Experience curves and the relatedness of technologies: Offshore and onshore wind energy.

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Experience curves and the relatedness of technologies: Offshore and onshore wind energy.

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Abstract

We develop a new theory of experience curves for related industries. This goes beyond spillovers, to account for the creation of a new industry that is, at its inception, technologically related to a mature industry. We apply it to the case of wind energy, which has been historically developed onshore and is currently experiencing rapid growth in deployment offshore. We look at the impact of modeling offshore wind as (1) a fully new technology, (2) a direct offshoot of onshore wind, and (3) a hybrid. We chart the cumulative installed capacity of offshore wind on a global scale against the levelized cost of electricity starting in 2010, and we find that assumptions about its relatedness to onshore wind are equally important as assumptions about future growth scenarios. We contrast these experience curve models with expert elicitations, which appear to underestimate recent trends in cost reduction for offshore wind. The results are consistent with the idea that experts view offshore wind as a direct offshoot of onshore wind. This research highlights a previously neglected factor in experience curve analysis, which may be especially important for technologies, such as offshore wind energy, that are expected to contribute significantly to climate change mitigation.

Keywords: *offshore wind, onshore wind, learning curves, technological change, energy technology, experience curves*

1. Introduction

Experience curves are widely used to forecast and understand technological change. It has long been observed that costs follow a pattern through time, dropping by a fairly constant percentage each time the cumulative number of units produced doubles [1]. This cost reduction has been attributed to learning-by-doing as well as R&D investments, i.e. learning-by-searching [2]. The process of learning as production increases can be represented as an *experience curve*, (often called a *learning curve*), where the cost of production declines at an exponential rate relative to total historical cumulative production (with cumulative production representing "experience").

For energy technologies, the literature has examined how cost of installation or levelized cost of electricity is reduced as a function of cumulative capacity installed. Experience curves imply that learning slows down through time as a technology becomes more mature, since it takes more and more production to double the previous capacity. Experience curves have been used extensively to forecast future cost reductions (see Section 2). There are, however, a number of uncertainties when using experience curves to forecast. Most attention has been on estimating the learning rate – the amount of cost reduction with each doubling – and on estimating future growth in production. Ferrioli et al (2009) investigated the idea that there may be independent learning processes in technology components; they showed that learning rates derived from cost observations are sensitive to assumptions about

which components are more or less mature, such that the same historical data can produce very different cost forecasts depending on assumptions that are used [3].

In this paper, we address another question: to what degree should a newer technology be modeled as an offshoot of a more mature technology, and to what degree should it be modeled as novel when forecasting technological change? More specifically, we ask how cumulative capacity should be defined for a newer, less mature technology that may be related to an older, more mature technology? To make this question concrete, we focus on offshore wind energy, which may be strongly related to its more mature predecessor, onshore wind. We develop a theory and explore the importance of assumptions about the relatedness of these two technologies.

We find, using forecasts for growth in the industry from the International Renewable Energy Agency (IRENA), that the assumptions of relatedness have the same magnitude of impact on forecast costs as assumptions about the growth scenario. Similarly, the differences between the most extreme relatedness assumptions are equivalent to changing the learning rate by 40-60%. Finally, we compare forecasts with different relatedness assumptions to a large expert elicitation survey of 163 of the world's foremost wind energy experts [4].

The rest of the paper is organized as follows: we provide some background and motivation through a literature review in Section 2. In Section 3, we present the theory of how relatedness impacts learning curves. The analyses and application of the experience curve models to offshore wind are presented in Section 4, and results are presented and discussed in Section 5. Finally, we conclude in Section 6.

2. Background and Motivation

Forecasting technological change and costs is important to inform energy and environmental policy. Government agencies need to understand future costs for the purpose of road-mapping and planning investments in energy technology innovation and for deployment of advanced energy technologies. In fact, one of the key justifications of policies that promote faster adoption and diffusion of a technology is the idea that technology costs fall faster with higher rates of adoption. As a result, an assessment of future technology costs is a key piece of information to design policy interventions such as subsidies, incentives, or streamlined regulations. In addition, understanding the potential evolution of technologies is important when crafting large environmental policies, the costs of which depend heavily on the costs of the technologies [5].

Experience curves, which model how the cost of production changes with cumulative production, are widely used in many settings. They have been used since the 1930s as a tool for understanding trajectories of historical technological change [1], including many energy technologies [6] [7]. Experience curves are also used to project future technological change, as an input for Integrated Assessment Models [8], and to inform energy policy [9]. Most studies focus on estimating the learning exponent or learning rate, which is the reduction in cost expected with a doubling in cumulative production.

Experience curve analysis is highly uncertain. Despite the popularity of experience curves, there is significant difficulty in applying them to future forecasts of technological change, due to uncertainty around appropriate data sources, functional forms, and models of causality [6] [7] [10] [11] [12]. One source of uncertainty is how to account for production and learning in technologies with different components, each of which may have a different learning rate and cumulative capacity. Prior research

has shown that, for technologies with separate components, learning rates derived from cost observations are sensitive to assumptions about which components are more or less mature, such that the same historical data can produce very different cost forecasts [3].

Offshore wind energy is an important technology for climate change mitigation. It is expected to play a major role in supplying low-carbon electricity globally, despite currently being in the early stages of development and implementation. Offshore wind represents less than 4% of overall wind capacity globally as of 2017 [13], but it has been proliferating in Europe (increasing 5-fold in 6 years, from 3 GW in 2011 to 16 GW in 2017). It is attractive because it can be sited near large population centers on the coasts, and the wind resource is strongest offshore. Cranmer and Baker [14] estimated that the climate value of offshore wind energy ranges between $246 billion to $2.5 trillion under central assumptions about damages and discount rate, and can reach over $30 trillion under certain assumptions like low discount rate, high damages, and low technology costs.

For complex systems such as wind turbines and power plants, component-based learning is expected to be particularly important. Complex products and systems are characterized by relatively high-cost, low-volume projects, with hierarchical structure and integration of many separate technologies [15], and learning may differ significantly across these components. Rubin et al [16] considered the differences between components of carbon capture and sequestration (CCS) systems when estimating future cost reductions. They used historical data on analogous technologies to represent the individual components, with learning rates varying from 5% to 27% and cumulative capacity ranging from 10 GW to 240 GW.

For wind energy, a few studies have proposed breakdowns of cost components with varying degrees of granularity. For Ferioli et al. [3], wind energy components are the activities of manufacturing, placing, and using wind turbines. Surana et al. [17] tracked trade and patenting across nine key wind energy components: forging, towers, control system, power converter, generator, blade, nacelle, gearbox, and bearing. Dubaric et al. [18] used patent classifications to track activity across three components: rotor form, regulation, and pitch adjustment.

In this paper we focus on the Levelized Cost of Electricity (LCOE), which is the cost per unit of electricity over the lifetime of the plant. The LCOE is an important metric to decide whether or not stakeholders proceed with a project; LCOE comprises a measure for revenue requirements based on the cost required to generate electricity [19]. It represents the minimum required revenue per unit of energy in order to break even [20]. In addition, it permits the comparison of different technologies like wind, solar, natural gas, while taking into account differences in life span, project size, capital expenses, risk, return, and capacity factors [21]. LCOE is imperfect, especially for comparing intermittent and non-intermittent technologies [22]. Nevertheless, developers and power plant producers may use the metric to compare the attractiveness of energy technologies, and policymakers can use LCOE for long-term planning and devising incentive mechanisms.

While offshore wind energy has been significantly more expensive than other generation technologies [23] [24] [25], it has decreased precipitously in recent years. The key drivers were innovations in the wind turbine technology, including higher hub heights and larger rotors diameters, and improvements in installation and logistics. In addition, increasing costs in deeper waters offshore appears to be offset by better wind resources [26]. It is worth noting that the cost of offshore wind was generally increasing before about 2011 [13] [23] [24] [25] [27] [20] [28] [29], similar to the “negative learning” experienced in other industries during the early phases of development [30] [31]. This period of negative learning for

offshore wind was followed by a period of positive learning with decreasing costs [13] [23] [24] [25] [27] [20] [28] [29]. In the IRENA data that we use in this paper, we see the LCOE of offshore wind decreasing consistently since 2014 [32].

In 2015, a large-scale expert elicitation study surveyed 163 of the world's foremost wind experts to better understand future costs of onshore and offshore wind [4]. The survey used the 2014 LCOE as a reference, and under the median scenario, found that experts anticipated 24–30% reductions by 2030 and 35–41% reductions by 2050 across onshore and fixed and floating offshore wind. It is not clear to what degree the experts viewed offshore wind as either an offshoot of onshore technology subject to slower learning, a new technology subject to faster learning, or something in between.

3. Theory of relatedness of technologies

In this section, we show how technological relatedness can be represented in experience curves. We consider an industry, similar to offshore wind, that may be related to a more mature industry, similar to onshore wind. **Equation (i)** presents a component model of the costs of the technology in this newer, emerging industry at time t, $\mathrm{C_t}$:

$$\mathrm{C_t} = \sum_{\mathrm{i=1}}^{N} \mathrm{c_{i,t}} \qquad \textbf{Eq. (i)}$$

Where $c_{i,t}$ is the cost for component i at time t. Assume that each technology component can be described as either fully mature, emerging, or somewhere in between. Let α_i measure the degree to which component i in the emerging industry is related to the same component in the mature industry. Then, the experience curve for the cost of component i at time t can be broken down as in equation (ii).

$$\mathrm{c_{i,t}} = \alpha_\mathrm{i} \mathrm{c_{i,0}} \cdot \left(\frac{\mathrm{N_{emerging,t} + N_{mature,t}}}{\mathrm{N_{emerging,0} + N_{mature,0}}}\right)^{-\mathrm{b}} + (1-\alpha_\mathrm{i})\mathrm{c_{i,0}} \cdot \left(\frac{\mathrm{N_{emerging,t}}}{\mathrm{N_{emerging,0}}}\right)^{-\mathrm{b}} \qquad \textbf{Eq. (ii)}$$

Where $N_{k,t}$ is the cumulative capacity of industry k (i.e. emerging or mature) at time t and b is a learning coefficient parameter. Note that we assume that, to the extent that a given component is based on mature technology, it will undergo learning from the entire cumulative capacity of the emerging and mature industries combined.

Summing across all components, we obtain a model for technology costs in the emerging industry that accounts for its overall degree of relatedness to mature technology:

$$\mathrm{C_t} = \sum_{\mathrm{i=1}}^{N} \alpha_\mathrm{i} \mathrm{c_{i,0}} \cdot \left(\frac{\mathrm{N_{emerging,t} + N_{mature,t}}}{\mathrm{N_{emerging,0} + N_{mature,0}}}\right)^{-\mathrm{b}} + \sum_{\mathrm{i=1}}^{N} (1-\alpha_\mathrm{i})\mathrm{c_{i,0}} \cdot \left(\frac{\mathrm{N_{emerging,t}}}{\mathrm{N_{emerging,0}}}\right)^{-\mathrm{b}} \qquad \textbf{Eq. (iii)}$$

$$\mathrm{C_t} = \mathrm{AC_0} \cdot \left(\frac{\mathrm{N_{emerging,t} + N_{mature,t}}}{\mathrm{N_{emerging,0} + N_{mature,0}}}\right)^{-\mathrm{b}} + (1-\mathrm{A})\mathrm{C_0} \cdot \left(\frac{\mathrm{N_{emerging,t}}}{\mathrm{N_{emerging,0}}}\right)^{-\mathrm{b}} \qquad \textbf{Eq. (iv)}$$

$$\mathrm{A} = \sum_{\mathrm{i=1}}^{\mathrm{N}} \alpha_\mathrm{i} \mathrm{c_{i,0}} / \mathrm{C_0} \qquad \textbf{Eq. (v)}$$

The value A gives us the overall relatedness between the two industries. In the case that $\mathrm{A} = 0$, we would call the technology fully emerging, and we would expect relatively rapid cost reductions in the emerging industry through time, as early industry growth is doubling quickly:

$$C_t = C_0 \cdot \left(\frac{N_{emerging,t}}{N_{emerging,0}}\right)^{-b} \quad \textbf{Eq. (vi)}$$

If, on the other hand, $A = 1$, then the technology in the newer industry is fully mature, wholly identical to the technology in the mature industry for the purposes of learning. Growth of the emerging industry, in this case, would be much less impactful on overall costs, as it builds on the large existing capacity for the mature industry:

$$C_t = C_0 \cdot \left(\frac{N_{emerging,t} + N_{mature,t}}{N_{emerging,0} + N_{mature,0}}\right)^{-b} \quad \textbf{Eq. (vii)}$$

Otherwise, if A takes values between 0 and 1, we call the technology a hybrid. In Section 4, we investigate the implications of these assumptions using offshore wind data.

3.1 The difference between relatedness and spillovers

We comment here on the distinction between the question of *relatedness* we have defined here, and the question of spillovers. Technological spillovers are knowledge flows across boundaries between technologies, such that the learning in one technology is also experienced as learning in another technology domain. Spillovers are an essential mechanism for technological learning in general [33], particularly for the development of clean energy technologies. [34]

The equation below shows a simple model of spillovers, where the parameter y indicates the strength of the spillovers from a mature industry into an emerging industry.

$$C_t = C_0 \cdot \left(\frac{N_{emerging,t}}{N_{emerging,0}}\right)^{-b} \cdot \left(\frac{N_{mature,t}}{N_{mature,0}}\right)^{-yb} \quad \textbf{Eq. (viii)}$$

This formulation is quite distinct from the concept of relatedness that we presented above. In the spillover model, the first installation of the emerging industry (e.g. offshore wind) in year 0 is assumed to be novel. From that point, every doubling of capacity for this industry implies at least a reduction in costs by a factor of 2^{-b}, in addition to any spillover learning from the mature industry (e.g. onshore wind).

The implication for cost reduction is significant; if one industry has strong knowledge spillovers into another, then the experience curve model in **equation viii** would project *faster* learning due to spillovers. In contrast, in **equation iv**, our relatedness experience curve model considers the degree to which two technology domains are directly related from the start, and it projects *slower* learning for an emerging industry that is derived from a mature one.

4. Application: Impacts on forecasts of offshore wind – methods

We apply the above model, from **equation iv,** to offshore wind to understand the impacts of assumptions about relatedness. We present the results of three different assumptions about relatedness alongside a generic best fit model and a large set of expert elicitations in order to put the results in context. We start this section by discussing the specifics of the experience curve analysis. We then present the details of the model, including future growth scenarios, assumptions of relatedness, and estimating learning rates.

4.1 The Experience Curve Model for Offshore Wind

We model the impacts of cumulative installed capacity on the LCOE for offshore wind energy. We choose LCOE as many research and development efforts have focused on minimizing LCOE [4]. The LCOE comprises different cost elements, such as the lifetime of the project, capital expenditure, operations cost, maintenance cost, discount rate, and energy produced in the year (See **Appendix A1** for the mathematical definition of LCOE). We note that there may be a tradeoff between higher capital costs and better lifetime, reliability, and efficiency in wind energy; thus capital cost is not perfectly correlated with LCOE. We use the cumulative installed capacity to represent accumulated experience in the initial design, construction, and installation of wind farms, where we expect the majority of learning to occur [32].

Table 1 translates the models from Section 3 into this context, using symbols defined in that section, where offshore wind is the emerging industry and onshore wind is the mature industry.

Table 1. Experience Curve Models for Offshore Wind.

Model	Experience Curve Model
Emerging	$C_t = C_0 \left(\frac{N_{\text{offshore},t}}{N_{offshore,0}}\right)^{-b}$
Hybrid	$C_t = AC_0 \left(\frac{N_{offshore,t} + N_{onshore,t}}{N_{offshore,0} + N_{onshore,0}}\right)^{-b} + (1-A)C_0 \left(\frac{N_{offshore,t}}{N_{offshore,0}}\right)^{-b}$
Mature	$C_t = C_0 \left(\frac{N_{offshore,t} + N_{onshore,t}}{N_{offshore,0} + N_{onshore,0}}\right)^{-b}$

In Section 5 we present projections for the LCOE of offshore wind between 2020 and 2050, using the three models above, two growth scenarios, and a fixed learning rate. In the following subsections, we present the two future capacity growth scenarios for wind energy; detail the assumptions around the relatedness of offshore and onshore wind technology; and discuss our choice of learning rate given the evolution of wind energy technology from a global domain perspective.

4.2 Growth Scenarios

We investigate two scenarios for the future growth of onshore and offshore wind, based on alternative pathways reported by IRENA [32]. We develop the two scenarios based on the values in [35] reported for each decade, and starting from the historical value in 2019. Specifically, we use the data found on IRENA Remap energy generation and capacity dashboard [35], which provides two scenarios: the Planned Energy Scenario, which we label *BAU*, is based on governments' current energy plans and other planned targets and policies; and the Transforming Energy Scenario, which we label *Transformative* assumes an ambitious energy transformation pathway based largely on renewable energy sources and steadily improved energy efficiency (see **Appendix A2**). For past data on installed cumulative capacity, we use the IRENA statistics report [36].

To model future growth in cumulative capacity, we use a three-parameter logistic growth curve presented in **equation ix**,

$$Log(N_t) = \frac{N_\infty}{1 + e^{-k(Log(t)-I)}} \qquad \textbf{Eq. (ix)}$$

where I represents the point of inflection, N_∞ is the upper asymptote of cumulative capacity, and k is a shape parameter. We find the best fit logistic curve using the historical data in 2019, and the data points

from 2030, 2040, and 2050 from IRENA (see **Table A1**). **Figure 1** illustrates the results, showing the cumulative growth in the upper panels and the annual growth rate in the lower panels. Note that the BAU scenario (in the left panels) has offshore and onshore with similar growth rates; the transformative has offshore wind growing at a faster rate than onshore.

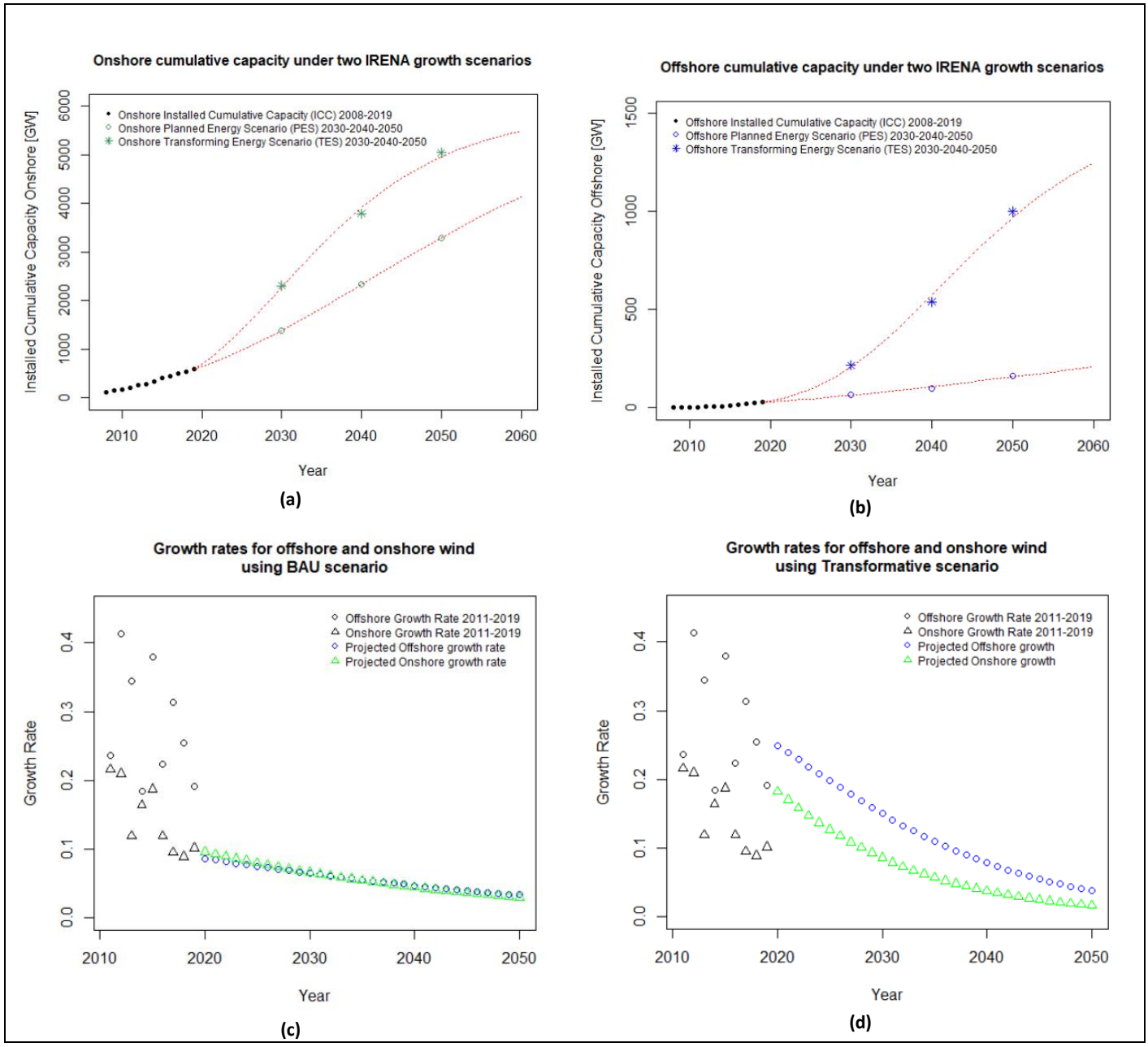

Figure 1. Growth of Installed Capacity of Wind Energy using BAU and Transformative energy pathways. The top panels show the cumulative capacity for BAU and Transformative scenarios for onshore (a) and offshore (b). The second row shows the annual growth rate for onshore and offshore wind for BAU (c) and Transformative (d) growth scenarios.

4.3 Relatedness

In order to understand the importance of the assumptions about relatedness, we generate experience

curves for offshore wind under three assumptions: that the technology is (1) entirely emerging; (2) a direct offshoot of onshore wind, based entirely on mature technology; or (2) a hybrid of emerging and mature technology. We consider how these assumptions about relatedness affect forecasts of offshore wind LCOE. We examine these models under the two future growth scenarios described above, fixing the learning rate (LR); and perform sensitivity on the LR, allowing us to understand the relative importance of assumptions about relatedness.

For the hybrid model, we model offshore wind as a combination of emerging and mature technology. We make a simplifying assumption, for illustrative purposes only: that the support structures for offshore wind are novel and not related to onshore wind, whereas everything above the water is related to onshore wind. One could argue that, except for specific considerations for external conditions, such as weather, ocean stresses, and other marine environment factors, the design of offshore wind turbine rotor-nacelle assembly closely mirrors that of its onshore counterpart [37]. We acknowledge that this gross simplification, however, ignores the differences between offshore and onshore turbines, as well as any relationship between support structures and the offshore oil and gas industry, among other things. We use this to illustrate the concept of hybrid technology and leave it to future work to estimate the actual relatedness.

Thus, we treat the tower, platform, and rotor-nacelle assembly as onshore wind-like technologies. There are two primary categories for offshore wind turbine support structures: fixed bottom and floating. For fixed bottom turbines, we treat the foundation, pile, and substructures as emerging technologies. For floating turbines, we treat the floating sub-structures, piles, and mooring as emerging technologies.

Table 2 shows the contribution to the LCOE from each portion from 2011 to 2017 [38] [39] [40] [41] [42] [43]. On average, considering the different support structures, the "above the water" technologies contribute roughly 40% of the capital cost, and the support structures contribute roughly 60%. [27]. Thus, we use a value of A=0.4 in our hybrid model.

Table 2. Historical Technological Contribution to Offshore Wind LCOE. This table illustrates the technological contribution to overall LCOE obtained from Costa [13].

Year	Mature Technology Contribution	Emerging Technology Contribution
2011	38%	62%
2013	38%	62%
2015	33%	67%
2016	35%	65%
2017	36%	64%

We apply ratios from **Table 2** to the offshore wind LCOE data from 2010 to 2019 [36] (interpolating between the years for which we don't have ratios) to find the historical contributions to LCOE from the mature and emerging technologies.

4.4 Learning Rates

We perform our analysis using a LR of 12.5%, which is the trimmed median of plausible LRs captured in our literature review focused on wind energy experience curve studies in the global (as opposed to regional) domain. **Figure 2** depicts plausible learning rates in global wind energy in order of publication

date.

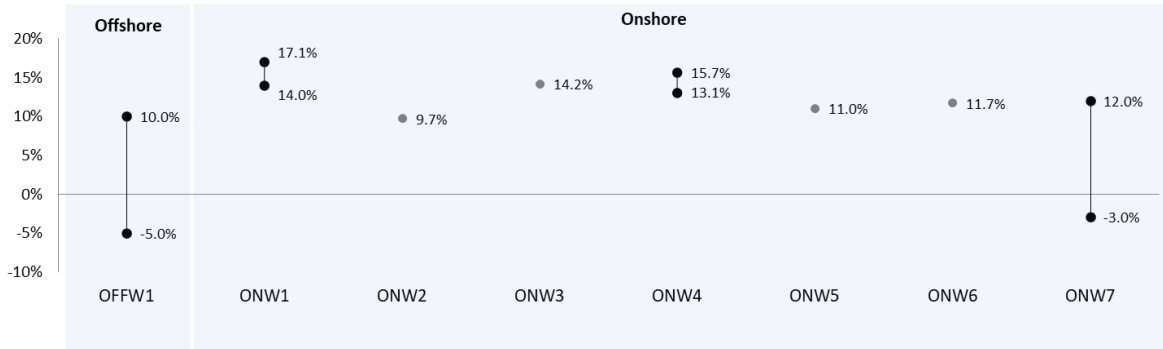

Figure 2. Comparison of plausible global domain Wind Energy learning rates (LR). This figure provide a comparison of reasonable global domain learning rates from studies developed in the past for wind energy: Offshore wind (OFFW) and Onshore Wind (ONW). The projects for offshore and onshore are labeled in published order. Projects are OFFW1: Period covered: 1991-2008 (Published in 2018) [44], ONW1: Period covered: 1975-2002 (Published in 2002) [45] , ONW2: Period covered: 1971-1997 (Published in 2004) [46] , ONW3: Period covered: 1981-1997 (Published in 2006) [47], ONW4: 1981-1997, ONW4: Period covered: 1980-1998 (Published in 2007) [48], ONW5: Period covered: 1981-2001 (Published in 2009) [49], ONW6: Period covered 1984-2005 (Published in 20011) [50], and ONW7: Period covered: 1971-2012 (Published in 2018`) [44]

For onshore technology, the median LR is about 12.5% (corresponding to a learning exponent b=0.1926). In the only published study on offshore wind LCOE using a global domain, based on data between 1991 and 2008, the LR was estimated to be between -5.0% and 10.0%, as a result of "negative" learning in these years [29] [30] [31]. We assume that the forward-looking LR of onshore and offshore wind will be the same.

As an additional point of comparison, we estimate a set of best fit lines, using past data to estimate the LR under each of the three models in **Table 1**. We repeat this using three starting points (2010, 2011, 2014), and find that the choice of starting point has a significant impact on the estimated LR, particularly as the estimated LCOE fluctuates considerably. We use starting points of 2010, 2011, and 2014: $0.161/kWh, $0.175/kWh, and $0.183/kWh, respectively, and data from [32]. We use a nonlinear least-square estimates. The results of the best fits, shown in **Table 3**, indicate that the LR for offshore wind could be anywhere between 4.7% and 23.3%. We note that these are short time periods and thus subject to considerable uncertainty. Our value of 12.5% is close to the median of these values.

Table 3. Learning Rates (LRs) from the best-fit experience curve

Span Period	Emerging Model	Hybrid Model	Mature Model
2010-2019	4.7%	5.5%	7.4%
2011-2019	9.4%	11.4%	16.8%
2014-2019	23.3%	43.2%	41.8%

5. Results and Analysis

5.1 Importance of assumptions about relatedness

This section focuses on our central results regarding the importance of technological relatedness to experience curve modeling. **Figure 3** (and **Table A3** in Appendix) illustrate the role played by assumptions about future growth and relatedness. We find that assumptions about relatedness are of similar magnitude of importance as assumptions about future growth scenarios.

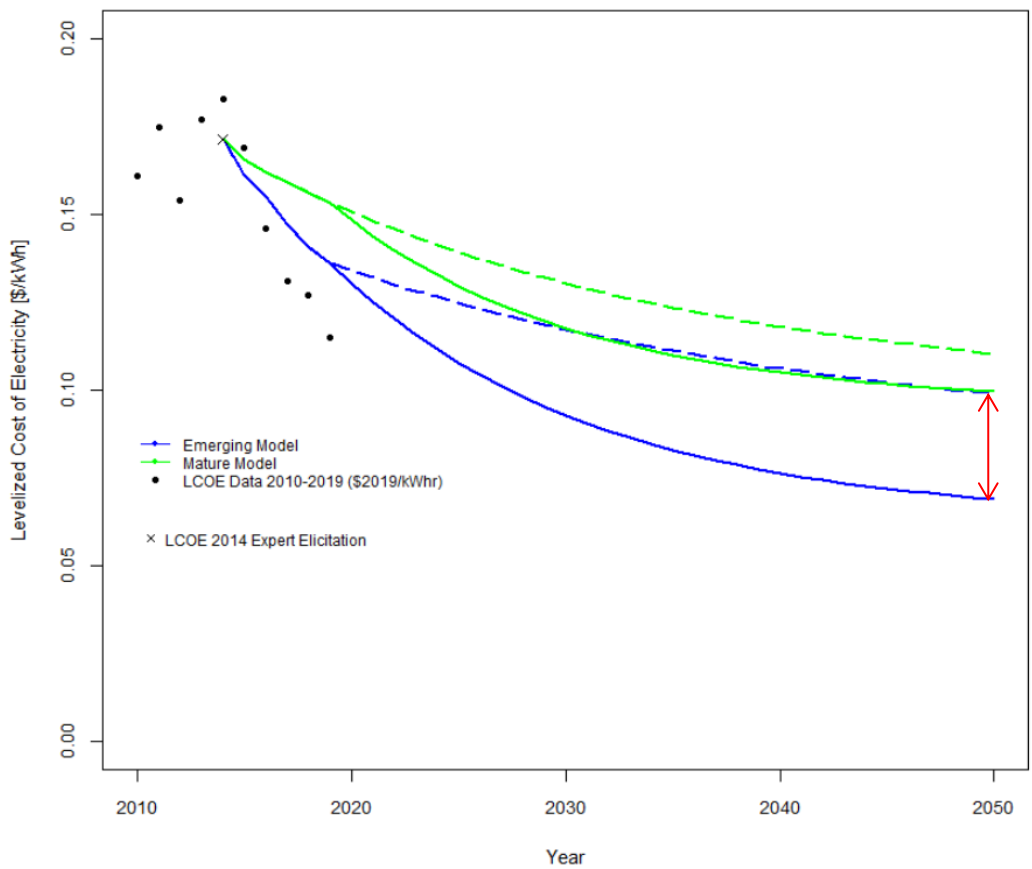

Figure 3. LCOE of Offshore Wind Trend: Mature and Emerging contrast. Emerging and Mature experience curve models with LR=12.5%. The dashed lines represent the BAU growth scenario, and the solid lines represents Transformative. The red arrow highlights that the difference between the emerging and mature projections in 2050 assuming Transformative growth, are about the same as the difference between the BAU and Transformative growth scenarios, assuming emerging.

In **Figure 3** we see that the difference in cost between the two growth scenarios under the assumption of emerging (the blue solid and blue dashed lines) is about equal to the difference between the assumption of emerging or mature under the transformative growth scenario (the blue solid and green solid lines). The difference between the relatedness assumptions is much smaller under the BAU growth scenario, as the two technologies are projected to grow at about the same rate in that scenario (See Figure 1, panel c). In fact, the difference between the blue and green dashed lines is driven by the difference in offshore versus onshore historical growth rates between 2014-2019; cost reductions are nearly identical in the projected years.

We also explore Learning Rates. We find that under the transformative growth scenario, the LR for the emerging model would have to be about 7.7% to be equivalent in 2050 to the mature model with

LR=12.5% (i.e. to move the solid blue line up to the solid green line). Looked at the other way around, the LR for the mature model would have to be 19.9% to be equivalent in 2050 to the emerging model with LR=12.5% (i.e. to move the solid green line down to the solid blue line). Thus, in this case assumptions about relatedness are equivalent to changing the learning rate by about 40-60%.

5.2 Results in Context and Comparison with expert views

In this section, we focus on the results in context of a large scale expert elicitation survey [4]. The survey, which took place in 2014, included a subset of 154 experts who provided estimates for offshore wind. The experts each provided an estimate for the LCOE of offshore wind in 2020, 2030, and 2050. Rather than provide a point estimate, the experts provided a 10th, 50th, and 90th percentile estimate at each date.

In **Figure 4**, we contrast the experts' cost projections with experience curves under the assumptions of mature, hybrid, or emerging technology, using a LR of 12.5%, and a starting point of the LCOE in 2014. These are compared with the full range of estimates provided by the experts, highlighting the mean of the experts' estimates for each of the 10th, 50th, and 90th percentiles. We also include the historical LCOEs of offshore wind, before and after 2014, and the best fit using data from 2014-2019 under the assumption of an emerging technology. The best fit curve does not differ significantly between the emerging, hybrid, and mature assumptions, thus we only show one curve.

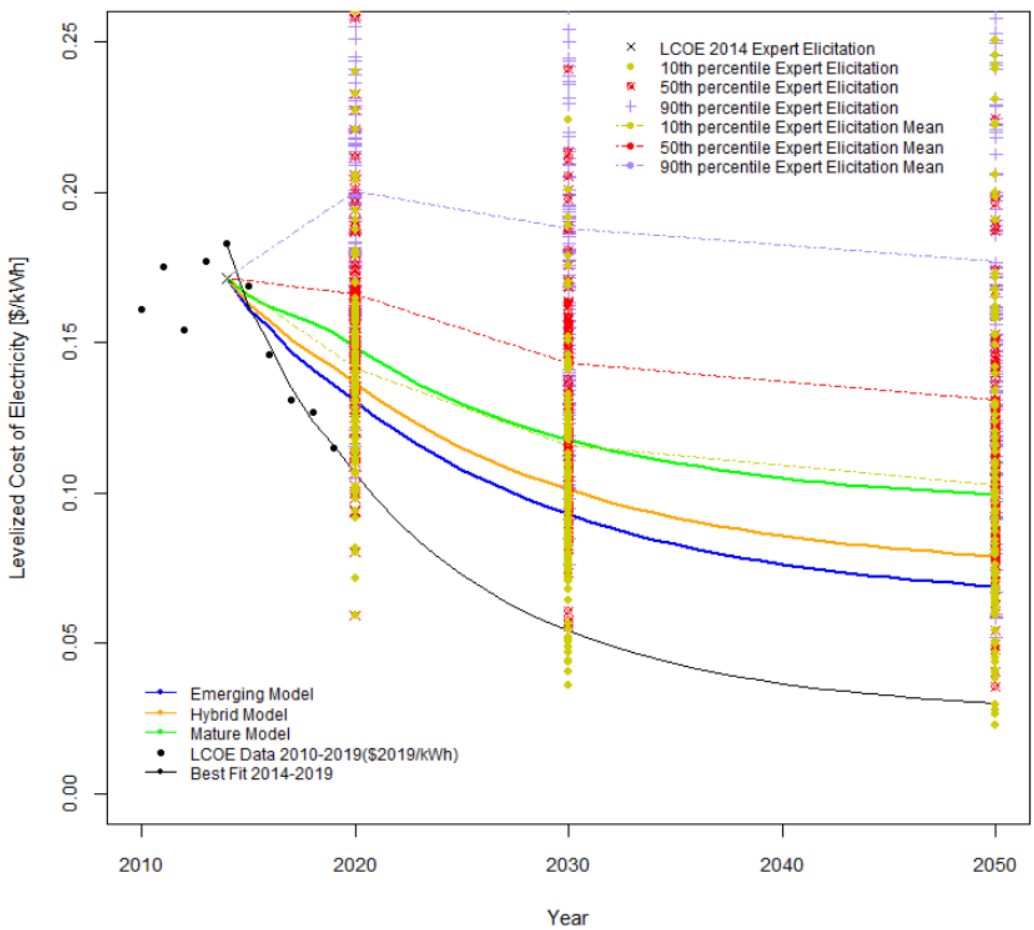

Figure 4. LCOE of Offshore Wind: Projections under Transformative Scenario Black dots show the actual data

LCOE 2010-2019. The emerging, hybrid, and mature models shown as blue, yellow, and green solid lines, using a learning rate of 12.5% and start date of 2014. The black line is the best fit based on data from 2014-2019 and emerging model. Individual estimates from the expert elicitation [4] are shown as violet, red, and yellow markers for the 90th, 50th, and 10th percentiles estimates, respectively; with the dashed lines showing the mean estimate among all experts for each percentile.

We start by noting that most experts under-estimated the reduction in costs between 2014 and 2019. About 80% of the experts would be surprised by the 2019 LCOE, in the sense that it is below their 10th percentile for 2020. One possible explanation is that before 2014, the year the expert elicitation study was conducted, costs were quite variable and did not show a clear downward trend.

Another possible driver for the underestimation of cost reductions by experts could be their implicit assumptions about offshore wind's relatedness to onshore wind. The most optimistic forecasts by the experts—the 10th percentile—is a close match for the mature model, while being far above the other two experience curve models. This may imply that the experts were looking at offshore wind as largely an offshoot of onshore wind, rather than an emerging technology. Of course, it may also reflect pessimism on the LR, on future growth, or perhaps a fundamental misunderstanding of technological change.

Even the fully emerging model—the most optimistic of the experience curves—appears to be underestimating actual cost reductions. The best fit curve from 2014-2019 implies that costs may reduce far more than both experience curve and expert elicitation methods of cost projection. Because this is a very short period of data, it is possible that these years were an anomaly, and that costs will move back toward the expert predictions and/or the experience curves. However, a more recent expert elicitation predicts that the faster rate of learning will be somewhat maintained, with a result of a median 50th percentile estimate of about $0.05/kWh and a range between $0.025 - 0.065/kWh in 2050 [51]. Moreover, a recent paper by Meng et al [52] has shown that both experts and models have underestimated recent cost reductions in a wide range of energy technologies; possibly due to a range of policy and social changes.

6. Conclusion

In this paper we introduced the concept of relatedness and how it impacts forecasts using experience curves. We point out that some components of a complex technology in an emerging industry may be closely related to a technology in a more mature industry, and thus care must be taken when identifying the starting point for cumulative capacity. We provide a method to mathematically model the experience curve for a hybrid technology that is only partially related to a more mature industry. We then use offshore and onshore wind data to illustrate the impacts that assumptions about relatedness have on experience curve forecasts.

We illustrate these findings in the context of a large scale expert elicitation and recent data on LCOE. We find that, for offshore wind, assumptions about relatedness have the same magnitude of impact as assumptions about future growth or assumptions about the learning rate. Specifically, we find that the impact on the forecast LCOE of offshore wind energy in 2050 of fully mature versus fully emerging is that same as the impact of the IRENA transformative growth scenario versus the IRENA BAU growth scenario. Similarly, we find that introducing the assumption of relatedness is equivalent to a change in

LR of 40-60%.

All in all, we find that relatedness is a previously under-appreciated source of uncertainty around experience curves. It plays a role equivalent to uncertainty around future growth or learning rates. Clearing up assumptions about relatedness is not enough to fully address the range of uncertainty in experience curve forecasts, but is a step in the right direction.

In constructing our hybrid model for offshore wind, we made a simple assumption on the relatedness of offshore and onshore wind. In fact, some experts believe that offshore wind foundations may be highly related to oil and gas, and that the turbines and control algorithms, while appearing similar to onshore wind, may be quite distinct. Future research might focus on ways to determine the relatedness of technologies, perhaps through expert judgement or patent analysis.

Finally, at a more philosophical level, considering relatedness may cause a rethinking around estimating learning rates. From the most fundamental theory of learning by doing, it is not clear why different technologies with similar markets and similar levels of complexity would learn at different rates. One hypothesis is that they do not learn at different rates, but rather they are starting at different levels of cumulative capacity due to relatedness. This hypothesis is open to future research.

Competing Interest

Authors have no competing interests to declare.

CRedit author statement - Contribution Role Taxonomy

Christian Hernandez-Negron: Conceptualization, Data curation; Formal analysis; Investigation; Methodology; Writing – Original Draft. **Erin Baker**: Conceptualization, Funding Acquisition, Methodology; Project Administration; Resources; Writing – Review and Editing. **Anna Goldstein**: Conceptualization; Funding Acquisition; Methodology; Writing – Review and Editing.

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Appendix

The appendix is organized as follows. **Section A1** provides the mathematical definition of the levelized cost of electricity of a technology used for the energy technologies by IRENA. **Section A2** provides detail on the IRENA pathways that we use to project cumulative installed capacity for offshore wind. **Section A3** provides details about the best-fit lines. **Section 4** provides details of projection using BAU and Transformative energy pathways scenario.

A1. Mathematical definition of the levelized cost of electricity

The levelized cost of electricity (LCOE) characterizes the cost of electricity necessary to recover all costs from manufacturing, installing, and operating an offshore wind project. As such, research and development efforts have been focused on minimizing LCOE. Following IRENA [53], we define LCOE of wind a technology mathematically in the form of

$$LCOE = \frac{\sum_{t=0}^{T} \left(\frac{I_t + M_t}{(1+r)^t}\right)}{\sum_{t=0}^{T} \left(\frac{E_t}{(1+r)^t}\right)}$$

Where, T is the lifetime of the system, t indexes the years, I_t is the investment expenditure (i.e. capital cost) in the year$t$, M_t is the operations and maintenance expenditures in the year t, E_t is the energy produced in year t, and r is the discount rate .

The developers and power plant producers may use the LCOE metric as a comprehensive planning tool to compare the attractiveness of energy technologies. Thus, investors are interested in LCOE to understand long-term economic trends, especially for renewables, such as offshore, in which the decrease in cost has dramatically improved their competitiveness.

A2. Energy pathways for offshore wind installed cumulative capacity assumptions

Table A1 shows the "climate-resilient" scenario/pathways for offshore wind. Data from the REmap model are available here. The description of the energy pathway as described from the Global Renewable Outlook of IRENA are:

> The ***"Planned Energy Scenario (PES)"*** is the primary reference case for this study, providing a perspective on energy system developments based on governments' current energy plans and other planned targets and policies (as of 2019), including Nationally Determined Contributions under the Paris Agreement unless the country has more recent climate and energy targets or plans.
>
> The ***"Transforming Energy Scenario (TES)"*** describes an ambitious, yet realistic, energy transformation pathway based largely on renewable energy sources and steadily improved energy efficiency (though not limited exclusively to these technologies). This would set the energy system on the path needed to keep the rise in global temperatures to well below 2 degree Celsius (°C) and towards 1.5°C during this century

Table A1. IRENA REmap Energy Pathways (get data here)

Subcategory	Case	CAGR* 2019-2050	2030	2040	2050
Onshore	Planned Energy Scenario (BAU)	5.69%	1387.3498	2333.9771	3299.8848
Offshore	Planned Energy Scenario (BAU)	5.83%	67.4761	99.8881	163.2830
Onshore	Transforming Energy Scenario (Transformative)	7.14%	2309.4465	3790.3833	5044.2967
Offshore	Transforming Energy Scenario (Tranformative)	12.20%	216.1030	539.7998	999.4521

**CAGR is the mean annual growth rate of a an amount (e.g investment) over a specified period of time longer than one year. It represents one of the most accurate ways to calculate and determine returns for individual assets, investment portfolios, and anything that can rise or fall in value over time. It is the rate of return that would be required for an amount (e.g. investment) to grow from its beginning value (e.g. balance) to its ending value, assuming the profits were reinvested at the end of each year of the investment's life span.*

We should note that the BAU for offshore is quite pessimistic, with a slower growth between 2030 and 2040 than onshore. On the other hand, with moderate annual growth for wind technology, we can better understand offshore wind cost behavior while contrasting with expert elicitation foresight. The offshore wind appears to be new technology, learning faster than would happen if it were an offshoot of onshore. With offshore wind being an emerging technology, it represents good news for climate change and implies a need to move forward with streamlined siting and permitting processes.

A3. Estimating the best fit

Following the definition of the equations in the theory of **Section 3** and application of **Section 4.1**, and under the assumptions of installed cumulative capacity described in section 4.2 we find a set of best fit lines. Specifically, in order to estimate the LR that is the best-fit to the past data, we find the learning coefficient, b, that minimizes the square error, defined as follows.

For emerging model;

$$\min_b \sum_t \left(C_t - \left[C_{off,0} \left(\frac{N_{off,t}}{N_{off,0}} \right)^{-b} \right] \right)^2$$

For the mature model;

$$\min_b \sum_t \left(C_t - \left[C_{off,0} \left(\frac{N_{off,t} + N_{on,t}}{N_{off,0} + N_{on,t}} \right)^{-b} \right] \right)^2$$

For hybrid:

$$\min_b \sum_t \left(C_t - \left[AC_{off,0} \left(\frac{N_{off,t}}{N_{off,0}} \right)^{-b} + (1-A) C_{off,0} \left(\frac{N_{off,t} + N_{on,t}}{N_{off,0} + N_{on,t}} \right)^{-b} \right] \right)^2$$

We estimate a total of six best fit lines; two for each of the above models, one starting in 2010 and one starting in 2014. Detailed results of the best fit is presented in Table A2.

- **Historical data and detailed results**

Table A.2 presents the fit and performance metrics, in terms of how well they minimize the error, of the six fits. All models perform similarly in terms of the various performance metrics. The emerging model performs very slightly better than the others. None of the models starting in 2010 perform well as the data is non-monotonic.

Table A2. Summary of best fit models. The upper part of the table shows the LR that minimizes the square error for each model (3 relatedness assumptions x 2 starting years); and presents some performance metrics. The lower part of the table, shows details. On the left side, we show the data; on the right side, the resulting fitted values, with projections for 2030 and 2050 under **Transformative growth scenario**.

				Results from the best-fit analysis		
				Span Period: 2010-2019 (2014-2019)		
			Models:	*Emerging*	*Hybrid*	*Mature*
			Assumptions:	considered an entirely new technology	behaves as a hybrid	a direct offshoot of onshore wind
			Learning coef. (b):	*0.0693 (0.3829)*	*0.0819 (0.8169)*	*0.1115 (0.7810)*
			Learning Rate	*4.7% (23.3%)*	*5.5% (43.2%)*	*7.7% (41.8%)*
			Performance Metrics			
			RMSE	*0.0182 (0.0039)*	*0.0183 (0.0216)*	*0.0188 (0.0043)*
			R^2	*0.3305 (0.9733)*	*0.3150 (0.0669)*	*0.2804 (0.9679)*
			MAD	*0.0146(0.0031)*	*0.0148 (0.0206)*	*0.0152 (0.00272)*
			MAPE %	*9.46 (2.15)*	*9.62 (15.55)*	*9.94 (1.84)*
	Installed Cumulative Capacity Data			**Levelized Cost of Electricity Forecast Transformative Growth Scenario**		
Year	Offshore	Onshore	**LCOE Data**	*Emerging*	*Hybrid*	*Mature*
	[MW]	*[MW]*	----------[$2019/KWh]----------			
2010	3056	177790	0.1610	*0.1610*	*0.1610*	*0.1610*
2011	3776	216239	0.1750	*0.1587*	*0.1583*	*0.1575*
2012	5334	261570	0.1540	*0.1549*	*0.1547*	*0.1542*
2013	7171	292744	0.1770	*0.1518*	*0.1519*	*0.1522*
2014	8492	340805	0.1830	*0.1500 (0.1830)*	*0.1499 (0.1821)*	*0.1496 (0.1830)*
2015	11717	404523	0.1690	*0.1467 (0.1618)*	*0.1467 (0.1432)*	*0.1467 (0.1596)*
2016	14342	452502	0.1460	*0.1446 (0.1497)*	*0.1447 (0.1275)*	*0.1448 (0.1459)*
2017	18837	495539	0.1310	*0.1419 (0.1349)*	*0.1424 (0.1083)*	*0.1433 (0.1353)*
2018	23629	539557	0.1270	*0.1397 (0.1237)*	*0.1404 (0.0945)*	*0.1418 (0.1260)*
2019	28155	594253	0.1150	*0.1380 (0.1156)*	*0.1387 (0.0843)*	*0.1403 (0.1165)*
2030				***0.1202 (0.0540)***	*0.1204 (0.0218)*	*0.1203 (0.0397)*
2050				***0.1081 (0.0299)***	*0.1087 (0.0089)*	*0.1091 (0.0201)*

*Root Mean Squared Error (RMSE), Coefficient of determination (R^2),Mean Absolute Deviation (MAD), Mean Absolute Percentage Error (MAPE)

- **LCOE projections using <u>BAU and Transformative</u> energy pathways scenarios**

Table A3 we compare the costs in 2030 and 2050 that result from the experience curves under as assumption of LR=12.5%.

Table A3. Projections of BAU transformative pathways scenarios for fixed LR=12.5%; and three relatedness assumptions. The first two columns are provided as a comparison, they include the projections using two best-fits starting in 2010 and 2014 under the BAU and Transformative growth scenario.

Models:	***Best Fit*** **Span Period:** **2010-2019 (2014-2019)**		***Emerging*** ***LR=12.5%*** ***Start 2014***		***Hybrid*** ***LR=12.5%*** ***Start 2014***		***Mature*** ***LR=12.5%*** ***Start 2014***	
Year:	**2030**	**2050**	**2030**	**2050**	**2030**	**2050**	**2030**	**2050**
Cases	[$/kWh]		[$/kWh]		[$/kWh]		[$/kWh]	
Business As Usual	*0.130* *(0.086)*	*<u>0.123</u>* *(0.061)*	*0.117*	<u>0.099</u>	*0.121*	0.103	*0.130*	0.110
Transformative	*0.120* *(0.054)*	*<u>0.108</u>* *(0.029)*	*0.092*	<u>0.069</u>	*0.101*	0.079	*0.117*	<u>0.099</u>

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Experience curves and the relatedness of technologies: Offshore and onshore wind energy.

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