Working Paper No. 2025-12

INET Oxford Working Paper Series
30 May 2025

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May 30, 2025

Summary

Since the 1980s, the global average of solar photovoltaic (PV) cost has decreased by about two orders of magnitude while the global average onshore wind cost has decreased by about one order of magnitude. But global averages are only part of the story: For both solar and wind, costs vary between countries by about an order of magnitude. We curate a comprehensive database of national costs and build predictive models for future costs by decomposing the levelized cost of electricity (LCOE) into its components and modeling them separately. For solar PV we find that since 1990 the module cost and the balance of system cost (BOS) have both declined roughly exponentially at rates of 12% per year. In contrast, wind turbine cost has declined roughly exponentially by 4% per year, while BOS cost has not declined at all. This suggests that total global wind cost will slowly approach a floor cost of about 35 USD/MWh, reaching about 43 USD/MWh in 2050, whereas global solar cost will continue to decline exponentially, reaching about 3-15 USD/MWh in 2050 and continuing to drop thereafter. For solar, around half of the cross-sectional variations in national LCOE costs is due to variations in capacity factors, though capital costs also play an important role. For wind, the cross-sectional variations are split approximately equally between capacity factor, capital costs, and investment costs. National BOS costs revert to global costs with a timescale of about 5-7 years, while variations in other factors are more persistent. We develop a simple model for predicting the deviations from global costs and show that it makes reasonable predictions with predictable errors. Finally, we compare our predictions to recent projections of integrated assessment models.

Introduction

The rapid decline of the costs of solar and wind energy over the last sixty years or so has changed views about the feasibility of the energy transformation, injecting a rare note of optimism into the climate debate. In hindsight, it is clear that this could have been predicted much earlier by simply extrapolating past trends; a few did this, but their voices received limited attention.[1–3] Paying more

*Acknowledgments: This work was supported by NSF APTO Grant Award 2403999. For helpful comments and feedback, we thank François Lafond, Benjamin Wagenvoort, Brendon Tankwa, Cameron Hepburn, and seminar and conference participants at the seventeenth annual meeting of the Integrated Assessment Modelling Consortium (IAMC), 2024.

attention to such forecasts would have made it possible to anticipate which technologies were likely to be cheap and plan and invest accordingly.[3–5]

National costs of renewables vary widely, so forecasts need to take this into account.[6] As we show here, the deviations across countries can be understood by decomposing the costs of renewables into their components. This turns out to also have implications for global costs; as we will see, extrapolating the revealed trends suggests that wind power will drop in cost more slowly and reach a floor, whereas solar will continue to drop exponentially for some time. This suggests that twenty years from now, solar energy will be substantially cheaper than wind energy.

The standard way to compare the costs of capital-intensive renewable technologies with those of more operationally expensive technologies such as fossil fuels is based on the *levelized cost of electricity* (LCOE), which is defined as the average annualized cost of generating one unit of electricity.[5,7] Here we decompose the formula for LCOE into its different components and develop a forecasting model for each component separately. This allows us to forecast national renewable electricity costs and better understand the drivers that determine them.

Decomposition of the LCOE

We consider the LCOE $\mathcal{L}_j$ of country j. Over its lifetime an asset produces electricity, which we measure in kWh, and incurs costs measured here in 2020 US dollars. The LCOE translates the fixed and ongoing costs for renewable electricity into an effective ongoing cost per year. We follow the standard approach of Bolinger et al.[5] and IRENA[7] and decompose the LCOE of an asset i in country j and year t as

$$\mathcal{L}_{ijt} \equiv \frac{\mathcal{I}_{ijt} * \mathcal{C}_{ijt} + \mathcal{O}_{ijt}}{\mathcal{Y}_{ijt}} \quad \text{(USD / kWh)}. \tag{1}$$

As explained in more detail below, the components of $\mathcal{L}_{ijt}$ are the total investment cost $\mathcal{I}_{ijt}$ (USD/kW), the capital recovery factor $\mathcal{C}_{ijt}$ (%/year), the annual operating and maintenance cost $\mathcal{O}_{ijt}$ (USD/kW/year), and the capacity factor $\mathcal{Y}_{ijt}$ (kWh/kW/year), also called annual electricity yield) (Table S1 in the Supplementary Information summarizes our notation.) While ideally this analysis should be done at the level of individual electricity-generating assets, since data is not available at this level, we are forced to operate at the country level. For convenience, we omit the indices ijt for the rest of this paper. We use the national average components $(\mathcal{I}, \mathcal{C}, \mathcal{O}, \mathcal{Y})$ to forecast the national average LCOE $\mathcal{L}$. While (1) does not hold exactly for the national averages, we show in Supplementary Information S3.1 that it is a good approximation.

The *investment cost* $\mathcal{I}$ includes both equipment costs and soft costs, such as installation and permitting costs, that occur before electricity production begins. It is typically measured in cost (USD) per electric capacity (kW). The investment cost can be further divided into the equipment cost and the Balance of System cost (BOS). The largest piece of equipment for solar energy is the photovoltaic module, and for wind, it is the turbine; in either case we define the cost as $\mathcal{M}$. The Balance of System (BOS) cost $\mathcal{J}$ aggregates all other equipment and soft costs included in the total investment cost I, so that we can decompose the investment cost as

$$\mathcal{I} = \mathcal{M} + \mathcal{J} \tag{2}$$

for both solar and wind

The *capital recovery factor* $\mathcal{C}$ depends on the assets' lifetime and the weighted average cost of capital (WACC). After an initial investment $\mathcal{I}$, the asset operator makes annual payments to its investors (who may or may not be the same entity as the asset operator). As a result, investors recover their initial investment plus a premium. $\mathcal{I} \cdot \mathcal{C}$ is the annual recovery of the original investment, expressed in USD/kW/year.

The *operating and maintenance cost* O is the annual expense of operating the renewable asset, averaged over the asset's lifetime. For renewables, it is typically measured in USD/kW/year (as opposed to USD/kWh for fossil fuels) since there is little to no variable cost that depends on fuel consumption.

The *capacity factor* $\mathcal{Y}_j$ is the annual electricity generation (kWh) per electric capacity (kW). It accounts for variable environmental characteristics, such as sunshine hours and average wind speed, and also includes asset downtime due to maintenance and other operational constraints.

For renewables, the total investment cost $\mathcal{I}$ is much bigger than the operating cost $\mathcal{O}$, typically by about two orders of magnitude. As we show, while the capital recovery factor and the capacity factor drive substantial variations in costs, they are essentially modifiers of the investment and operating costs, so that the LCOE goes to zero when $\mathcal{I}$ and $\mathcal{O}$ go to zero, regardless of $\mathcal{C}$ and $\mathcal{Y}$.

The important components of the LCOE for wind and solar are shown in Figure 1, which makes key properties of the components of the LCOE apparent from visual inspection alone. (See also the summary in Table 1).

- In panel 1(a), we see that solar investment costs have dropped by almost three orders of magnitude since 1975, at an average rate of 12% per year. Since 2000, when data on BOS costs first became available, the module cost and BOS cost of solar have been comparable, and have dropped at similar rates. National costs vary substantially, with a standard deviation that is currently about 306 USD/kW, which has also dropped roughly exponentially over time.

- In panel 1(b), wind investment costs have also dropped, though at a much slower average rate of about 3% per year. Together with declines in the cost of capital, this is the main driver of LCOE declines. In 1980 wind was more than an order of magnitude cheaper than solar; it is now, on average, slightly more expensive. The standard deviation of wind investment costs is about 437 USD/kW and has not declined. While turbine costs have declined by an average of 4% per year since 1980, they vary based on origin, with Chinese-built turbines currently about a factor of 3 cheaper than western-built turbines. Most importantly, while BOS costs are highly variable, with a standard deviation of about 400 USD/kW, over a span of almost three decades, *average BOS costs have not declined.*[8]

- In panels 1(c) and 1(d), the cross-sectional standard deviation of the capacity factors varies by about 0.5 MWh/kW for wind and solar. The average has remained roughly constant for solar and increased slightly for wind. However, it is important to note that capacity factors are not realized values but rather are estimates. Thus trends may reflect changes in weather, unplanned downtime or forecasting methodology rather than real increases in lifetime capacity factors. (If early projects occupy the most favorable sites, one would expect capacity to decrease, but this is the opposite of what is observed).

- In panels 1(e) and 1(f) we see that capital recovery factors vary substantially, with a cross-sectional standard deviation of about 3.4% for solar and 5.7% for wind. This variation is driven by interest rates, which are generally higher and more volatile in less developed countries. As a result, capital recovery factors are generally lower for developed countries and higher for less developed countries where investors require higher returns on their investments. Capital recovery factors have declined continuously by around 1% annually in most countries between the 1990s and 2020 but can be subject to rapid changes. The high volatility in Argentina's interest rates, or the sharp increase in interest rates in 2020 illustrates this.

Table 1 presents typical values for each component of LCOE and each technology in 2023. We see that BOS costs are the dominant component of the investment cost for solar energy, as much as 3.5 times module costs, whereas for wind, BOS costs and turbine costs are comparable. BOS costs vary by as much as a factor of 7.5 for wind and a factor of 3 for solar. The capital recovery factor varies by as much as a factor of 4 due to differences in the financial environment. The capacity factor varies by more than a factor of 2 for both solar and wind. In summary, all the factors of LCOE except for solar module cost and operating and maintenance vary widely. While operating costs are small enough to be negligible, BOS costs, capital recovery factors and capacity factors are all important determinants of the variability of national costs.

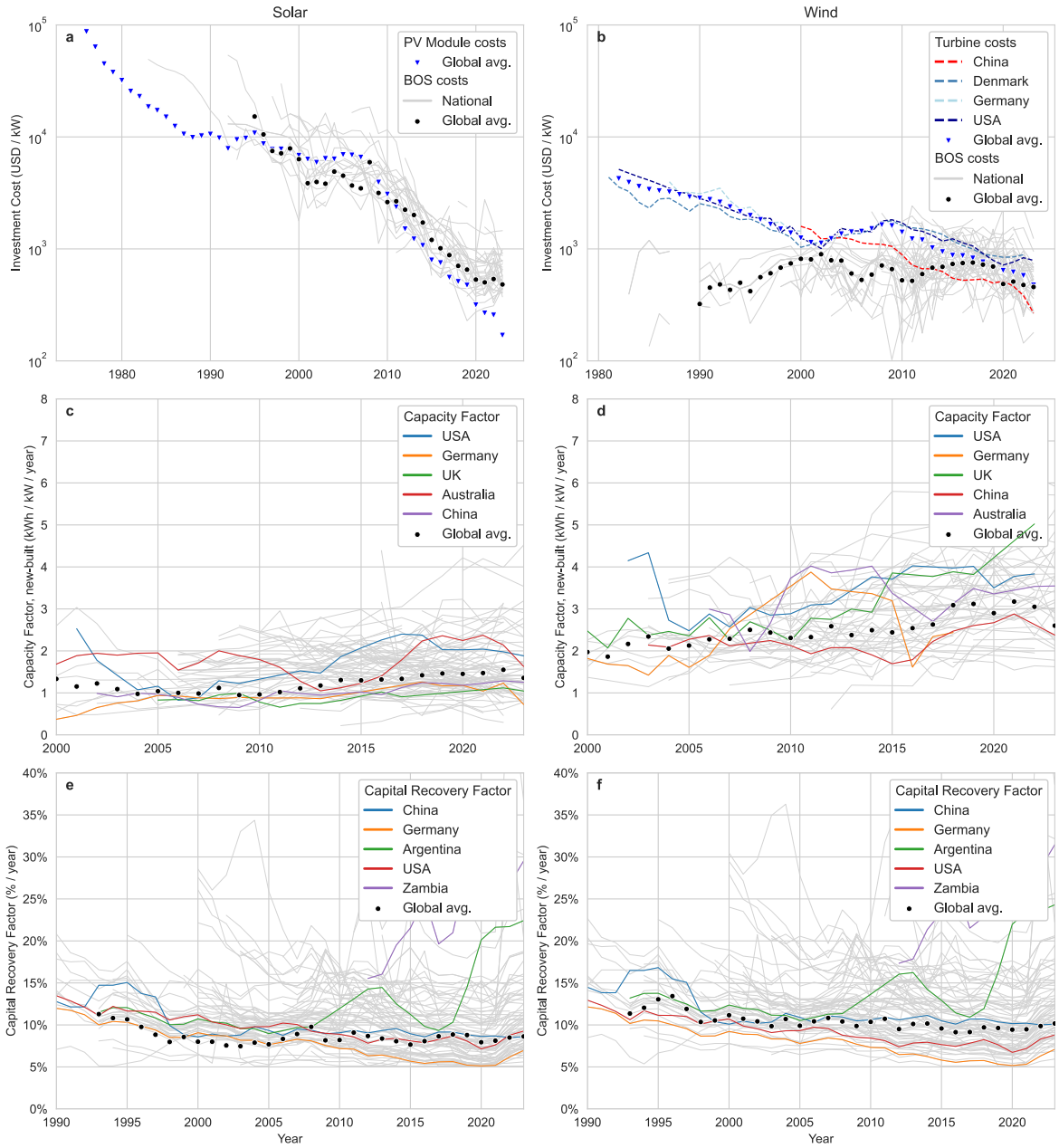

Figure 1: **Historical evolution of solar (left) and wind (right) LCOE components. (a, b)** Investment cost components over time. Gray lines show national BOS costs. Black dots indicate the global average BOS cost. Blue triangles show the global average PV module costs for solar and turbine costs for wind. For wind, we see that turbines manufactured in China have been cheaper than western-manufactured alternatives after around 2005. All cost data in this paper is inflation- and currency-adjusted to 2020 USD. **(c, d)** National capacity factors over time. We observe large variations and temporal fluctuations for national capacity factors driven mostly by external weather factors. Wind has higher capacity factors than solar in most countries. The global average, indicated by black dots, appears to be increasing in both technologies. This is driven primarily by additional countries entering the dataset, not by a long-term increase in national capacity factors. **e, f** National capital recovery factors (CRFs) over time. CRFs are very similar for solar and wind since they both depend largely on the national financial market. Changing market conditions over time and between countries cause large fluctuations and cross-sectional variation. (We neglect $\mathcal{O}$ because we were unable to find good data, and in any case it is small)

Technology	Component	Cost range	Model
Solar	Module cost $\mathcal{M}$	260 USD / kW	Global forecast for costs decline based on Wright's law, conditional on global Solar deployment
Solar	BOS cost $\mathcal{J}$	300 - 900 USD / kW	Global average BOS cost declines are forecast based on (global) Wright's law and national deviations are forecast using a mean-reverting process
Wind	Turbine cost $\mathcal{M}$	400 - 900 USD / kW	Regional forecast for cost decline in either Western or Chinese turbines, based on Wright's law, conditional on manufacturing location and global wind deployment
Wind	BOS cost $\mathcal{J}$	200 - 1500 USD / kW	No long-term trend. Both global average BOS costs and national deviations are based on mean-reverting processes
Solar Wind	Capital recovery factor $\mathcal{C}$	5 - 20 %/year	We assume the asset lifetime and the weighted average cost of capital (WACC), which depends on future risk-free rates and technology-specific markups, are given.
Solar Wind	Operating & Maintenance O	$I \cdot 1\%$/year (Solar), $I \cdot 3\%$/year (Wind)	Constant forecast relative to the total investment cost I, no long-term trend relative to I_j
Solar Wind	Capacity Factor $\mathcal{Y}$	10 - 25 % (Solar), 25 - 45 % (Wind) of 8240 hours / year	No long-term trend. We use an average for each country and technology, which depends on geography and the local electricity system.

Table 1: **Overview of Solar and Wind component models.** Typical component values are given for the year 2023. The component models for solar and wind differ based on the available data and empirically tested differences. For example, future solar BOS costs are forecast using Wright's law and a model for the national deviations, while future wind BOS costs are forecast using a mean-reverting process.

Forecasting the components of LCOE

The fact that the components of renewable technology costs have followed different trends suggests that it is useful to forecast each of them separately and then combine the forecasts. This is useful for both national and global forecasting and helps to understand why national costs vary so much. For this purpose, it is convenient to work with logarithms. Since operating and maintenance costs for renewables are relatively small and data is largely unavailable, we assume that they are a constant proportion of total investment costs, $\mathcal{O} = \gamma \cdot \mathcal{I}$, where $\gamma \approx 1\%$ for solar and 3% for wind.[9–11] Substituting and taking the log of Equation (1) yields the additive expression

$$\log \mathcal{L} \approx \log \mathcal{I} + \log(\mathcal{C} + \gamma) - \log \mathcal{Y}. \tag{3}$$

Figure 1 suggests that these terms behave differently through time and that the behavior of wind differs from that of solar, so that there is value in considering them separately, and in decomposing the investment cost $\mathcal{I}$ into its components $\mathcal{M}$ and $\mathcal{J}$.

Moore's and Wright's laws provide the two best methods discovered so far to forecast average global costs based on historical data.[2,12–14] Moore's Law predicts that costs will decline roughly exponentially over time, while Wright's Law predicts a rough power law relationship between costs and cumulative deployment of a technology, where the word "rough" is used to indicate that these relationships are noisy. Moore's and Wright's laws have been tested on about 60 technologies and shown to provide better forecasts than several alternatives[2,12–14]. Nagy et al.[12] showed that Moore's law and Wright's law forecasts are similar because in all the data sets studied so far, production increases roughly exponentially while costs decline roughly exponentially, which makes Wright's and Moore's laws equivalent. This will likely change once wind and solar become mature technologies and the rapid exponential growth of their deployment slows down. In this case, their forecasts will differ, but with our current state of knowledge, the best method of forecasting remains an open question.[15]

If we assume that the trends observed in Figure 1 persist, then in the future both module costs and BOS costs for solar will drop roughly exponentially according to Moore's law, as they have in the past.

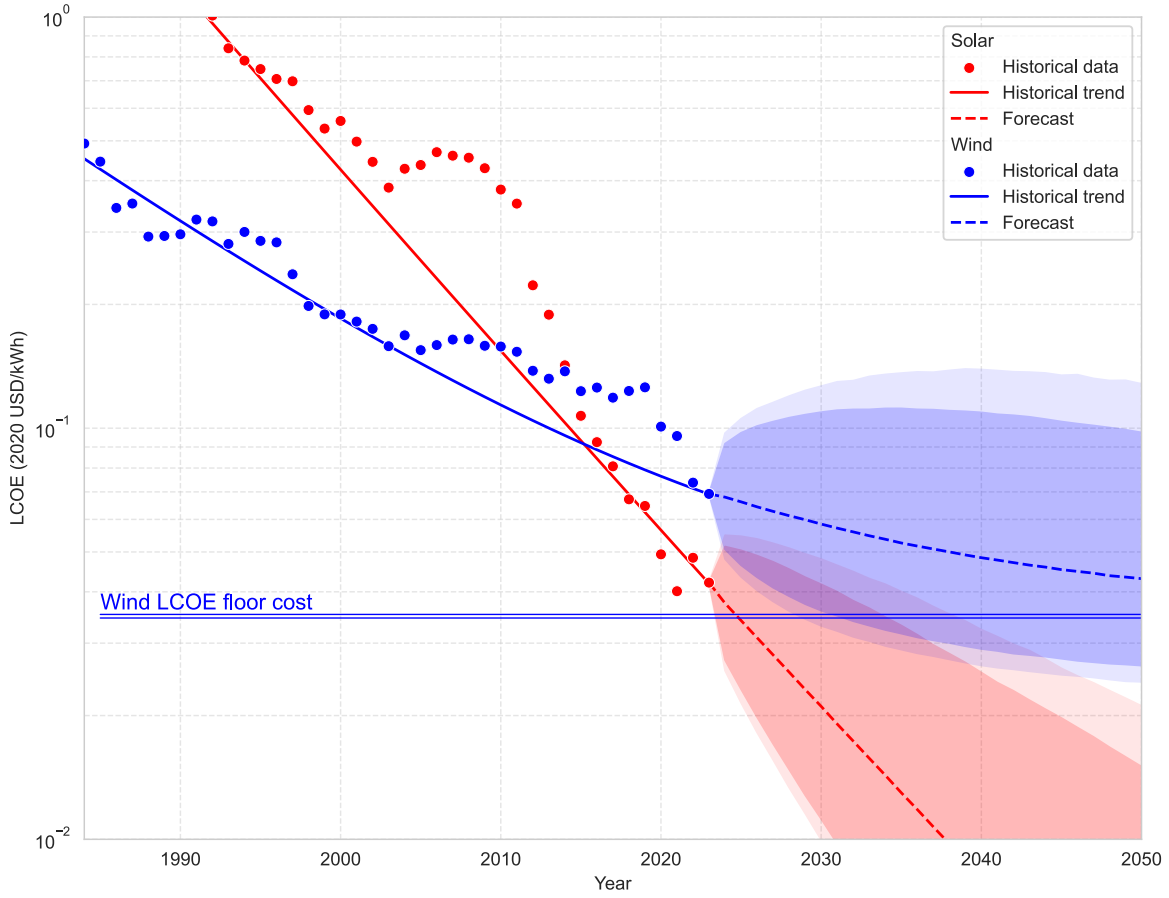

Figure 2: **Historical evolution and forecast of global average solar (red) and wind (blue) LCOE.** Dots show the historical evolution of global average solar and wind LCOE. The solid line indicates the historical long-term trend based on decreasing PV modules, wind turbines, and solar BOS costs. The dotted line indicates our long-term forecast for each technology, with shaded areas indicating the 50% and 90% confidence intervals. For wind, we forecast a floor cost of around 35 USD/MWh due to the constant long-term trend in BOS costs.

In contrast, wind turbine costs will drop roughly exponentially, but its BOS costs will remain roughly constant. This implies that wind will reach a floor cost of 35 USD/MWh. The resulting forecasts for solar and wind are compared in Figure 2. We forecast that solar costs will continue to drop roughly exponentially, reaching a cost of about 3 USD/MWh in 2050, whereas the rate of decline in overall wind costs slows down, reaching a cost of 43 USD/MWh in 2050, and eventually plateauing at its floor cost of about 35 USD/MWh. Thus, in 2050, solar energy will become around an order of magnitude cheaper than wind energy. We could also have used Wright's Law, but then we would have needed to postulate a scenario for future production. If we had assumed that deployment continues at current roughly exponential rates, then the forecasts would have been the same as they are under Moore's law. This is unlikely because under current rates of exponential deployment solar and wind would become the sole providers of useful energy around 2036 due to the large efficient gains in a fully electrified energy system.[3,16] Thus, before this point is reached, deployment must slow down. In this case the forecast of the two methods differ, and under Wright's law we expect their costs in 2050 to be somewhat higher than predicted above. As shown in the SI, under plausible decarbonization scenarios from Way et al.,[3] the difference has little effect on wind, and increases median solar costs to 12-15 USD/MWh in 2050.

We want to stress that, although it has become standard in the literature to use Wright's law to forecast technological change, there are strong dissenters in favor of Moore's law;[17] a study of

technological change during World War II indicates that stimulating demand causes prices to drop under Wright's law, but it also shows that Wright's law and an overall exponential trend have roughly the same predictive power.[15] Hence here for simplicity we use Moore's law, and present more detailed evidence using Wright's law in the appendix.

The trends we observe here are plausible for more fundamental reasons. The use of larger turbines and higher hub heights has been a major factor in making wind energy cheaper, next to reduced material need, manufacturing scale, and labor productivity.[18] The lack of decline in BOS costs for wind observed here suggests that as turbines become larger, they also become more difficult to install, offsetting cost reductions from learning.[8] Solar photovoltaic panels, in contrast, have maintained a similar size and there are no such confounding factors, so as solar farms become larger, a combination of economies of scale and learning make the installation costs and possibly the other components of BOS costs drop. It is nonetheless remarkable that module costs and BOS costs for solar have decreased at such similar rates.

To assign errors to these forecasts, we use the method developed by Farmer and Lafond,[2] which was originally applied to module costs alone but has also been tested in forecasting the costs for many technologies. This method takes into account errors caused by parameter estimation and the noisy fluctuations causing deviations from pure exponential behavior. It has been tested on more than 50 time series and has been shown to do a good job of predicting forecasting errors. It has so far produced good predictions of future renewable costs, with forecasts typically within 95% confidence intervals.[3] Here, we assume that the capacity factor and cost of capital remain constant on average, which is plausible since capacity factor is largely determined by geography and the cost of capital is largely determined by the financial climate in each country. Our forecasts can be used to determine the impact of different exogenous financial conditions on local renewable costs. This is particularly important for developing countries, where high financing costs can either hinder renewable adoption or foreign financing mechanisms may be used to accelerate a clean electricity grid.[19–22]

As a reality check, we regress the components of the logarithm of the LCOE on the right side of Equation (3) against the total LCOE (which is obtained from other sources but subject to data cleaning). The regression explains about 99% of the variance in the national LCOE data, and the regression coefficients are all within a 95% confidence interval of one, indicating that the data are fairly consistent (see Section S3.1 in the Supplementary Information). The fact that we do not explain 100% of the variance is because there are some non-zero residuals, which have a heavy-tailed distribution, indicating data errors. Thus, while the data are not perfectly consistent, the errors caused by the inconsistencies are relatively small in relation to the expected forecasting errors.

To provide some insights into the variation in national prices at a given time we study the cross-sectional deviations of the national costs from the global average. It is more convenient to work in terms of logarithms, so we define the variables $\lambda_{jt} = \log \mathcal{L}_{jt}$, $\iota_{jt} = \log \mathcal{I}_{jt}$, $\kappa_{jt} = \log(\mathcal{C}_{jt} + \gamma)$ and $\upsilon_{jt} = \log \mathcal{Y}_{jt}$, which implies that $\lambda_{jt} = \iota_{jt} + \kappa_{jt} + \upsilon_{jt}$. Taking the variance of both sides gives

$$Var(\lambda_{jt}) = Var(\iota_{jt}) + Var(\kappa_{jt}) + Var(\upsilon_{jt}) + \text{cross covariance terms}, \tag{4}$$

or in words, the variance of the logarithm of the LCOE is the sum of the variance of investment costs plus the variance of the capacity factor plus the variance of the capital costs, plus cross-corvariance terms. Because the individual terms of the LCOE decomposition depend on very different factors, we expect the cross-covariance terms to be close to zero. The cost of capital is determined by economics and politics, the capacity factor is largely determined by weather, and the investment cost is determined by technology and installation costs. This is confirmed: When we estimate the cross-covariance terms we find that they are all with two standard deviations of zero. We can compute the fractional contributions of each term by dividing each term on the right by $Var(\lambda_{jt})$, see Table 2. This implies that for solar about 50% of the variance in cost is due to the capacity factor, 25% due to investment cost and 25% due to the cost of capital. In contrast, for wind only 30% is due to the capacity factor, 30% is due to investment cost and about 40% is due to the cost of capital.

Solar (2022)

Component	Cross-sectional mean	$\log \mathcal{L}$ share	Variance share
$\mathcal{L}$	97 USD/MWh	(100%)	(100%)
$\mathcal{I}$	985 USD/kW	42%	25%
$\mathcal{Y}$	1.2 MWh/kW	43%	50%
$\mathcal{C} + \gamma$	8% + 1%	15%	25%

Wind (2022)

Component	Cross-sectional mean	$\log \mathcal{L}$ share	Variance share
$\mathcal{L}$	112 USD/MWh	(100%)	(100%)
$\mathcal{I}$	1440 USD/kW	43%	32%
$\mathcal{Y}$	2.1 MWh/kW	45%	27%
$\mathcal{C} + \gamma$	9% + 3%	12%	41%

Table 2: **Cross-sectional standard deviation and variance of LCOE and its components.** For the year 2022, we compute the cross-sectional mean and standard deviation of the LCOE and its components (unweighted). We can further use Equation (4) to estimate the share of the variance that each component contributes to the variance of the logarithm of the LCOE. We leave out the cross-variance terms, contributing less than 10% for solar and less than 5% for wind.

Forecasting national costs

To construct a model for predicting national costs based on historical data, we build on previous work in forecasting global costs[2,13]. We use already well-tested methods to make global forecasts and construct new models for forecasting national deviations from global forecasts. For each component of the LCOE, we pool the data for each country and build a single model for all countries. Our approach is in contrast to previous studies that built separate models for each country.[23–26] Building separate models for each country means that ratio of parameters to data is high, which causes overfitting. To make optimal forecasts one needs to strike the right balance in the bias-variance tradeoff. Bias refers to whether or not a model is capable of fitting the data, and variance refers to errors in parameter estimation, which result in overfitting. In situations like this where data is limited, variance is usually the dominant source of error, and it is essential to keep models simple.[16]

We forecast each component of the LCOE as follows.

Module costs. We take advantage of the fact that module costs are essentially global[27] and make use of methods developed in previous studies,[2,13] as discussed above. Since these have been validated by making out-of-sample forecasts for many different technologies, we do not need to test them here. There are a few exceptions, such as Japan, which produces and sells a majority of its solar panels domestically.[28] We capture the associated costs in the BOS costs through equation (2) but cannot differentiate the effects of domestic panel production from other effects increasing national BOS costs.

Turbine costs. Wind turbines are manufactured primarily in the West (US & Europe) and China, with Chinese turbines now costing around one-third of Western turbines.[7] We can use either the previous global forecasts[2,13] for the average cost of Western vs. Chinese turbines or differentiate between the two locations and forecast them separately. However, we cannot identify the preferred method due to low statistical significance of any comparison. For simplicity, we apply the global forecasts here.

Balance of system costs. Forecasting BOS costs is complicated by the fact that BOS costs behave very differently for solar and wind. As noted, solar BOS costs closely track module costs, whereas wind BOS costs fluctuate, but the global average is roughly flat. This means that we need to take somewhat different approaches for solar and wind.

We begin with solar. As seen in Figure 1, solar energy national BOS costs closely track global BOS

costs. While the cross-sectional variation is substantial, it is much smaller than the variation in time, which spans almost two orders of magnitude. This makes the national BOS costs highly correlated. To cope with this problem we first take logarithms and then decompose the national costs into the global average and the national deviations from the global average. Since the global average behaves very similarly to the module costs, we use the same methods to forecast it as noted above.

Because they are essentially stationary, to forecast the national deviations of the BOS costs for solar or wind, or the global BOS costs for wind, we use an AR(1) model of the form

$$x_{j,t+1} = \rho x_{jt} + \sigma n_{jt}, \tag{5}$$

where ρ is a reversion parameter, with$\rho \approx 0.85$ for solar deviations, $\rho \approx 0.7$ for wind deviations and $\rho \approx 0.5$ for global wind costs. $n_{jt} \sim N(0,1)$ is Gaussian noise with mean zero and standard deviation one and σ controls the noise level. For both solar and wind x_t is the logarithmic deviation of the BOS cost at time t, i.e. $x_{jt} = \log \mathcal{J}_{jt} - \frac{1}{N_t}\sum_{j=1}^{N_t} \log \mathcal{J}_{jt}$. Note that there are no country-specific parameters. This means that all countries revert to the same global mean, which is roughly what we observe.

Capacity factors are given mostly by geography, so they can be taken as country-specific constants, corresponding to their historical average for each country. We can either estimate the parameter based on historical electricity generation (subject to noise from annual weather patterns) or ex-ante estimates by project developers (subject to noise and biases from different estimation methods). For wind, we estimate the capacity factors based on historial electricity generation since ex-ante estimation baises can be large. For solar, there is little difference between both methods. Here, we use ex-ante estimates by project developers for slightly higher out-of-sample accuracy. We ignore the rising trend of capacity factors as we believe it is spurious.

Capital recovery costs are determined by the national government bond yields. The best way to treat this depends on the purpose of the forecast. For someone who wants to know hypothetically how costs might change if bond yields change, it is appropriate to make conditional forecasts treating this as an exogenous variable. However, for our purposes here we want to make unconditional forecasts, so we assume bond yields to remain constant at their current national levels.

To test our models, we divide the data into training sets (also called the in-sample data) and test sets (also called the out-of-sample data). We fit the parameters of our model on the training set and validate the model on the test set. We take 5-year moving windows as training sets (e.g., 2000-2004) and the remaining data in the future relative to this point as the test set (e.g., 2005-2024). We do not attempt to validate the global components of the model, as we have only two very short time series, and any tests would be meaningless, and the global models have already been tested on many technologies in previous work. In Figure 3 we compare predicted vs. actual values for the deviations of the BOS costs from the global average. As expected given our use of an AR model, the correlations decay exponentially with a time constant of $1/(1-\rho) = 6.6$ years for solar and 5 years for wind. This is because national deviations are not persistent – they revert to the global mean. A plausible interpretation is that this is due to learning effects across countries.

To quantify this, we compute the number of degrees of freedom, which is a measure of the effective number of independent variables in the time series (See definition in the SI). If we use the raw BOS costs for solar we find only 9 degrees of freedom. In contrast, the logarithmic deviations from the national average have about ten degrees of freedom, meaning that tests of forecast performance in the validation set are much more statistically significant. The situation for wind is simpler, due to the fact that for wind the national BOS cost time series have about 17 degrees of freedom, whether or not we subtract the global average.

Discussion

Our work here shows the value of decomposing costs into their components. Our most important result is that the BOS costs for solar have dropped in tandem with module costs, while the BOS costs of wind have remained roughly constant. This indicates that if trends continue, wind costs will reach a

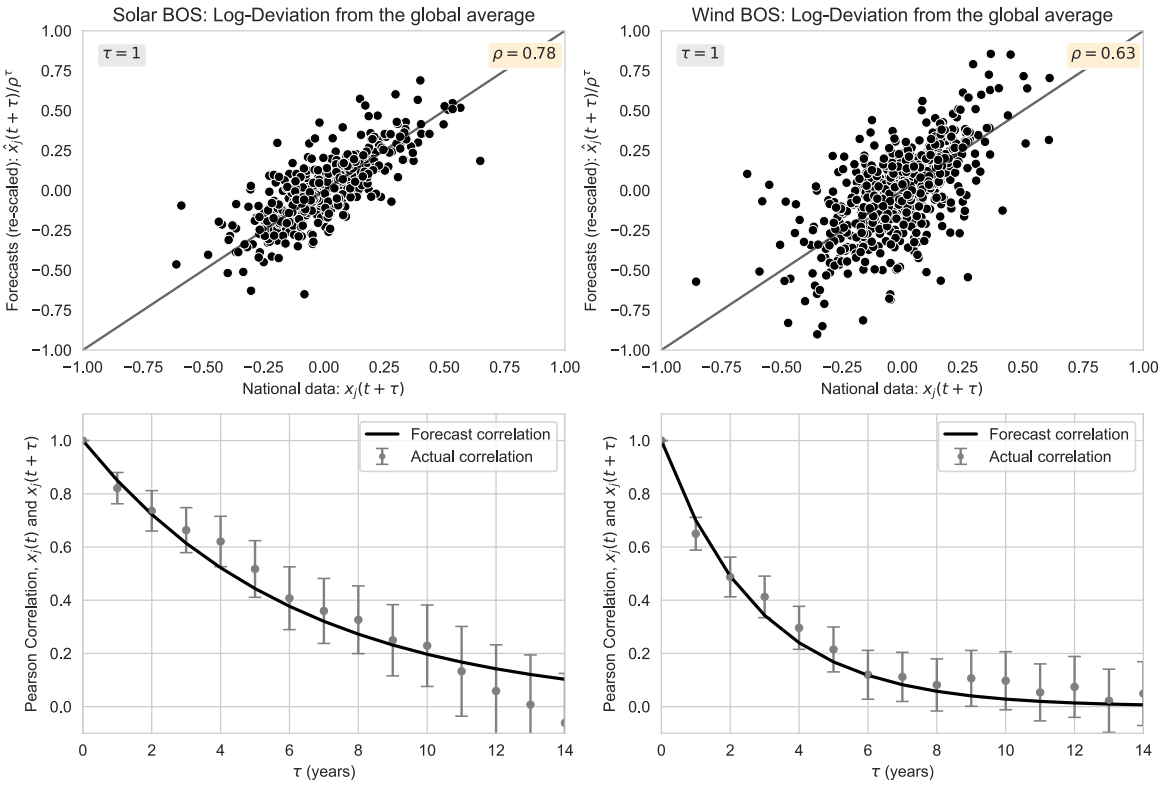

Figure 3: **Forecast and actual deviation of national BOS costs from the global average for solar (left) and wind (right). Top panels** X-axis shows the national (log-10) deviations from the global average x_j for times $t+\tau$, with $\tau = 2$. Y-axis shows the forecast for $x_j(t+\tau)$ made at times τ, $\hat{x}_j(t+\tau)$, re-scaled to match the cross-sectional variance of the data. Data and forecast are highly correlated with Pearson correlation coefficients of ~ 0.78 for solar and ~ 0.63 for wind. **Bottom panels** Correlation between $x_j(t)$ and $x_j(t+\tau)$ with 95% confidence intervals (dots) and $\hat{x}_j(t+\tau)$ (black line) for different values of τ.

plateau while solar costs will continue to drop exponentially. A plausible explanation for this is that the physical nature of solar panels has hardly changed, and solar farms are easy to build, while the cost declines in wind turbines are substantially due to using bigger turbines, which makes them harder to install.

Our second result is that the difference between national BOS costs tend to revert to the global mean. This suggests that there is substantial learning transmitted across countries that occurs on a timescale of a few years.

Unlike investment costs or capacity factors, the cost of capital depends on economic factors that are potentially under the control of policymakers in governments or international organizations like the IMF. The cost of capital accounts for about 25% of the variance for solar and 40% for wind, so the differences are substantial. This also means that global changes in interest rates, such as the higher interest rates now, can have a substantial effect on cost competitiveness.

As a side note, many people think that China is the main reason that solar energy became so cheap. China has certainly played a role in reducing costs, but the IEA only mentions Chinese solar module manufacturing entering global markets from 2007 onward. While the cost of solar electricity now is roughly 10,000 times cheaper than it was in 1957, it declined by a factor of about 1,000 between 1957 and 2005. This should be compared to its drop by a factor of 10 since 2006[29]. Chinese solar modules are currently about a factor of 6 cheaper than in protected markets such as Japan, i.e. roughly speaking, China accounts for about half of the recent factor of 10 reduction in global prices[27]. This indicates that China only accounts for about $(10/2)/10{,}000 = 0.05\%$ of the total cost decline in solar energy prices.

In the past the projections of integrated assessment models for renewable costs were very poor, substantially overestimating future renewable costs. This is in contrast to time series-based forecasts, which have done quite well.[3] The good news is that, as shown in the Supplementary Material, the projections of integrated assessment models are now much more closely aligned with ours. Nevertheless, some challenges remain, such as keeping scenarios up to date and ensuring that the ensemble of scenarios reflects the uncertainty around future technology costs.[30,31] We hope that the improved forecasts we give here will be useful in honing IAM forecasts further.

Methods

Data collection and cleaning

Validating our forecasts is essential.[16] Statistical validation, however, has substantial data requirements. To maximize the available data and develop a widely applicable model, we apply and validate the same methods across a novel sample of 102 countries for solar and 111 countries for onshore wind. Here, we provide a brief overview of the dataset. Additional details are given in Supplementary Information S2.

We collected and extensively cross-validated national average data for LCOE $\mathcal{L}_j$, total investment cost I_j, cost of capital, electric capacity, and electricity generation by manually scraping the extended scientific and gray literature. Next to the investment cost shown in Figure 1 and LCOE shown in Figure 2, Figure 4 shows the capacity of installed solar and wind projects for different countries. We see that national capacities have grown by up to 3 orders of magnitude for wind (e.g., South Africa) and 4 orders of magnitude for solar (e.g., Saudi Arabia) in the last two decades alone. So far, there is no statistically significant departure from the exponential trend.[16]

Due to the diversity of sources, the data is naturally noisy and subject to inconsistent data-cleaning and aggregation procedures. This particularly applies to the LCOE $\mathcal{L}_j$. For example, data providers sometimes fill data gaps are sometimes filled using ad-hoc assumptions. To reduce inconsistencies we perform several corrections on the LCOE data. These corrections are largely modelled on IRENA's data[7] since it is the largest single source of LCOE data in our dataset and arguably the most prominent source of global and country-level data.

Cost of capital. We harmonize the LCOE data by using a consistent cost of capital across time and countries. For data prior to 2021, IRENA applies simplified cost of capital assumptions. After 2021, they use more granular data.[32] We therefore correct the data to obtain a consistently granular cost of

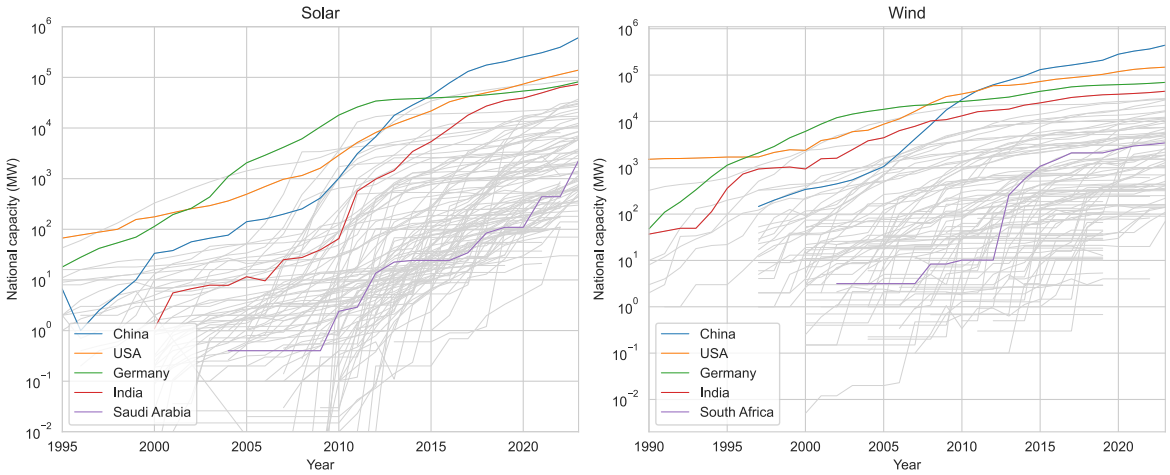

Figure 4: **Solar (left) and onshore wind (right) capacities for different countries and years** Over the last 40 years, solar and wind capacities have grown approximately exponentially across the world. While there is significant fluctuation between countries and years, there hat not significant departure from exponential growth so far.[16]

capital throughout time and across countries. The impact of this correction on our model is minimal since we take the cost of capital as given.

Capacity factor. For solar, IRENA's capacity factor closely aligns with other sources. For wind, we find significant discrepancies due to different estimation methods. IRENA largely relies on ex-ante estimates by project developers. These can be materially different from ex-post estimates based on the actual electricity generated (see also Appendix S3.7). To harmonize our data, we use the capacity factor based on electricity generation for wind. This correction can be a limitation to our LCOE forecasts, which is why we validate the capacity factor forecasts independently.

Operating and maintenance cost. While IRENA does not provide detailed information on their operating and maintenance cost prior to 2010, we identify some inconsistencies across the dataset. We harmonize these inconsistencies throughout the data by using our assumptions for the operating and maintenance costs that are based on an independent dataset not used in any other LCOE forecasts. This limits data correction impacts on the LCOE forecasts but does not avoid them completely. However, since the operating and maintenance costs constitute but a small part of the LCOE, the resulting noise is small compared to the variance in other LCOE components.

LCOE decomposition

Decomposing the LCOE $\mathcal{L}_{jt}$ into its components is a non-trivial task due to the nonlinearity of equation (1). As a consequence, Equation (3) does not hold precisely but requires an additional error term,

$$\log \mathcal{L}_{jt} = \log \mathcal{I}_{jt} + \log(\mathcal{C}_{jt} + \gamma) - \log \mathcal{Y}_{jt} + \log \mathcal{E}_{jt}, \tag{6}$$

where $\log \mathcal{E}_{jt}$ is an additional random variable characterized by an unknown distribution.

We can use our dataset on the LCOE and its components to determine the distribution of $\log \mathcal{E}_{jt}$. We find that $\log \mathcal{E}_{jt}$ does not exhibit significant autocorrelation. Furthermore, the sample mean and sample variance of $\log \mathcal{E}_{jt}$ do not significantly change over time and across countries. Although some countries and years display notably larger values of $\log \mathcal{E}_{jt}$, their difference is not statistically significant due to the small sample size. Consequently we model $\log \mathcal{E}_{jt}$ as an independent and identically distributed (i.i.d.) random variable, independent of indices j and t.

However, we also find that $\log \mathcal{E}_{jt}$ can take some very large empirical values, indicating that it follows a fat-tailed distribution, such as a Cauchy distribution. This observation prompts further

investigation into whether these extreme values result from the non-linearities inherent in the LCOE calculation or from potential data inconsistencies.

Unfortunately, asset-level data required to study this effect is scarce. A notable exception to this is the dataset provided by Berkley Lab,[33] which consolidates the investment costs for over 2.4 million solar photovoltaic assets in the United States between 2000 and 2023. Their public dataset covers around 5% of total U.S. solar capacity in the US, although coverage varies substantially by year. Using this data, we see that single assets can cause large and frequent fluctuations in the differences between the weighted average of I_{ijt} and the weighted average of $\log I_{ijt}$ of up to an order of magnitude. These variations directly translates into large fluctuations in $\log \mathcal{E}_{jt}$ between consecutive years. For instance, in 2016, the dataset includes one asset with a capacity of 424 MW and exceptionally low installation costs. The asset size is an order of magnitude larger than all other assets in 2015 and 2016 and five orders of magnitude lower in costs than the annual average. Consequently, $\log \mathcal{E}_{jt}$ fluctuates by an order of magnitude between 2015 and 2016. If we exclude these outliers, extreme values in $\log \mathcal{E}_{jt}$ vanish. This implies that large values of $\log \mathcal{E}_{jt}$ are in large parts caused by data issues and we should not use a fat-tailed distribution to model it.

Instead, we discard extreme values of $\log \mathcal{E}_{jt}$ and adopt a normal distribution to forecast future national LCOE values.

Solar module and wind turbine component model

For both solar modules and wind turbines, we employ the experience curve model developed by Lafond et al.[13] to forecast global average costs, conditioned on the global cumulative deployment of each respective technology.

In the case of solar modules, this approach is particularly straightforward, as the majority of modules are manufactured in China and traded internationally.

For wind turbines, distinctions exist between Western-manufactured and Chinese-manufactured turbines, impacting investment costs and the LCOE. Nonetheless, due to data limitations, we cannot determine with statistical significance whether a locally-specific experience curve model would yield improved forecasts compared to the global alternative. Therefore, we adopt the simpler global model.

We do not independently validate these models, as Lafond et al.[13] have already extensively validated the approach across a dataset encompassing over 50 technologies.

Balance of system component model

Through regression analysis, we confirm that solar Balance of System (BOS) costs exhibit a significant experience rate, similar in magnitude to that observed for solar modules. In contrast, we find no significant cost reduction or experience exponent for wind BOS components over the past four decades.

We next examine the cross-correlation structure present within our dataset. Both solar and wind national time series demonstrate significant correlations, with solar showing notably strong correlations, resulting in only nine effective degrees of freedom.

Additionally, we analyze the autocorrelation structure in our dataset, revealing significant autocorrelation at both global average and national scales. This autocorrelation indicates that an autocorrelated forecasting model is suitable for predicting future national deviations from global averages.

For solar, we further compare various forecasting models aimed at predicting future national costs. However, due to substantial cross-sectional correlations, our out-of-sample tests do not yield statistically significant differences between models. Nonetheless, drawing upon theoretical insights from the time-series forecasting literature, we identify a global average model with autocorrelated national deviations as the most appropriate method for projecting future solar BOS costs.

Finally, for both solar and wind technologies, we perform an out-of-sample validation of our stochastic forecasts. To achieve statistical significance, we specifically assess national deviations from global averages and compare forecast percentiles against a theoretical prior derived from surrogate data.

Capacity factor component model

There are two methods to estimate the capacity factor $\mathcal{Y}_{jt}$. Using our dataset, there are two options to estimate the trend-stationary capacity factor. 1) We can estimate the ex-post capacity factor from historical electric capacity and generation. 2) We can use our data for $\mathcal{L}_{jt}$, I_{jt}, $\mathcal{C}_{jt}$ and γ in Equation (6) to recover a priori capacity factors used in LCOE estimates from the literature. The LCOE-based method yields an ex-ante estimate provided by data suppliers, whereas the electricity-based approach provides an ex-post estimate derived from recent historical generation, serving as a reference for anticipating ex-ante capacity factors.

For solar, the differences between the two estimation methods are minor. We apply the ex-ante capacity factor derived from the LCOE-based approach due to its marginally superior out-of-sample predictive performance.

For wind, the two methods differ substantially. The LCOE-based approach indicates a significant upward trend in capacity factors, whereas the electricity-based method reveals no such trend—a discrepancy previously documented in the literature.[34–36] Given our objective of accurately predicting actual electricity generation relative to installed capacity, we adopt the electricity-based method, treating future capacity factors as constants specific to each country.

LCOE forecasts

Utilizing the decomposition of the LCOE into its components and applying the forecast models developed for each component, we generate forecasts for national-level LCOE values. Additionally, we forecast the global average LCOE, as illustrated in Figure 2, based on projections of global average components.

For solar modules and wind turbines, we directly employ global forecasts derived from experience curves. The future costs are contingent upon projected global cumulative deployment levels for each technology. In the forecasts presented in Figure 2, we assume an annual deployment growth rate of 30% for solar and 20% for wind. Alternatively, scenario-based deployment projections, such as those outlined by Way et al.[3] can be applied.

Similarly, solar BOS costs are forecast using the experience curve model. For wind BOS costs, we employ an AR(1) model to project global average costs, resulting in a stochastic floor-cost estimate in the investment cost I_j of roughly 450 USD/MW. This corresponds to a floor cost in LCOE $\mathcal{L}_j$ of roughly 35 USD/MWh.

Regarding the capacity factor and capital recovery factor, we estimate current global averages and assume these values remain constant over time. This assumption is appropriate under the condition that the distribution of future renewable energy deployment mirrors historical patterns. However, the increasing affordability of solar energy may facilitate greater adoption in lower-income regions, potentially altering the distribution of global capacity factors and capital recovery factors, thereby influencing future global average LCOE forecasts.[19,20,37]

IAM scenario comparison

We apply our forecasts for the total investment costs I_j to different IAM scenarios from the AR6 IPCC report database.[38] The purpose of this exercise is to compare the forecasts for future national investment costs to the costs projected by respective IAM scenarios and identify potential issues with the latter.

Our forecasts for I_j are conditional on global solar and wind deployment. Since we require annual deployment scenario data, we consider the global solar and wind deployment in 2040 and interpolate linearly with the global solar and wind deployment in 2020, our base year. The reason for this approach over using the 5-year scenario data directly is that a majority of scenarios show a capacity in 2020 that is below what was actually observed and total investment costs that are larger than today's costs. If we were to use the scenario data as it is, it would not be a fair comparison since our forecasts are sensitive to these input values. Next to linear interpolation, we can also interpolate the log-deployment. We

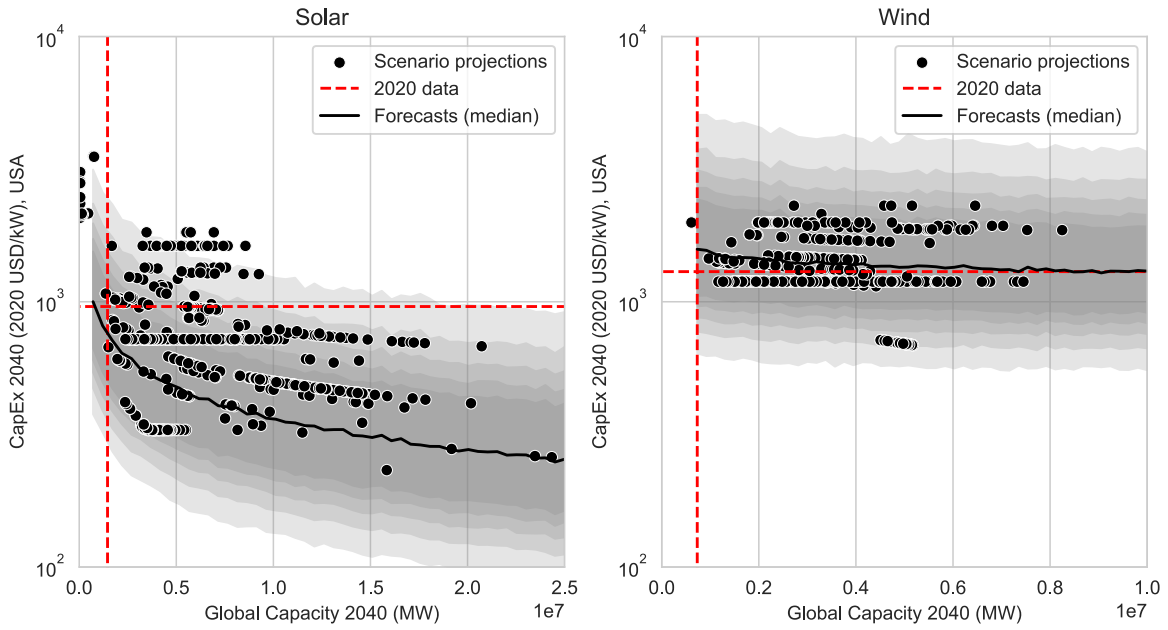

Figure 5: **Solar and wind total investment cost projections reported in IAM scenarios against probabilistic projections from our model.** The dots show the total investment cost projections for the US in different IAM scenarios. The x-axis shows the associated global solar / wind capacity. We compare them with the investment cost projections obtained from our model. The gray areas show 50-90% confidence intervals in 10% steps. The blue line shows the median cost from our model. The red dotted lines show the global capacity and investment cost in the US for 2020. For wind, the IAM projections generally align well with the median forecast. For solar, over 80% of projected IAM costs are above the median costs forecast through our model. In both cases, the probabilistic forecasts show significantly more uncertainty around the median forecasts than the IAM projections represent.

omit from showing the results of this analysis here since there is no material difference from the linear interpolation.

For each possible value of future renewable deployment, we forecast the associated total investment costs and compare them to the IAM scenario projections. Figure 5 shows our forecasts and the scenario projections, conditional on the global solar and wind deployment. For wind, we see that the IAM projections align well with our forecasts. For solar, there is less alignment, with 80% of scenario costs above our median forecast. The reason for this is that future solar costs are sensitive to their current costs. IAM scenarios are quickly outdated, leading to these discrepancies. In some cases, the scenarios even project renewable capacity in 2040 to be lower than today. In both cases, our forecasts show substantially more uncertainty than the set of IAM scenarios. For solar, over 90% of scenario costs are above our 25th forecast percentile, for wind it is over 80% of scenarios.

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