Levelized cost-based learning analysis of utility-scale wind and solar in the United States

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Background and motivation

- Learning curves are commonly used to project the future cost of renewable generation, based on past experience.
- Learning curve theory holds that for each doubling of output, costs fall by a certain percentage, known as the learning rate.
  - The learning rate (LR) is derived from past experience, and can be applied to future output projections.
- For tractability (e.g., in terms of data availability), past studies have often focused on CapEx learning—i.e., regressing the cost of installed capacity (CapEx) against the cumulative deployment of capacity over time.
  - But CapEx is just a means to an end—i.e., renewable generation—and is just one of several inputs into the LCOE equation (along with OpEx, useful life, financing costs, and capacity factor—see the LCOE equation on the right), all of which can benefit from learning.
  - Moreover, to date, industry has rightly focused on minimizing LCOE, not CapEx (though the two often go hand in hand).
- In this study, we focus on LCOE-based learning for utility-scale wind and solar by calculating plant-level LCOE over time and using that history to generate LCOE-based learning curves.

Though there are several variations on how to calculate LCOE, in this study we adopt the approach used in NREL’s Annual Technology Baseline (ATB):

\[
LCOE = \frac{(\text{CapEx} \times \text{CRF} \times \text{Tax Factor}) + \text{OpEx}}{\text{Annual Energy Production (AEP)}}
\]

where

- \(\text{CapEx}\) = installed cost in 2020 $/kW
- \(\text{CRF}\) = the “capital recovery factor” derived from the real weighted-average cost of capital (WACC) and useful project life
- \(\text{Tax factor}\) = accounts for income tax and the tax-deductibility of depreciation
- \(\text{OpEx}\) = aggregate operational expenses in levelized 2020 $/kW-year
- \(\text{AEP}\) = levelized kWh/kW-year
What we bring to the table

- We apply high-quality granular data to calculate plant-level LCOE for the majority of utility-scale wind and solar PV plants operating in the United States (one of the largest markets in the world)
  - This bottom-up, plant-level approach provides the granularity needed to control for exogenous influences (as described in the next bullet), while also enabling us to assess the relative contributions of each of the five key input parameters to historical LCOE reductions over the entire history of both technologies.

- We normalize the plant-level LCOE estimates for a variety of exogenous influences unrelated to wind and solar advancements
  - These include regional variation in labor and construction costs, as well as the wind and solar resource; changes in materials prices; the impact of exchange rate movements and import tariffs on imported equipment costs; macroeconomic changes to the WACC; and legislative changes to corporate income tax rates.

- We diverge from the majority of the literature by estimating historical learning rates based on normalized LCOE rather than CapEx.

- We assess whether historical learning rates have been constant (the typical assumption) or whether they have instead changed over time.

- We apply this methodology equally to wind and solar in order to comparably assess learning, via a common approach, for two of the central technologies needed for power-sector decarbonization.
  - In contrast, most of the learning curve literature has focused on individual technologies, making cross-technology comparisons difficult.
Empirical data history

- LBNL’s annual *Land-Based Wind Market Report* and *Utility-Scale Solar* report series provide broad data coverage back to the start of each market in the US:
  - **Wind sample**: 908 plants (>5 MWAC) totaling 106.5 GWAC built from 1982-2020 (87% of total U.S. wind capacity operating at the end of 2020)
  - **Solar sample**: 822 utility-scale (i.e., ground-mounted and >5 MWAC) PV plants totaling 33.7 GWAC built from 2007-2020 (87% of total utility-scale PV capacity operating at the end of 2020)
  - Relatively few plants in the early years of each market is more of a market issue—i.e., a slow ramp in deployment—than a sampling issue

- We have empirical CapEx and capacity factor (AEP) data for each wind and solar plant in our sample
  - These are the two most important drivers of LCOE

- All other LCOE inputs (besides CapEx and capacity factor) vary by COD year (i.e., are applied uniformly to all plants built in a given year), and are based primarily on other LBNL sources
  - For example, OpEx and project life assumptions come mostly from recent LBNL industry surveys
  - Financing costs are based on LBNL tracking over time (and are also benchmarked to external sources, particularly for wind extending back into the prior century)
Basic approach—virtually the same for wind and solar

- Calculate “raw LCOE” (i.e., actual, non-normalized) for each plant
- Calculate “normalized LCOE” for each plant, by normalizing each LCOE input as appropriate to control for exogenous influences that are unrelated to learning
  - Normalize CapEx for: (1) regional variations in construction and labor costs, given shifting deployment among regions over time; (2) raw materials prices (steel for wind, steel and silicon for PV); (3) exchange rate movements, given that some equipment is imported; and (4) tariffs (solar only)
  - Normalize capacity factor (AEP) for the wind and solar resource quality of built sites over time (e.g., due to regional shifts in deployment)
  - Normalize wind and solar finance costs against broader, economy-wide finance trends (i.e., only give learning credit for wind and solar financing cost reductions that go beyond those seen in the broader economy over the same period)
  - Normalize tax rates to remove the effect of changes over time (i.e., set tax rates for all years to 2020 levels)
  - We did not normalize OpEx or useful life
- Roll up “raw” and “normalized” plant-level LCOE to annual time series (generation-weighted average) based on COD
- Calculate historical learning rates (as a function of cumulative capacity) on the “normalized LCOE” annual time series
  - Calculate learning rates over the full duration of each market (1982-2020 for wind and 2007-2020 for solar)
  - Also check for “change points” in learning rates, to identify periods of faster or slower learning, which can shed light on key drivers of learning
- Apply full-period historical learning rates to future projections of cumulative capacity, in order to project LCOE
Historical raw (non-normalized) LCOE of utility-scale wind and PV in the United States

- Circles show the LCOE of individual plants
- Columns show the generation-weighted average LCOE in each year
- Volatility in early years (pre-2000 wind, pre-2010 solar) driven by small sample size
Normalized LCOE controls for exogenous influences unrelated to learning

- Dashed lines show raw LCOE (and match the columns from the prior slide), while the solid lines show the normalized LCOE.
- Normalized time series initially start at a lower LCOE (which reduces the full-period learning rates) and are less-volatile over time.
LCOE-based learning curves for utility-scale wind and PV exhibit distinct epochs

- Full-period learning rate of 15% for wind and 24% for solar (both based on normalized LCOE time series)
- Two change points for wind: ~2006 and ~2010
- One change point for solar: ~2014
- Both wind (40%) and solar (45%) have recently exhibited accelerated learning through 2020
Learning curves for individual components of LCOE shed light on LCOE drivers

- All four LCOE components exhibit learning, but have learning rates that are less than our full-period LCOE learning rates of 15% for wind and 24% for solar
  - Suggests that LCOE learning reflects, and benefits from, learning in each individual LCOE component (i.e., more than just CapEx)

- For wind, expectations for design life have increased sharply in recent years, while capital costs have dropped significantly (though the sharp decline in capital costs may simply be a correction to the increase from 2006-2010)

- For PV, recent capital and operating cost declines have accelerated with rapid deployment through 2020, as has the increase in design life

The dashed vertical lines correspond to the LCOE change points identified on the prior slide.
CapEx has been the largest, but not the only, driver of LCOE reduction

- Left-most column shows the total LCOE reduction (in $/MWh) since the early years of each technology
- Other columns show the relative contribution of each component to the total LCOE reduction
- For wind, CapEx (particularly in the early years) and capacity factor (in the later years) have been most important
- For solar, CapEx has dominated

Interactions between variables prevent numbers from being additive

Purpose is to show relative magnitude of LCOE drivers
To project LCOE, we apply the full-period LCOE-based learning rates to wind and solar capacity projections.

- Wind capacity projections are global and include both land-based and offshore (where specified).
- PV capacity projections are global and include both utility-scale and distributed (where specified).
- We focus on the “average” projection—the solid black lines.
Projected LCOE based on full-period learning rates

- Solar’s LCOE is projected to fall below wind’s by 2025.
- Solar’s confidence interval is wider due to its shorter history (14 years versus 39 years for wind).
A narrow focus on CapEx learning can underestimate future LCOE reductions

- Orange lines apply CapEx learning rates to CapEx, but hold all other LCOE inputs constant at 2020 levels (effectively assuming no learning for any other LCOE input besides CapEx)
- This CapEx-only approach—which approximates much of the learning literature—underestimates LCOE reduction potential
Thank you!

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