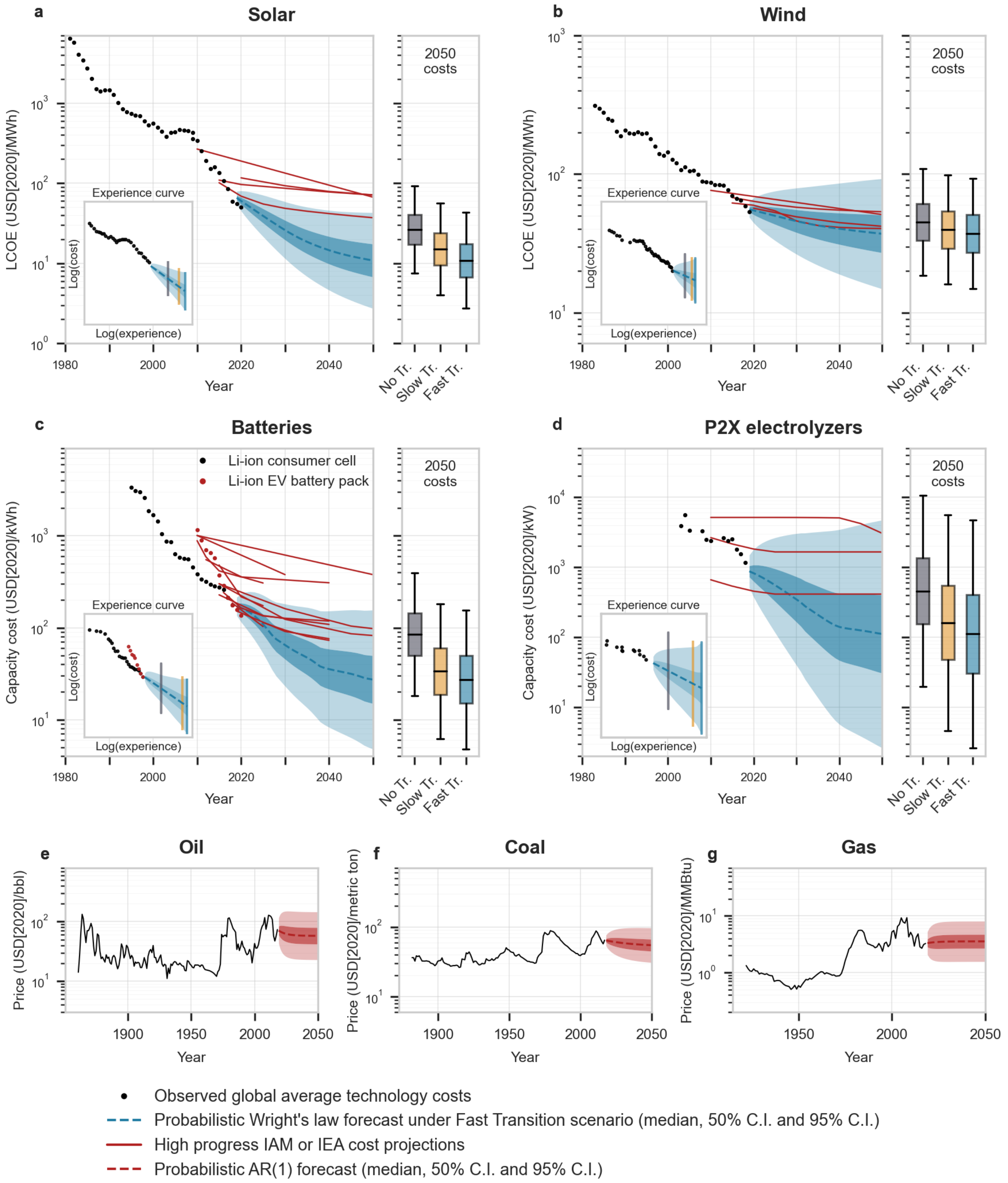

Figure 3: **Technology forecasts.** (a - d) The main plots show cost forecast distributions under our Fast Transition scenario for solar PV, wind, batteries and polymer electrolyte membrane (PEM) electrolyzers; the 50% confidence interval is dark blue and the 95% confidence interval is light blue. These are compared to several representative current and past projections corresponding to "optimistic" mitigation scenarios made by IAMs and the IEA (red lines). (See Extended Data Figure 7.) For batteries we show both consumer cells and electric vehicle (EV) battery pack prices, though these are now almost identical; our forecasts are based on consumer cells while the IEA forecasts shown are based on EV batteries. The box and whisker plots in the right-hand panels compare cost forecasts in 2050 under our three different scenarios (defined shortly). The insets show historical experience curves and forecasts, with progress rates that are independent of the scenario, and vertical lines indicating how far each technology moves down the probabilistic experience curve in each scenario. Panels (e - g) give probabilistic cost forecasts for oil, coal and gas based on the AR(1) time series model. (See SN6 for details of data sources and model calibration.)

The stochastic version of Wright's law we use here captures the historical volatility of past performance and the resulting estimation error, and projects this uncertainty forward in future cost distributions. It thus provides cost ranges that are supported by empirical evidence, as opposed to the *ad hoc* ranges that are often used[43]. The insets show costs vs. experience and emphasize that median costs develop identically *as a function of experience* in all scenarios. The side panels of Figure 3 illustrate that under Wright's law forecasts depend on the scenario; as a result, under a rapid transition, we reach lower costs sooner.

From single technologies to a full system model

Technology cost forecasts are conditional on *scenarios*, which specify energy technology deployment trajectories as a function of time. Our approach to scenario construction differs from that currently used in standard energy-economy models. In integrated assessment models, scenarios are the result of optimizing discounted consumption (as measured by GDP) under constraints on carbon emissions[44]. In simulation models such as the IEA's World Energy Model, scenarios are the result of choosing the cheapest available technologies through time, subject to policy choices. Both of these methods require many cost forecasts to be made, either exogenously or endogenously, during the scenario construction process, via some combination of models and expert forecasts. (Expert forecasts have a poor track record[45].) Thus scenarios depend on cost forecasts and vice versa, and small forecasting errors can quickly get amplified, leading to scenarios that are inconsistent with empirically observed trends.

We instead follow earlier energy system models[46] and construct scenarios exogenously by specifying how much energy or storage will be provided by each technology as a function of time (SN2.1). We classify energy services into four categories – transport, industry, buildings and energy sector self-use (SN1.3) – and assume that end-use sector demand grows at the historically observed overall rate of 2% per year. We impose the constraint that all scenarios must reliably provide identical levels of energy services throughout the economy. This method has the advantage of being simple and transparent, and allows us to follow long-standing deployment trends, which are at least known to have been feasible from the past until the present. This is in contrast to the optimal scenarios generated by IAMs, which typically do not even attempt to match historical behavior[47].

The three scenarios that we consider are shown in Figure 4. They run from 2019 to 2070, and were chosen to represent three distinctly different energy system pathways. In the Fast Transition scenario (panels a, d, g), renewable energy and storage technologies maintain their current deployment growth rates for a decade, replacing fossil fuels in two decades. Following a standard S-curve, once renewables become dominant, deployment slows to grow at 2% per year. Short term storage and electrification of most transport are achieved with batteries, while long term energy storage and all hard-to-electrify applications are served by power-to-X fuels, i.e. by using electricity for hydrogen electrolysis and either directly using hydrogen or using it to make other fuels such as ammonia and methane as needed[48]. This corresponds to an "electrify almost everything" scenario, with full sector-coupling[49]. In the Slow Transition scenario (panels b, e, h), in contrast, current rapid deployment trends for renewables slow down immediately, so that fossil fuels are phased out more slowly and continue to dominate until mid-century. Finally, in the No Transition scenario (panels, c, f, i), the energy system remains similar to its current form and each source of energy grows proportionally, making this close to typical "worst case" scenarios (which were until recently called "business as usual" scenarios). (Scenario details are shown in SN4.)

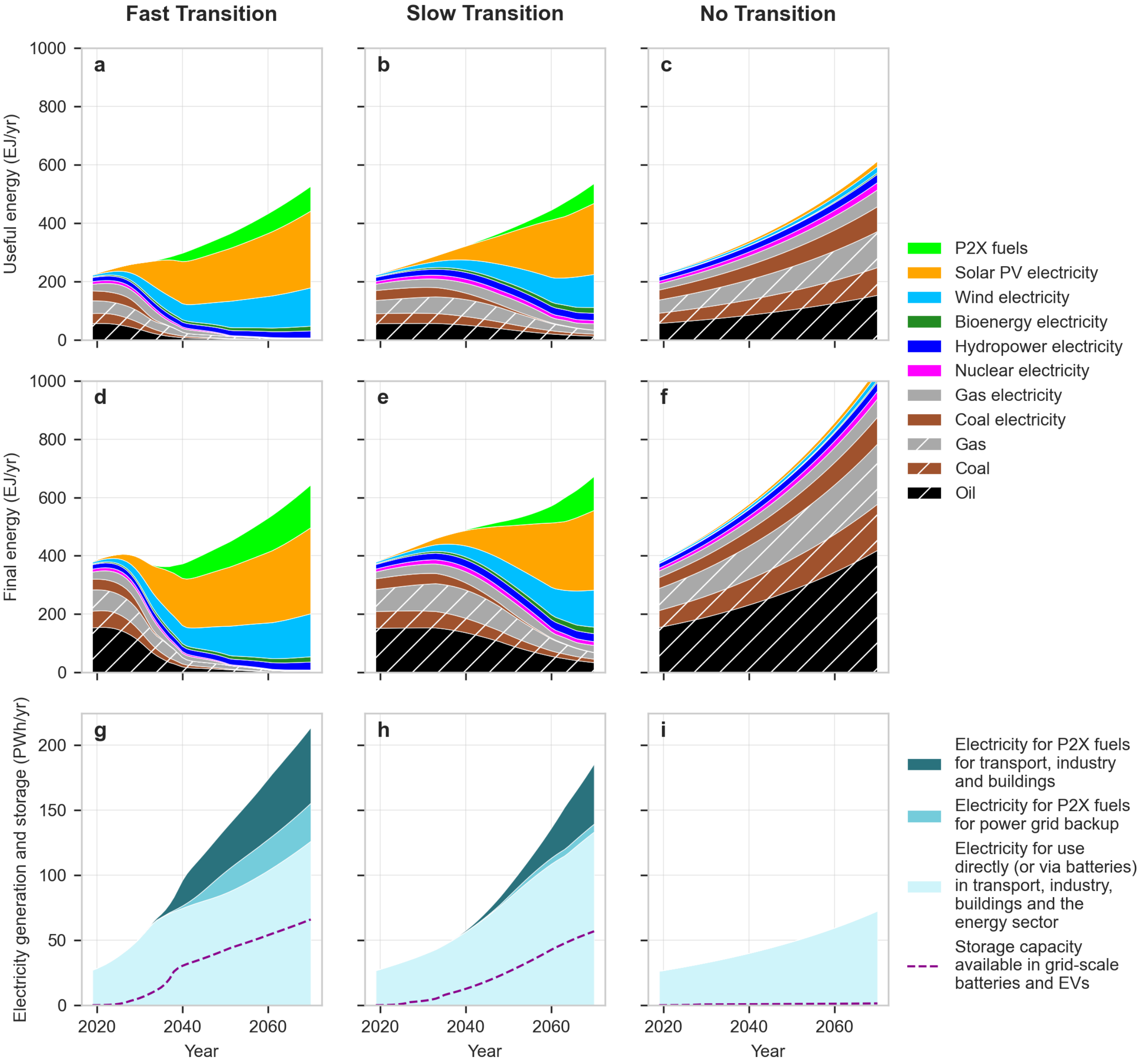

Figure 4: **Scenarios**. The three columns represent each of the scenarios. The rows are: (1) Annual useful energy provided by each technology as a function of time. (2) Annual final energy provided by each technology as a function of time. (3) Annual electricity generation and storage in grid-scale batteries and EV batteries; total generation is divided between final electricity delivered to the economy and electricity used to produce P2X fuels for hard-to-electrify applications and for power grid backup.

Our approach is based on two key design principles: 1) include only the minimal set of variables necessary to represent most of the global energy system, and the most important cost and production dynamics, and 2) ensure all assumptions and dynamics are technically realistic and closely tied to empirical evidence (SN1.1). This means that we focus on energy technologies that have been in commercial use for sufficient time to develop a reliable historical record.

We choose a level of model granularity well suited to the probabilistic forecasting methods used, i.e. one that allows accurate model calibration, and ensures overall cost-reduction trends associated with cumulative production are captured for each technology. Our model design can be run on a laptop, is easy to understand and interpret, and allows us to calibrate all components against historical data so that the model is firmly empirically grounded. The historical data does not exist to do this on a more granular level.

Consistent with our two design principles, we have deliberately omitted several minor energy technologies. Co-generation of heat, traditional biomass, marine energy, solar thermal energy, and geothermal energy were omitted either due to insufficient historical data or because they have not exhibited significant historical cost improvements, or both. Liquid biofuels were also excluded because any significant expansion would have high environmental costs (SN1.5.4). Finally, carbon capture and storage (CCS) in conjunction with fossil fuels was omitted because i) it is currently a very small, low growth sector, ii) it has exhibited no promising cost improvements so far in its 50 year history, and iii) the cost of fossil fuels provides a hard lower bound on the cost of providing energy via fossil fuels with CCS (SN1.6.1). This means that within a few decades electricity produced with CCS will likely not be competitive even if CCS is free. The major technologies that we do include cover 90% of current final energy, excluding energy carriers that are already renewable such as bioenergy and biofuels, plus petrochemical feedstock, which is not an energy carrier. See SN1 for a complete description of the model.

Since renewables are intermittent, storage is essential. In the Fast Transition scenario we have allocated so much storage capacity using batteries and P2X fuels that the entire global energy system could be run for a month without any sun or wind (SN3). This is a sensible choice because both batteries and electrolyzers have highly favorable trends for cost and production (SN6.11-6.12). From 1995 to 2018 the production of lithium ion batteries increased at 30% per year, while costs dropped at 12% per year, giving an experience curve comparable to that of solar PV[50]. Currently, about 60% of the cost of electrolytic hydrogen is electricity, and hydrogen is around 80% of the cost of ammonia[51], so these automatically take advantage of the high progress rates for solar PV and wind.

To understand these scenarios it is important to distinguish *final energy*, which is the energy delivered for use in sectors of the economy, from *useful energy*, which is the portion of final energy used to perform energy services, such as heat, light and kinetic energy (SN1.2). Fossil fuels tend to have large conversion losses in comparison to electricity, which means that significantly more final energy needs to be produced to obtain a given amount of useful energy. Switching to energy carriers with higher conversion efficiencies (e.g. moving to electric vehicles) significantly reduces final energy consumption[52,11]. Our Fast Transition scenario assumes that eventually almost all energy services originate with electricity generated by solar PV and wind, making and burning P2X fuels or using batteries when it is impractical to use renewables directly. As shown by comparing Figures 4(g) and 4(i), the Fast Transition substantially increases the role of electricity in the energy system.

How much will each scenario cost?

There are many different approaches to modelling energy system pathway costs[53,54]. We use the "direct engineering costs" approach, in which the overall cost of a scenario is computed by adding up the costs of the component technologies (SN1.8). We sum the costs of direct-use oil, coal and gas; electricity generated by seven different technologies; plus utility-scale grid batteries and electrolyzers; and additional infrastructure for expansion of the electricity grid (SN3.7). For electricity generation costs we use the LCOE metric. This is particularly advantageous here because then the experience curve formulation inherently captures historical progress trends in all LCOE components, including capital costs, capacity factors, and interest rates, which would otherwise be hard to forecast separately. We estimate infrastructure costs that are not directly covered by technologies included in the model, e.g. for fuel storage and distribution (SN1.6.4) or for fueling or charging light duty vehicles (SN1.6.5), and argue that they are roughly the same across scenarios.

To apply our probabilistic technology cost forecasting methods in a given scenario, we employ a Monte Carlo approach, simulating many different future cost trajectories, then exponentially discounting future costs to calculate the expected net present cost of the scenario, up to 2070 (SN5.5, SN7.1). Figure 5(a) shows median total costs through time for each scenario, showing how the Fast Transition rapidly transfers energy expenditures from fossil fuels to renewables. Figure 5(b) shows that, although there is considerable uncertainty, the net present cost is likely to be substantially lower. Figure 5(d) shows how the Fast Transition rapidly decreases energy system emissions, making it feasible to achieve the Paris Agreement if non-energy related sources of emissions are also brought under control (SN8.6.1). In contrast, the Slow Transition is not as cheap as the Fast Transition. This is because the current high spending on fossil fuels continues for decades and the savings from renewables are only realized much later. Nonetheless, it also generates savings relative to No Transition.

Previous analyses have suggested that whether or not it makes good economic sense to quickly transition to clean energy technologies depends on the discount rate[22,55]. In Figure 5(c) we show a striking result: *the Fast Transition is likely to be substantially cheaper at all reasonable discount rates.* Using the 1.4% social discount rate recommended in the Stern Review[56], for example, the expected net present saving is roughly $14 trillion. The median value, which gives a better indication of the net present saving likely to be realized in practice, is roughly $26 trillion. (The distribution of costs is roughly log-normal, so means and medians are substantially different.) Note that there is some evidence that technological progress does not slow when technologies reach their saturation phase[57]. If this is true, then costs continue to drop at their current pace according to Moore's law, and the Fast Transition saves substantially more relative to the other scenarios (see SN7.4).

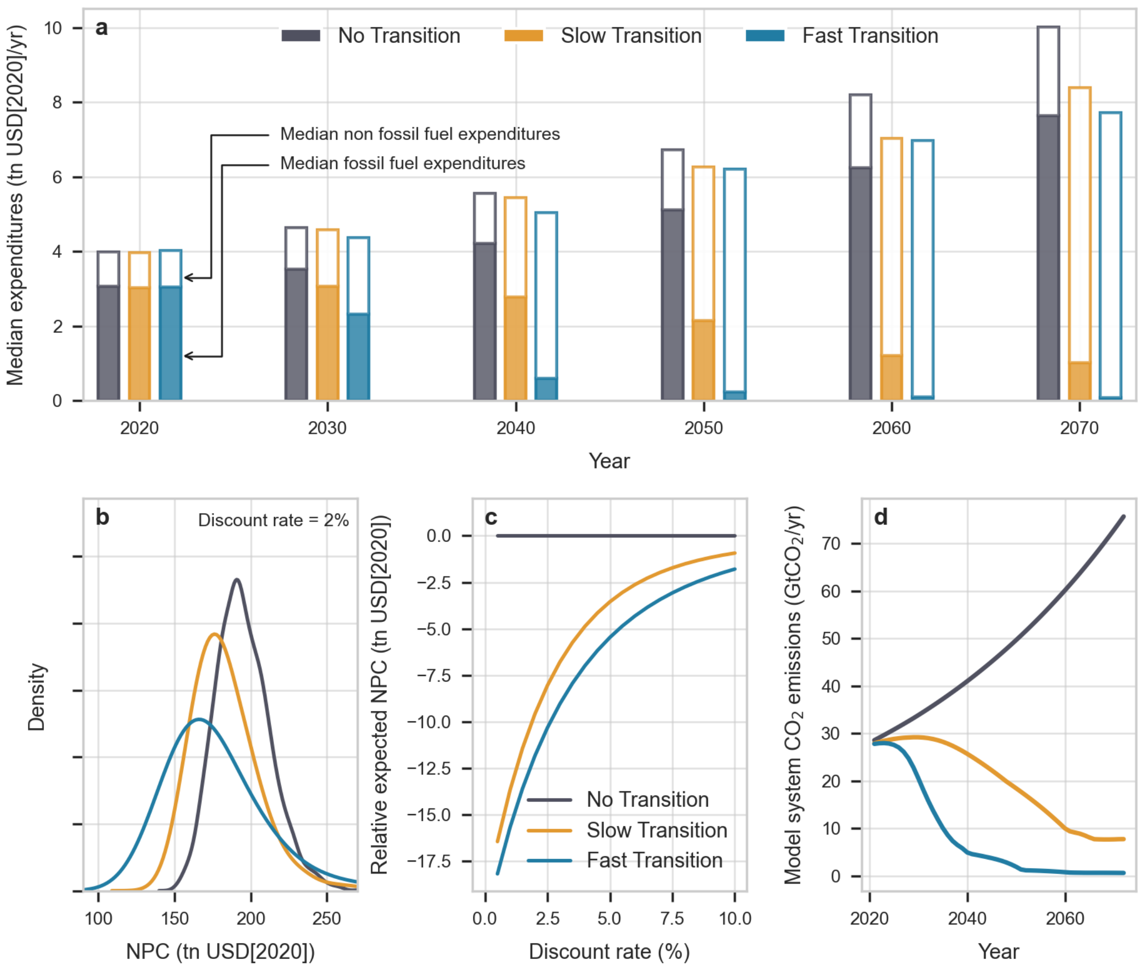

Figure 5: **Scenario costs and emissions.** (a) Median annual expenditures on fossil fuel and non fossil fuel technologies in each scenario in trillions of dollars (tn USD). (b) Forecast distributions of the net present cost (NPC) of each scenario, for a fixed discount rate of 2%. (c) Expected net present cost of each scenario relative to the No Transition scenario as a function of the discount rate. (d) Carbon emissions as a function of time.

We constructed an additional scenario in which nuclear plays a dominant role in replacing fossil fuels (SN4.4), but this is substantially more expensive than the baseline. For example, using a 1.4% discount rate the mean cost is about 15 trillion dollars more than No Transition and 27 trillion more than the Fast Transition (SN7.1).

To enhance the credibility of our estimates we have used consistently conservative assumptions regarding the costs, performance and operational requirements of clean energy technologies, and done the opposite for fossil fuels. Our systematic use of technologies with appropriate price histories means that in many cases we were forced to neglect solutions that are promising avenues of cost reduction, such as demand-side management of power grids and end-use efficiency improvements[11]. As a result, it is likely that the future costs of the renewable transition will be substantially lower than the estimates presented here (SN1.8).

Our analysis is based on global averages, but there is a wide geographic variation in energy costs. Within countries, renewables tend to be deployed first in regions where their costs are favorable, but that is not the case globally (SN8.4). In any case, under the Fast Transition regional cost differences are quickly overcome through time. For solar PV, for example, historically the 95th percentile of geographical cost variation at a given point in time became equivalent to the 5th percentile in less than a decade (SN8.4). Because costs are summed, global averages are sufficient to estimate costs, and we expect that future efforts will take advantage of geographic variation to achieve even cheaper solutions.

Although the Fast Transition happens quickly it is still possible to replace the energy system without excessive stranding of capital. Lifetimes of large energy infrastructure projects typically range from 25 to 50 years, meaning that on average about 2-4% of capacity needs replacing in any given year. In addition, useful energy demand grows at 2% per year. These two factors make it possible for renewables to replace most of the existing energy system in 20 years and replace the remaining 5% within a few decades without necessarily stranding assets beyond their economic lifetime.

Discussion

As we have not systematically searched the space of all possible scenarios, we do not claim that the Fast Transition scenario presented here is the cheapest possibility. Given the relatively low cost of gas, it could be possible to achieve cheaper scenarios by using gas in place of P2X fuels in some applications, but these of course would not be zero-emissions systems. Similarly, while fossil fuel costs have not historically trended down, competition from renewables may force them down, though this is feasible only at substantially reduced production levels where the cheapest fossil fuel producers are competitive[58]. This suggests that, while most of the Fast Transition is aligned with market forces, policies that discourage the use of fossil fuels will likely still be needed to fully decarbonize energy.

In response to our opening question, "Is there a path forward that can get us there cheaply and quickly?", our answer is an emphatic "Yes!". Our quantitative analysis supports other recent efforts using up-to-date data and technology assumptions that reach a similar conclusion[59,60,13,14,15,16]. The key is to maintain the current high growth rates of rapidly progressing clean energy technologies for the next decade. This is required to build up the industrial capabilities and technical know-how necessary to produce, install and operate these technologies at scale as fast as possible so that we can profit from the resulting cost reductions sooner rather than later.

The belief that the green energy transition will be expensive has been a major driver of the ineffective response to climate change for the last forty years. This pessimism is at odds with past technological cost-improvement trends, and risks locking humanity into an expensive and dangerous energy future. While arguments for a rapid green transition often cite benefits such as the avoidance of climate damages, less air pollution and lower energy price volatility (SN8.6), these benefits are often contrasted against discussions about the associated costs of transitioning[44]. Our analysis suggests that such trade-offs are unlikely to exist: *a greener, healthier and safer global energy system is also likely to be cheaper*. Updating expectations to better align with historical evidence could fundamentally change the debate about climate policy and dramatically accelerate progress to decarbonise energy systems around the world.

Methods

Time-series models

We employ two time-series models for forecasting technology costs. The first is a first-difference stochastic form of *Wright's law*, developed and tested by Lafond et al.[18], which models costs dropping as a power law of cumulative production. Let c_t be the cost and z_t be the experience of a given technology at time t, and let $u_t \sim \mathcal{N}(0, \sigma_u^2)$ be an IID draw from a normal distribution. Then future costs are predicted using the iterative relationship

$$\log c_t - \log c_{t-1} = -\omega(\log z_t - \log z_{t-1}) + u_t + \rho u_{t-1}. \quad (1)$$

This relationship has three parameters. For a given technology, the experience exponent ω characterizes the average rate at which costs drop as a function of experience, and the noise variance σ_u^2 characterizes the variability of this relationship. The autocorrelation parameter ρ characterizes the persistence of fluctuations in cost improvements. To avoid overfitting we use $\rho = 0.19$ for all technologies, which was found by Lafond et al.[18] to be a good overall choice for 50 different technologies. (We also did a comparison of all our results replacing Wright's Law by a generalized form of Moore's Law (see SN7.4)).

When applying the model to technologies with falling costs, as shown in Figure 3, two features of the model must be stressed. First, the Wright's law model does not simply "assume" that if costs fell in the past then they will fall in future – indeed, costs are predicted to rise with a non-zero probability that depends directly on observed data in the past. Second, despite the downward trends, all cost forecast distributions are always strictly positive, since costs develop in log space.

For fossil fuels we use an AR(1) process of the form

$$\log c_t = \log c_{t-1} + \beta(\mu - \log c_{t-1}) + \epsilon_t, \qquad \text{with IID } \epsilon_t \sim \mathcal{N}(0, \sigma_\epsilon^2), \tag{2}$$

where $\mu = \mathbb{E}[\log c_t]$ is the unconditional mean of the logarithm of cost, σ_ϵ is the volatility of the noise process and β is the rate of mean reversion. For more details on forecasting methods see SN5.

Scenario construction

We construct energy transition scenarios by assuming that growth rates follow logistic (or "S") curves with a specified start and end point consistent with the growth of total useful energy. We model the conversion process based on average final-to-useful energy conversion efficiency factors given by DeStercke[61]. The endpoint of each scenario in 2070 is defined by the shares of technologies providing electricity generation and the shares of energy carriers providing final energy. The start points for all scenarios are identical and match the current shares in 2018. Details of all growth rates, timings and energy carrier mixes for each scenario are given in SN2 and SN4.

Data availability

We use data from many sources, mostly free and openly available on the internet, but occasionally via standard university-wide subscription licenses held by the University of Oxford.

Production data comes mostly from the International Energy Agency[62] and BP's Statistical Review of World Energy[63]. Cost data is much harder to find and comes from a wide variety of sources including, among others, Lazard's Levelized Cost of Energy Analyses[64], the International Renewable Energy Agency[65], the U.S. Energy Information Administration's Annual Energy Outlooks[66], Bloomberg New Energy Finance (BNEF) and Bloomberg L.P. (via Bloomberg Terminal). For more details on data sources see SN6. All data will be made available upon request (following publication in a journal).

Code availability

The code used in this analysis will be made available upon request (following publication in a journal).

References

[1] Felix Creutzig, Peter Agoston, Jan Christoph Goldschmidt, Gunnar Luderer, Gregory Nemet, and Robert C. Pietzcker. The underestimated potential of solar energy to mitigate climate change. *Nature Energy*, 2(9):17140, Aug 2017. ISSN 2058-7546. doi: 10.1038/nenergy.2017.140. URL https://doi.org/10.1038/nenergy.2017.140.

[2] Mengzhu Xiao, Tobias Junne, Jannik Haas, and Martin Klein. Plummeting costs of renewables - are energy scenarios lagging? *Energy Strategy Reviews*, 35:100636, 2021. ISSN 2211-467X. doi: https://doi.org/10.1016/j.esr.2021.100636. URL https://www.sciencedirect.com/science/article/pii/S2211467X21000225.

[3] Marc Jaxa-Rozen and Evelina Trutnevyte. Sources of uncertainty in long-term global scenarios of solar photovoltaic technology. *Nature Climate Change*, 11(3):266–273, Mar 2021. ISSN 1758-6798. doi: 10.1038/s41558-021-00998-8. URL https://doi.org/10.1038/s41558-021-00998-8.

[4] Auke Hoekstra, Maarten Steinbuch, and Geert Verbong. Creating agent-based energy transition management models that can uncover profitable pathways to climate change mitigation. *Complexity*, 2017:1967645, Dec 2017. ISSN 1076-2787. doi: 10.1155/2017/1967645. URL https://doi.org/10.1155/2017/1967645.

[5] Hiroto Shiraki and Masahiro Sugiyama. Back to the basic: toward improvement of technoeconomic representation in integrated assessment models. *Climatic Change*, 162 (1):13–24, Sep 2020. ISSN 1573-1480. doi: 10.1007/s10584-020-02731-4. URL https://doi.org/10.1007/s10584-020-02731-4.

[6] Marta Victoria, Nancy Haegel, Ian Marius Peters, Ron Sinton, Arnulf Jäger-Waldau, Carlos del Cañizo, Christian Breyer, Matthew Stocks, Andrew Blakers, Izumi Kaizuka, Keiichi Komoto, and Arno Smets. Solar photovoltaics is ready to power a sustainable future. *Joule*, 5(5):1041–1056, 2021. ISSN 2542-4351. doi: https://doi.org/10.1016/j.joule.2021.03.005. URL https://www.sciencedirect.com/science/article/pii/S2542435121001008.

[7] Nicholas Stern. Economics: Current climate models are grossly misleading. *Nature*, 530(7591):407–409, Feb 2016. ISSN 1476-4687. doi: 10.1038/530407a. URL https://doi.org/10.1038/530407a.

[8] Robert S. Pindyck. Climate change policy: What do the models tell us? *Journal of Economic Literature*, 51(3):860–72, September 2013. doi: 10.1257/jel.51.3.860. URL https://www.aeaweb.org/articles?id=10.1257/jel.51.3.860.

[9] J Doyne Farmer, Cameron Hepburn, Penny Mealy, and Alexander Teytelboym. A third wave in the economics of climate change. *Environmental and Resource Economics*, 62(2): 329–357, 2015.

[10] David L. McCollum, Ajay Gambhir, Joeri Rogelj, and Charlie Wilson. Energy modellers should explore extremes more systematically in scenarios. *Nature Energy*, 5(2):104–107, Feb 2020. ISSN 2058-7546. doi: 10.1038/s41560-020-0555-3. URL https://doi.org/10.1038/s41560-020-0555-3.

[11] Amory B Lovins, Diana Ürge-Vorsatz, Luis Mundaca, Daniel M Kammen, and Jacob W Glassman. Recalibrating climate prospects. *Environmental Research Letters*, 14(12): 120201, 2019.

[12] S. Pye, O. Broad, C. Bataille, P. Brockway, H. E. Daly, R. Freeman, A. Gambhir, O. Geden, F. Rogan, S. Sanghvi, J. Tomei, I. Vorushylo, and J. Watson. Modelling net-zero emissions energy systems requires a change in approach. *Climate Policy*, 21(2):222–231, 2021. doi: 10.1080/14693062.2020.1824891. URL https://doi.org/10.1080/14693062.2020.1824891.

[13] Arnulf Grubler, Charlie Wilson, Nuno Bento, Benigna Boza-Kiss, Volker Krey, David L. McCollum, Narasimha D. Rao, Keywan Riahi, Joeri Rogelj, Simon De Stercke, Jonathan Cullen, Stefan Frank, Oliver Fricko, Fei Guo, Matt Gidden, Petr Havlík, Daniel Huppmann, Gregor Kiesewetter, Peter Rafaj, Wolfgang Schoepp, and Hugo Valin. A low energy demand scenario for meeting the 1.5 °c target and sustainable development goals without negative emission technologies. *Nature Energy*, 3(6):515–527, 2018. ISSN 2058-7546. doi: 10.1038/s41560-018-0172-6. URL https://doi.org/10.1038/s41560-018-0172-6.

[14] Marta Victoria, Kun Zhu, Tom Brown, Gorm B. Andresen, and Martin Greiner. Early decarbonisation of the european energy system pays off. *Nature Communications*, 11 (1):6223, Dec 2020. ISSN 2041-1723. doi: 10.1038/s41467-020-20015-4. URL https://doi.org/10.1038/s41467-020-20015-4.

[15] Gang He, Jiang Lin, Froylan Sifuentes, Xu Liu, Nikit Abhyankar, and Amol Phadke. Rapid cost decrease of renewables and storage accelerates the decarbonization of china's power system. *Nature Communications*, 11(1):2486, May 2020. ISSN 2041-1723. doi: 10.1038/s41467-020-16184-x. URL https://doi.org/10.1038/s41467-020-16184-x.

[16] Dmitrii Bogdanov, Manish Ram, Arman Aghahosseini, Ashish Gulagi, Ayobami Solomon Oyewo, Michael Child, Upeksha Caldera, Kristina Sadovskaia, Javier Farfan, Larissa De Souza Noel Simas Barbosa, Mahdi Fasihi, Siavash Khalili, Thure Traber, and Christian Breyer. Low-cost renewable electricity as the key driver of the global energy transition towards sustainability. *Energy*, 227:120467, 2021. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2021.120467. URL https://www.sciencedirect.com/science/article/pii/S0360544221007167.

[17] J Doyne Farmer and François Lafond. How predictable is technological progress? *Research Policy*, 45(3):647–665, 2016.

[18] François Lafond, Aimee Gotway Bailey, Jan David Bakker, Dylan Rebois, Rubina Zadourian, Patrick McSharry, and J Doyne Farmer. How well do experience curves predict technological progress? a method for making distributional forecasts. *Technological Forecasting and Social Change*, 128:104–117, 2018.

[19] Keywan Riahi, Elmar Kriegler, Nils Johnson, Christoph Bertram, Michel den Elzen, Jiyong Eom, Michiel Schaeffer, Jae Edmonds, Morna Isaac, Volker Krey, Thomas Longden, Gunnar Luderer, Aurélie Méjean, David L. McCollum, Silvana Mima, Hal Turton, Detlef P. van Vuuren, Kenichi Wada, Valentina Bosetti, Pantelis Capros, Patrick Criqui, Meriem Hamdi-Cherif, Mikiko Kainuma, and Ottmar Edenhofer. Locked into copenhagen pledges — implications of short-term emission targets for the cost and feasibility of long-term climate goals. *Technological Forecasting and Social Change*, 90:8–23, 2015. ISSN 0040-1625. doi: https://doi.org/10.1016/j.techfore.2013.09.016. URL https://www.sciencedirect.com/science/article/pii/S0040162513002539.

[20] Volker Krey, Fei Guo, Peter Kolp, Wenji Zhou, Roberto Schaeffer, Aayushi Awasthy, Christoph Bertram, Harmen-Sytze de Boer, Panagiotis Fragkos, Shinichiro Fujimori,

Chenmin He, Gokul Iyer, Kimon Keramidas, Alexandre C. Köberle, Ken Oshiro, Lara Aleluia Reis, Bianka Shoai-Tehrani, Saritha Vishwanathan, Pantelis Capros, Laurent Drouet, James E. Edmonds, Amit Garg, David E.H.J. Gernaat, Kejun Jiang, Maria Kannavou, Alban Kitous, Elmar Kriegler, Gunnar Luderer, Ritu Mathur, Matteo Muratori, Fuminori Sano, and Detlef P. van Vuuren. Looking under the hood: A comparison of techno-economic assumptions across national and global integrated assessment models. *Energy*, 172:1254 – 1267, 2019. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2018.12.131. URL http://www.sciencedirect.com/science/article/pii/S0360544218325039.

[21] Daniel Huppmann, Elmar Kriegler, Volker Krey, Keywan Riahi, Joeri Rogelj, Katherine Calvin, Florian Humpenoeder, Alexander Popp, Steven K. Rose, John Weyant, Nico Bauer, Christoph Bertram, Valentina Bosetti, Jonathan Doelman, Laurent Drouet, Johannes Emmerling, Stefan Frank, Shinichiro Fujimori, David Gernaat, Arnulf Grubler, Celine Guivarch, Martin Haigh, Christian Holz, Gokul Iyer, Etsushi Kato, Kimon Keramidas, Alban Kitous, Florian Leblanc, Jing-Yu Liu, Konstantin Löffler, Gunnar Luderer, Adriana Marcucci, David McCollum, Silvana Mima, Ronald D. Sands, Fuminori Sano, Jessica Strefler, Junichi Tsutsui, Detlef Van Vuuren, Zoi Vrontisi, Marshall Wise, and Runsen Zhang. IAMC 1.5°C Scenario Explorer and Data hosted by IIASA. Technical report, IIASA, August 2019. URL https://doi.org/10.5281/zenodo.3363345.

[22] William D Nordhaus. Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences*, 114(7):1518–1523, 2017.

[23] C. Wilson, A. Grubler, N. Bauer, V. Krey, and K. Riahi. Future capacity growth of energy technologies: are scenarios consistent with historical evidence? *Climatic Change*, 118(2): 381–395, May 2013. ISSN 1573-1480. doi: 10.1007/s10584-012-0618-y. URL https://doi.org/10.1007/s10584-012-0618-y.

[24] Charles D. Ferguson, Lindsey E. Marburger, J. Doyne Farmer, and Arjun Makhijani. A US nuclear future? *Nature*, 467(7314):391–393, sep 2010. ISSN 0028-0836. doi: 10.1038/467391a. URL http://www.nature.com/articles/467391a.

[25] Béla Nagy, J Doyne Farmer, Quan M Bui, and Jessika E Trancik. Statistical basis for predicting technological progress. *PloS one*, 8(2):e52669, 2013.

[26] D.E. Carlson. The Status and Outlook for the Photovoltaics Industry. Technical report, BP, 2006. URL https://www.aps.org/meetings/multimedia/upload/The_Status_and_Outlook_for_the_Photovoltaics_Industry_David_E_Carlson.pdf.

[27] Noah Kittner, Felix Lill, and Daniel M. Kammen. Energy storage deployment and innovation for the clean energy transition. *Nature Energy*, 2(9):17125, Jul 2017. ISSN 2058-7546. doi: 10.1038/nenergy.2017.125. URL https://doi.org/10.1038/nenergy.2017.125.

[28] E De Cian, J Buhl, S Carrara, M Bevione, S Monetti, and H Berg. Learning in integrated assessment models and initiative based learning-an interdisciplinary approach. *PATHWAYS Deliverable*, 3, 2016.

[29] Ajay Gambhir, Isabela Butnar, Pei-Hao Li, Pete Smith, and Neil Strachan. A review of criticisms of integrated assessment models and proposed approaches to address these, through the lens of beccs. *Energies*, 12(9), 2019. ISSN 1996-1073. doi: 10.3390/en12091747. URL https://www.mdpi.com/1996-1073/12/9/1747.

[30] Heebyung Koh and Christopher L. Magee. A functional approach for studying technological progress: Extension to energy technology. *Technological Forecasting and Social Change*, 75(6):735–758, 2008. ISSN 0040-1625. doi: https://doi.org/10.1016/j.techfore.2007.05.007. URL https://www.sciencedirect.com/science/article/pii/S0040162507001230.

[31] Heebyung Koh and Christopher L Magee. A functional approach for studying technological progress: Application to information technology. *Technological Forecasting and Social Change*, 73(9):1061–1083, 2006.

[32] Stephan Alberth. Forecasting technology costs via the experience curve—myth or magic? *Technological Forecasting and Social Change*, 75(7):952–983, 2008.

[33] Jessika E Trancik, Joel Jean, Goksin Kavlak, Magdalena M Klemun, Morgan R Edwards, James McNerney, Marco Miotti, Patrick R Brown, Joshua M Mueller, and Zachary A Needell. Technology improvement and emissions reductions as mutually reinforcing efforts: Observations from the global development of solar and wind energy. Technical report, MIT, 2015.

[34] William D. Nordhaus. The perils of the learning model for modeling endogenous technological change. *The Energy Journal*, Volume 35(1), Jan 2014. ISSN 1944-9089. doi: 10.5547/01956574.35.1.1. URL http://www.iaee.org/en/publications/ejarticle.aspx?id=2546.

[35] Jan Witajewski-Baltvilks, Elena Verdolini, and Massimo Tavoni. Bending the learning curve. *Energy Economics*, 52:S86–S99, 2015. ISSN 0140-9883. doi: https://doi.org/10.1016/j.eneco.2015.09.007. URL https://www.sciencedirect.com/science/article/pii/S0140988315002601. Frontiers in the Economics of Energy Efficiency.

[36] Arnulf Grübler, Nebojša Nakićenović, and David G. Victor. Dynamics of energy technologies and global change. *Energy Policy*, 27(5):247–280, may 1999. ISSN 03014215. doi: 10.1016/S0301-4215(98)00067-6.

[37] Gabrial Anandarajah, Will McDowall, and Paul Ekins. Decarbonising road transport with hydrogen and electricity: Long term global technology learning scenarios. *International Journal of Hydrogen Energy*, 38(8):3419–3432, 2013.

[38] Clara F Heuberger, Edward S Rubin, Iain Staffell, Nilay Shah, and Niall Mac Dowell. Power capacity expansion planning considering endogenous technology cost learning. *Applied Energy*, 204:831–845, 2017.

[39] Joseph DeCarolis, Hannah Daly, Paul Dodds, Ilkka Keppo, Francis Li, Will McDowall, Steve Pye, Neil Strachan, Evelina Trutnevyte, Will Usher, et al. Formalizing best practice for energy system optimization modelling. *Applied energy*, 194:184–198, 2017.

[40] Justin Ritchie and Hadi Dowlatabadi. Evaluating the learning-by-doing theory of long-run oil, gas, and coal economics. Working paper, Resources For The Future, 2017.

[41] Robert S. Pindyck. The long-run evolution of energy prices. *The Energy Journal*, 20(2):1–27, 1999. ISSN 01956574, 19449089. URL http://www.jstor.org/stable/41322828.

[42] James McNerney, J Doyne Farmer, and Jessika E Trancik. Historical costs of coal-fired electricity and implications for the future. *Energy Policy*, 39(6):3042–3054, 2011.

[43] Oliver Fricko, Petr Havlik, Joeri Rogelj, Zbigniew Klimont, Mykola Gusti, Nils Johnson, Peter Kolp, Manfred Strubegger, Hugo Valin, Markus Amann, Tatiana Ermolieva, Nicklas Forsell, Mario Herrero, Chris Heyes, Georg Kindermann, Volker Krey, David L. McCollum, Michael Obersteiner, Shonali Pachauri, Shilpa Rao, Erwin Schmid, Wolfgang Schoepp, and Keywan Riahi. The marker quantification of the shared socioeconomic pathway 2: A middle-of-the-road scenario for the 21st century. *Global Environmental Change*, 42:251–267, 2017. ISSN 0959-3780. doi: https://doi.org/10.1016/j.gloenvcha.2016.06.004. URL https://www.sciencedirect.com/science/article/pii/S0959378016300784.

[44] L. Clarke, K. Jiang, K. Akimoto, M. Babiker, G. Blanford, K. Fisher-Vanden, J.C. Hourcade, V. Krey, E. Kriegler, A. Löschel, D. McCollum, S. Paltsev, S. Rose, P.R. Shukla, M. Tavoni, B.C.C. van der Zwaan, and D.P. van Vuuren. Transformation Pathways. In: Climate Change 2014: Mitigation of Climate Change. Technical report, IPCC, 2014. URL https://www.ipcc.ch/site/assets/uploads/2018/02/ipcc_wg3_ar5_chapter6.pdf.

[45] Jing Meng, Rupert Way, Elena Verdolini, and Laura Diaz Anadon. Comparing expert elicitation and model-based probabilistic technology cost forecasts for the energy transition. *Proceedings of the National Academy of Sciences*, 118(27), 2021. ISSN 0027-8424. doi: 10.1073/pnas.1917165118. URL https://www.pnas.org/content/118/27/e1917165118.

[46] Andrii Gritsevskyi and Nebojsa Nakicenovi. Modeling uncertainty of induced technological change. *Energy Policy*, 28(13):907–17909, 2000.

[47] Evelina Trutnevyte. Does cost optimization approximate the real-world energy transition? *Energy*, 106:182–193, 2016.

[48] Steven J. Davis, Nathan S. Lewis, Matthew Shaner, Sonia Aggarwal, Doug Arent, Inês L. Azevedo, Sally M. Benson, Thomas Bradley, Jack Brouwer, Yet-Ming Chiang, Christopher T. M. Clack, Armond Cohen, Stephen Doig, Jae Edmonds, Paul Fennell, Christopher B. Field, Bryan Hannegan, Bri-Mathias Hodge, Martin I. Hoffert, Eric Ingersoll, Paulina Jaramillo, Klaus S. Lackner, Katharine J. Mach, Michael Mastrandrea, Joan Ogden, Per F. Peterson, Daniel L. Sanchez, Daniel Sperling, Joseph Stagner, Jessika E. Trancik, Chi-Jen Yang, and Ken Caldeira. Net-zero emissions energy systems. *Science*, 360(6396), 2018. ISSN 0036-8075. doi: 10.1126/science.aas9793. URL https://science.sciencemag.org/content/360/6396/eaas9793.

[49] T. Brown, D. Schlachtberger, A. Kies, S. Schramm, and M. Greiner. Synergies of sector coupling and transmission reinforcement in a cost-optimised, highly renewable european energy system. *Energy*, 160:720–739, 2018. ISSN 0360-5442. doi: https://doi.org/10.1016/j.energy.2018.06.222. URL https://www.sciencedirect.com/science/article/pii/S036054421831288X.

[50] Micah S. Ziegler and Jessika E. Trancik. Re-examining rates of lithium-ion battery technology improvement and cost decline. *Energy Environ. Sci.*, 14:1635–1651, 2021. doi: 10.1039/D0EE02681F. URL http://dx.doi.org/10.1039/D0EE02681F.

[51] IEA. The Future of Hydrogen. Technical report, International Energy Agency, 2019.

[52] Nick Eyre. Energy efficiency in the energy transition. *European Council for an Energy Efficient Economy Summer Study Proceedings*, pages 247–254, 2019.

[53] Volker Krey. Global energy-climate scenarios and models: a review. *WIREs Energy and Environment*, 3(4):363–383, 2014. doi: https://doi.org/10.1002/wene.98. URL https://www.onlinelibrary.wiley.com/doi/abs/10.1002/wene.98.

[54] Ottmar Edenhofer, Kai Lessmann, Claudia Kemfert, Michael Grubb, and Jonathan Köhler. Induced technological change: Exploring its implications for the economics of atmospheric stabilization: Synthesis report from the innovation modeling comparison project. *The Energy Journal*, 27:57–107, 2006. ISSN 01956574, 19449089. URL http://www.jstor.org/stable/23297057.

[55] JOHN BROOME. The ethics of climate change. *Scientific American*, 298(6):96–102, 2008. ISSN 00368733, 19467087. URL http://www.jstor.org/stable/26000646.

[56] Nicholas Stern. *The economics of climate change: the Stern review*. Cambridge University Press, 2007.

[57] JongRoul Woo and Christopher L. Magee. Relationship between technological improvement and innovation diffusion: an empirical test. *Technology Analysis & Strategic Management*, 0(0):1–16, 2021. doi: 10.1080/09537325.2021.1901875. URL https://doi.org/10.1080/09537325.2021.1901875.

[58] J. F. Mercure, H. Pollitt, J. E. Viñuales, N. R. Edwards, P. B. Holden, U. Chewpreecha, P. Salas, I. Sognnaes, A. Lam, and F. Knobloch. Macroeconomic impact of stranded fossil fuel assets. *Nature Climate Change*, 8(7):588–593, 2018. ISSN 17586798. doi: 10.1038/s41558-018-0182-1. URL http://dx.doi.org/10.1038/s41558-018-0182-1.

[59] Caroline Zimm, José Goldemberg, Nebojsa Nakicenovic, and Sebastian Busch. Is the renewables transformation a piece of cake or a pie in the sky? *Energy Strategy Reviews*, 26:100401, 2019. ISSN 2211-467X. doi: https://doi.org/10.1016/j.esr.2019.100401. URL https://www.sciencedirect.com/science/article/pii/S2211467X1930094X.

[60] Michael Grubb, Claudia Wieners, and Pu Yang. Modeling myths: On dice and dynamic realism in integrated assessment models of climate change mitigation. *WIREs Climate Change*, 12(3):e698, 2021. doi: https://doi.org/10.1002/wcc.698. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/wcc.698.

[61] S. De Stercke. Dynamics of energy systems: A useful perspective. IIASA interim report, IIASA, Laxenburg, Austria, 2014. URL http://pure.iiasa.ac.at/id/eprint/11254/.

[62] IEA. World Energy Outlook 2019. Technical report, International Energy Agency, 2019.

[63] BP. BP Statistical Review of World Energy 2019. Technical report, BP plc, 2019.

[64] Lazard. Lazard's Levelized Cost of Energy ("LCOE") Analysis Versions 2-13. Technical report, Lazard, 2019.

[65] IRENA. Renewable Power Generation Costs in 2018. Technical report, International Renewable Energy Agency, Abu Dhabi, 2019.

[66] EIA. Annual Energy Outlook reports 1979-2019. Technical report, U.S. Energy Information Administration, 2019.

[67] IRENA. Renewable Power Generation Costs in 2020. Technical report, International Renewable Energy Agency, Abu Dhabi, 2021.

[68] IEA. Offshore Wind Outlook 2019. Technical report, International Energy Agency, Paris, 2019.

Acknowledgemnts

This work was supported by funding from Partners for a New Economy (RW, JDF); Baillie Gifford (JDF); the European Union's Horizon 2020 research and innovation programme under grant agreement No. 730427 (COP21 RIPPLES) (RW); the Oxford Martin School Post-Carbon Transition Programme (MI, PM). The authors gratefully acknowledge all these sources of financial support, and additionally the Institute for New Economic Thinking at the Oxford Martin School for its continuing support.

Author contributions

JDF conceptualized the study; RW and JDF designed the methodology; RW developed the model and curated data, RW and MI performed analysis and investigation; JDF, MI, PM and RW wrote the manuscript.

Competing interests

The authors declare no competing interests.

Additional Information

Supplementary Information is available for this paper.
Correspondence and requests for materials should be addressed to RW

Extended data

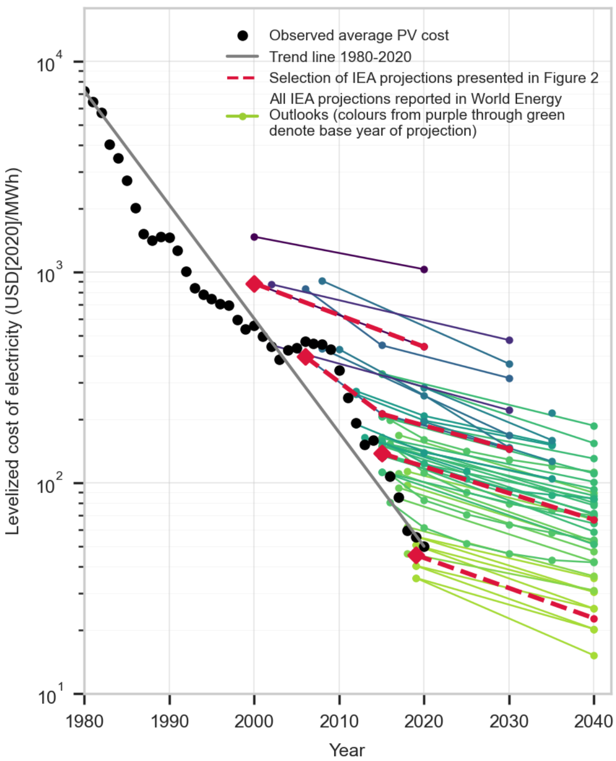

Figure 6: **IEA PV LCOE projections**. All PV LCOE projections found in the IEA's World Energy Outlook (WEO) reports are shown in colours varying from purple through light green. (Note that "projection" here means conditional forecast – these are forecasts that are conditional upon a whole array of modelling assumptions regarding the scenario within which the forecast is embedded.) The first such projection was found in the WEO 2001. The four projections we selected to plot in Figure 2 are shown in red, and were chosen as examples of "high progress" projections. The first two, published in the WEOs from 2001 and 2008, may be considered high progress projections because in those reports, cost ranges were provided, and we simply picked the lowest point of those ranges. The upper ends of the ranges are much higher. The second two (beginning in 2015 and 2019) may be interpreted as"high progress" projections because they correspond to the highest mitigation scenarios available in the WEOs from which they are sourced (WEO 2016 and 2020). Note however that in those reports, only region-specific cost projections were provided, so we have plotted the simple global average of those values in the high mitigation scenarios. Observed values are from the Performance Curve Database (described in Nagy et al.[25]) up to 2010 and from BNEF thereafter. See SN6 for more details on data sources.

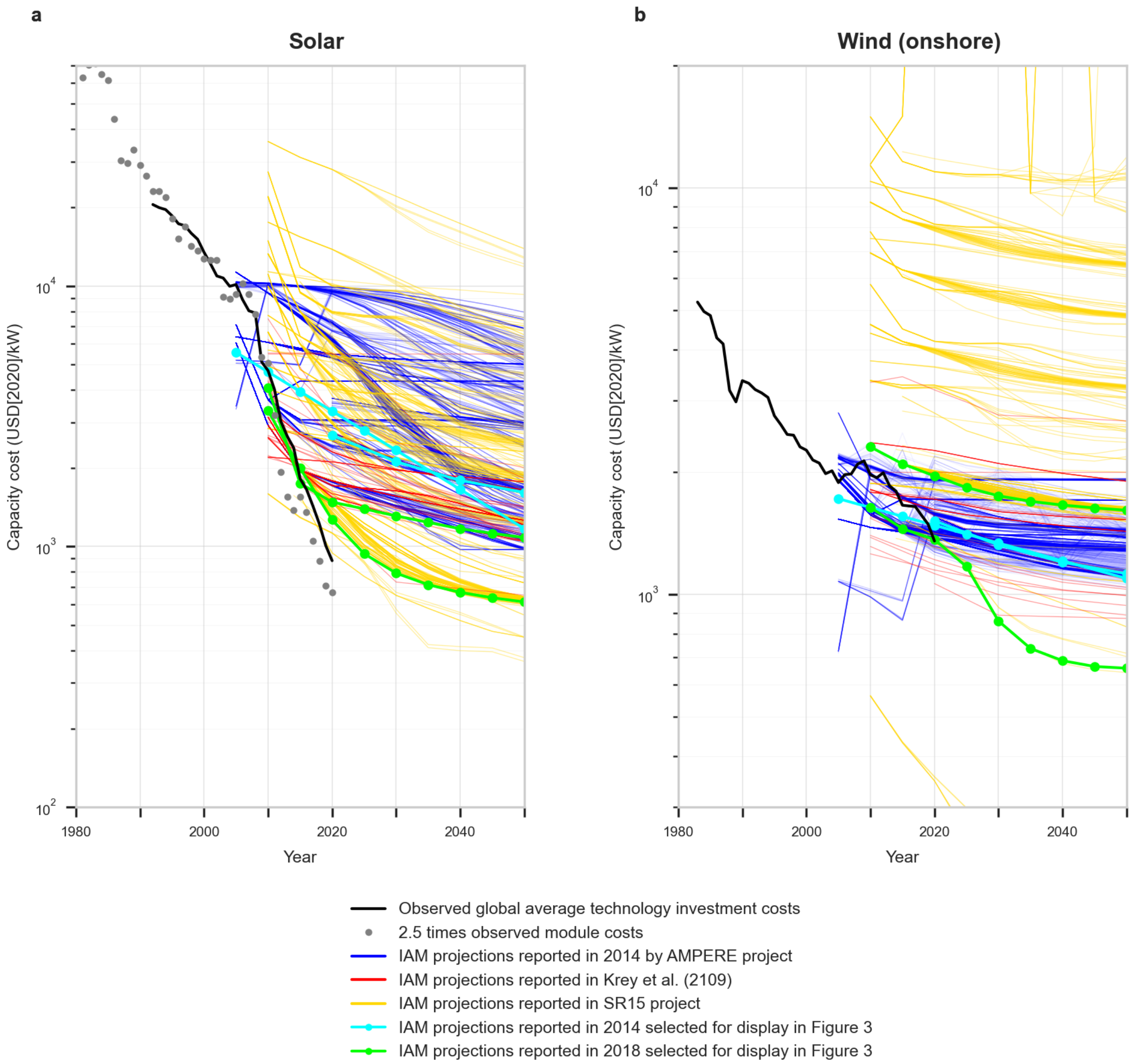

Figure 7: **PV and wind capital cost projections reported by IAMs**. Capital cost projections reported by various modelling comparison projects are shown as blue, red and yellow lines for (a) PV and (b) onshore wind. Each line corresponds to a single scenario. To construct and plot the LCOE projections in Figure 3 we selected two capacity cost projections reported in 2014 (cyan lines) and two reported in 2018 (green lines). These may be interpreted as "high progress projections" because they are among the lowest in their cohorts (i.e. the cyan lines are on the low end of the suite of blue lines, and the green lines are on the low end of the suite of red and yellow lines). Note that they are (in seven out of eight cases) global average values, whereas many other projections are region-specific. For PV, the projections plotted are: 1. [model: MESSAGE, scenario: 'AMPERE3-450', region: World] (from AMPERE[19]), 2. [model: DNE21, scenario: 'AMPERE3-450', region: World] (from AMPERE[19]), 3. [model: IMAGE 3.0, scenario: 'Baseline', region: China] (from Krey et al. 2019), 4. [model: REMIND-MAgPIE 1.7-3.0, scenario: 'SMP_1p5C_early', region: World] (from SR15[21]). For wind, the projections plotted are: 1. [model: MESSAGE, scenario: 'AMPERE3-450', region: World] (from AMPERE[19]), 2. [model: DNE21, scenario: 'AMPERE3-450', region: World] (from AMPERE[19]), 3. [model: AIM/CGE 2.1, scenario: 'TERL_15D_LowCarbonTransportPolicy', region: World] (from SR15[21]), 4. [model: REMIND-MAgPIE 1.7-3.0, scenario: 'SMP_1p5C_early', region: World] (from SR15[21]). To calculate the LCOEs, we used the technology lifetimes, operations and maintenance (O&M) values, and discount rate reported in Krey et al.[20]. We used global average capacity factors of 0.18 for PV and 0.3 for wind, based on recent data reported by IRENA[67] and the IEA[68]. Observed data sources for PV are given in Table S19. Wind data is from IRENA[67].