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Innovations in the Wind Energy Sector*

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Abstract

When technological innovations are implemented in the wind energy sector, we should observe reductions in the production cost of electricity. However, the accuracy of inferring the rate of innovation from production cost reductions is open to challenge when those costs change due to factors not attributable to technological innovation. This study applies an engineering model to generate time-series of wind energy production cost data as the measure of innovation. This approach enables us to exclude factors which are not attributable to technological innovation. In order to illustrate the importance of our measure of innovation, we conduct a learning curve analysis which measures the correlation between deployment of wind energy technology and cost reductions in electricity production. Our data delivers an improved fit of the learning curve in wind energy technology relative to alternative measures of innovation from the literature.

Keywords: Innovation, Levelized Engineering Cost of Energy, Wind Turbine Vintages, Learning Curve
JEL codes: O31, O32, Q28, D83

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1 Introduction

Technological innovations can reduce costs of electricity production in the wind energy sector. Despite the achieved reduction in costs, many producers still receive subsidies to allow them to compete with conventional power producers. Understanding the drivers of technological innovation is a first step towards constructing effective policies to accelerate innovation process to an extent that the subsidies are no longer required. However, we cannot fully understand the drivers of innovation without an accurate measure of innovation itself. This paper focuses on generating a more accurate innovation measure for wind energy technologies, which the current literature does not provide. We illustrate the importance of our data by conducting a learning curve analysis - a widely applied method in the energy literature to predict reductions in the costs of electricity production.

Innovation in this paper refers to any type of wind turbine modification which produces electricity at a lower cost than did its predecessor. If we directly use production cost reductions as the measure for innovation, we will obtain biased results, because production costs can also change due to factors unrelated with technological innovation, such as interest rates, material prices, exchange rates, and wind speed fluctuations.

In order to derive an accurate measure of innovation, we apply an engineering model (Malcolm & Hansen, 2002; Poore & Lettenmaier, 2000-2002) and estimate the cost of the wind electricity production of wind turbines installed each year in the US from 1998 to 2017. The engineering model calculates the costs of electricity production based on the engineering properties of installed turbines, their material composition and the corresponding material prices in the selected year. This approach can effectively exclude from the estimated production cost the factors unrelated to technological innovation, such as interest rate, material price and exchange rate fluctuations. This is the major motivation for using the engineering model in this paper. We refer to our production cost data as an 'innovation measure' or levelized engineering cost of energy ($LECOE$) series.

We illustrate the usefulness of our measure of innovation by conducting a learning curve analysis. A learning curve measures the correlation between deployment of wind technology and electricity production cost reduction. Using our levelized engineering cost of energy measure delivers an improved fit of the learning curve in comparison to alternative data. This is crucial as the learning curve is a popular tool in the energy literature to measure technological innovation. In addition, learning rates are frequently used in other electricity market modeling practices which influence policy decisions. Therefore, learning rates inferred from improved data should be more reliable for informing successful policies.

The paper is organized in the following way: section 2 describes the process of generating our innovation data for wind technology in the US and compares it with other studies; section 3 summarizes and analyzes wind technology support policies in the US; section 4 evaluates these policies in the context of learning curve literature, and section 5 concludes.

2 Measuring Innovation in Wind Energy Technologies

2.1 Defining the Levelized Cost of Energy ($LCOE$)

Technological innovations are reflected in cost reductions in energy production. Other, non-innovative factors may also contribute, and we aim to eliminate these. To describe how we accomplish this, it is helpful to define the terminologies used in the study. In this section, we define the components of production cost.

Traditionally, the production cost of electricity is assessed using the levelized cost of energy ($LCOE$) (e.g., McKenna, Hollnaicher, & Fichtner, 2014). $LCOE$ includes all capital and operating costs throughout the useful life of a wind turbine. A simple formula for calculating $LCOE$ is the following (Ramadhan & Naseeb, 2011):

$$LCOE = \frac{CRF \times CapEx + O\&M}{AEP} \tag{1}$$

Capital Cost ***(***$CapEx$***).*** Capital cost includes: (i) the cost of a turbine, (ii) the balance of system cost (BOS), which includes development costs of the wind farm, permits, engineering and management, roads for site access, foundation, transportation, assembly, installation and electrical infrastructure costs. Investment costs are expressed in \$/MW, where MW measures the turbine capacity. Turbine capacity is the maximum amount of electricity that a particular wind turbine can generate in an hour. Generated electricity depends on the wind speed. The maximum amount can be reached above some threshold wind speed. We denote the capital cost of a turbine as $CapEx$ and

$$CapEx = \frac{\text{Turbine Cost} + BOS}{\text{Turbine Capacity}} \tag{2}$$

Capital Recovery Factor (CRF). We can represent capital cost as a discounted sum of annual fixed payments throughout a wind turbine's useful life. These fixed payments, or the rental rate of capital, is a product of capital cost and a capital recovery factor (CRF), where CRF equals to $\frac{i(1+i)^n}{(1+i)^n-1}$ (Chabot & Saulnier, 2001). In this formula, n is the expected useful life of a turbine and i is discount rate. The rental rate is measured in \$/MW/year.

Operations and Maintenance Costs (O&M). Operations and maintenance costs (O&M) include replacement of wind turbine components, insurance, land lease and all other costs that occur from the time the wind farm starts operation. Some of these costs are fixed each year and does not depend on the amount of electricity produced, and some are variable. However, for convenience, we convert this cost to \$/MW/year.

Annual Energy Production (AEP). Wind turbines can reach maximum turbine capacity at a certain wind speed. However, wind speed varies throughout a day, at various seasons and across geographic locations. In fact, wind turbines rarely produce at their maximum capacity. Therefore, in order to calculate the production costs of a unit of electricity, we need to know the electricity production per MW of turbine capacity per year. The unit of measurement is MWh/MW/year, which can be phrased as effective hours in operation annually.

2.2 Identifying Gaps in the Literature

Before describing the process used to generate our measure of innovation, we explain why we did not rely on measurements from prior studies. Firstly, the vast majority of papers on innovation in wind energy technology (e.g., Hayward & Graham, 2013; Grafström & Lindman, 2017; Yu, Li, Che, & Zheng, 2017; Huenteler, Schmidt, Ossenbrink, & Hoffmann, 2016; Wiebe & Lutz, 2016) use changes in average capital expenditures or average turbine price per unit capacity as the measure of innovation. Using only capital expenditures in the literature may be a result of a lack of production cost data. This approach is problematic because, as turbines become larger, capital expenditures per unit capacity may rise[1]. Considering only capital expenditures as the measure of innovation in this case would suggest technological decay. However, as turbines become taller, effective hours in operation also increase and this may compensate for rises in the capital costs.

Another problem is that the most frequently cited International Energy Agency's (1991-2008) capital expenditure data is not of equal quality across countries. In this source, some countries report all components of capital costs, while others only report parts of it. For example, for some countries, the *BOS* cost component is missing. In addition, capital expenditure data or turbine price data reflect the exchange rate, material prices, and/or interest rate fluctuations, none of which contributes to technological innovation (Bolinger & Wiser, 2012). Thus, these factors should be eliminated when deriving measurements of innovation.

McKenna et al. (2014) uses the same wind turbine component-cost-scaling model (Fingersh, Hand, & Laxson, 2006) as we do, in order to calculate the LCOE across various wind turbine designs that are matched with a particular wind resource and the terrain of a geographic location in Germany. However, McKenna et al. (2014) do not attempt to produce series that describe trends in technological development. Instead, the authors try to produce a high resolution image of the theoretical cost potential of wind energy across different locations. In contrast, we only identify technological innovation trends where small site-specific variations are not of crucial importance.

Several papers use a different approach to measure innovation. Qiu and Anadon (2012) measure production costs using average tariffs that potential wind farm developers were bidding to receive in the Chinese wind energy concession program of 2003-2007. Tang and Popp (2016) criticize the approach of Qiu and Anadon (2012) arguing that wind farm investors are inclined to underbid their costs in order to win auctions. Instead, Tang and Popp (2016) use the levelized cost of energy data from Chinese wind energy subsidy project that covers 2002-2009. Their data represents the expected levelized cost of energy estimated by eligible investors. Even if truthfully reported, this data is likely to reflect fluctuations in the factors that do not contribute to technological innovation, such as material price, exchange rates, and interest rate fluctuations. This is due to the fact that investors' expectations are most likely based

[1]The reason for the rising capital expenditures is that wind speed rises as it reaches higher altitudes. Stronger wind exerts more force on the turbine, requiring heavier materials to withstand these forces (Hemami, 2012)

on actual turbine prices.

We found only one source (Wiser & Bolinger, 2018), which delivers an innovation measure that follows $LCOE$ notion from equation 1, in which the series are sufficiently long, and comparable to our innovation data. Wiser and Bolinger (2018) measure the capital cost ($CapEx$) component of $LCOE$ based on the average investment cost of newly installed turbines each year. In addition, they compute the AEP component based on the empirical data of the actual average production of these turbines. Similarly to the papers mentioned above, the problem with this approach is that wind farm investment costs may reflect interest rates, material price, and exchange rate fluctuations. In addition, historical electricity production data may reflect variations in geographical, annual, seasonal and daily wind resources. Our paper estimates both $CapEx$ and AEP components of $LCOE$ using an engineering model. We will discuss this in more details in section 2.5.

To summarize, many papers do not rely on the traditional notion of $LCOE$ and measure innovation by using capital expenditures or turbine prices. Several papers proxy $LCOE$ using other methods. Nevertheless, the estimated values are likely to reflect fluctuations of variables unrelated to technological innovation. Furthermore, the data series of these papers are quite short and may not represent actual innovation trends.

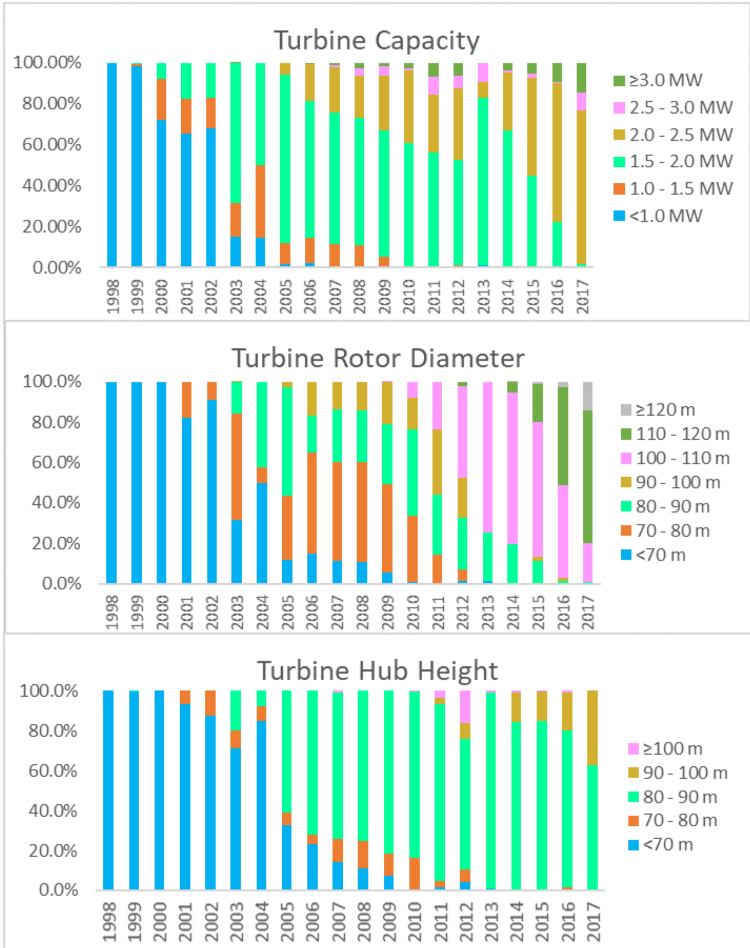
2.3 Deriving our Innovation Measure

In this section we derive our innovation measure, discuss the strengths and the weaknesses of our method and compare our $LECOE$ data to alternative series.

Each year new wind turbines are installed in the US. The average characteristics of the turbines installed change annually due to innovation. Key characteristics including turbine capacity, rotor diameter, and hub height are the major determinants of the technological progress of wind turbines. The fact that production rates improve at higher altitudes and that stronger wind exerts more force on wind turbines implies that the major innovation in wind technology has to come from increases in the size of turbines. Figure 1 confirms that the wind turbines have been persistently increasing in size.

The figure shows the distribution of key turbine characteristics by year of installation. According to the figure, on average, older turbine models are gradually

Figure 1: *Distribution of Wind Turbine Vintage Characteristics*



Notes. The figure shows that the key wind turbine vintage characteristics have been gradually updated. Therefore, we argue that the average characteristics of wind turbines installed annually represent the frontier technology in the year of installation. Source. Wiser and Bolinger (2018)

replaced by new ones. Therefore, we argue that the frontier technology is advancing. For these reasons, we use the average key characteristics of turbines installed in a particular year as a representative of frontier technology in that year. For convenience, we refer to the hypothetical wind turbine model possessing the key characteristics of turbines installed in a particular year as *vintage*.

Several studies, which we characterize as engineering models, use the key turbine characteristics as inputs to derive the mass of turbine components (Malcolm & Hansen, 2002; Poore & Lettenmaier, 2000-2002). Once the turbine mass is properly estimated and the material composition of the turbine is known, we can use material prices to calculate the cost of turbine components. Similarly, these key turbine characteristics can be used to assess productivity of the turbines. Hence, we can exploit engineering models to estimate $LCOE$ in equation 1. We refer to $LCOE$

estimated using engineering models as levelized engineering cost of energy ($LECOE$).

We calculate the $LECOE$ of each wind turbine vintage installed in the US from 1998 to 2017. The data for average key characteristics is taken from Wiser and Bolinger (2018) and is documented in the Appendix table A1. Below, we begin calculating $LECOE$ from the simplest components of equation 1.

Capital Recovery Factor (CRF). CRF is a function of the useful life of a wind turbine and a discount rate. In the literature, the discount rate is calculated as a weighted interest rate to finance capital[2] (e.g Mone, Smith, Maples, & Hand, 2015). Certainly, the discount rate may differ across vintages due to the fact that the set of firms installing new wind farms in a particular year face different market-specific and company-specific conditions which affect the interest rate. We abstract from these short-run interest rate fluctuations to focus only on engineering factors affecting the costs of electricity production. Therefore, we use the same discount rate across the vintages.

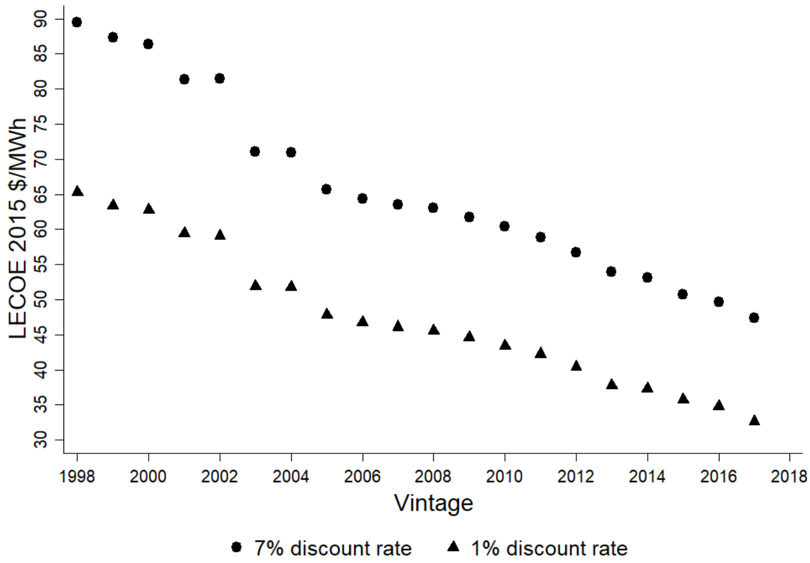
Our data is expressed in 2015 dollars because the engineering cost model is expressed in 2015 dollars (Dykes, K, personal communication, January 29, 2019). Taking the discount rate of 7% is appropriate during this period (Mone et al., 2017). In fact, the magnitude of the discount rate is not crucial. As long as we fix the discount rate across vintages, changing it affects the level, but not the trend, of our $LECOE$ data. The purpose of our analysis is to identify the trends in innovation correctly. Figure 2 illustrates this point and shows our $LECOE$ data measured using 7% and 1% discount rates, respectively.

Regarding the useful life of the wind turbines, we do not have empirical evidence about the improvement of wind turbines' useful life with technological innovation. In fact, wind farms installed in 1998 when our data-set starts, are expected to still be in operation. Therefore, we do not vary *useful life* across vintages. Manufacturers typically assign 20 years of useful life to wind turbines, so the literature frequently assumes the same (Mone et al., 2017). We follow this practice, and it delivers a CRF

[2] Weighted interest rate calculates the rate to be paid as the interest on debt and the rate of return on equity depending on the proportion of the debt and equity in the total investment cost. The formula is the following: rate of return on equity $\times$ equity share in the portfolio + interest on debt $\times$ debt share in the portfolio $\times$ $(1 -$ income tax rate$)$. The argument against using weighted interest rate is that individual firms usually face increasing marginal interest rates to finance new projects. However, we do not focus on firm-level differences, instead we depict an industry-level picture. When many wind farms enter the market, it is reasonable to assume that the interest rates remain constant, because not all owners of new wind farms face financial limitations. In addition, using a weighted interest rate is a common practice in the energy literature.

of approximately 9.5% for each vintage.

Figure 2: *Impact of Discount Rates on the Levelized Engineering Cost of Energy*



Notes. The figure plots our *LECOE* data calculated using 7% and 1% discount rates. This illustrates that changing the discount rate for all vintages does not affect trend of the data.

***Annual Energy Production** (AEP).* As mentioned earlier, *AEP* measures the annual effective operational hours of a wind turbine. Calculating the *AEP* of a wind turbine depends on the wind speed distribution at the site and the power curve of the turbine. Wind speed density reflects the probabilities of various wind speeds occurring in an hour at a site at a certain altitude. The power curve measures the amount of electricity generated at each wind speed bar, based on the turbine characteristics. Multiplying the probability of each wind speed bar by the corresponding power expected to be produced and summing these products delivers the *AEP* of a wind turbine.

Hence, calculating *AEP* partly depends on turbine characteristics and partly on wind conditions and geographic location. Since we want to capture productivity changes due solely to technological innovation, we do not vary the wind speed distribution and other location-specific parameters across the vintages. The idea is to measure the improvement in the productivity of a new wind turbine if we put it in exactly the same location as the old one.[3]

[3]Fixing the wind resource parameters might be questionable if wind turbines were increasingly installed on lower wind speed areas due to geographic constraints. In this case we would suspect that the wind turbines were specifically designed for these locations and do not necessarily represent the frontier technologies. However, we show in figure A2 that such crowding out of new wind farms has not occurred so far.

To measure the AEP[4], we estimate the power curve of each vintage using the vintage characteristics documented in table A2 as inputs. In addition, we fix wind and location-specific parameters across vintages at the levels recommended in Mone et al. (2017). The recommended wind and location-specific parameters reflect the average wind conditions and the altitude of a representative site in the interior of the US, where most wind farms are located. To understand the theoretical model behind the AEP estimation, readers are referred to Fingersh et al. (2006). The estimated AEP for each vintage is documented in table A2.

Capital Cost (CapEx). Deriving $CapEx$ accurately is the most challenging of the $LECOE$ components. Below we derive capital costs for each vintage using engineering wind turbine component-mass scaling models. The National Renewable Energy Laboratory (NREL) provides the most extensive engineering turbine-scaling studies. The WindPACT project (Malcolm & Hansen, 2002; Poore & Lettenmaier, 2000-2002) represents NREL's first attempt to measure scaling of the mass of a turbine with its key characteristics.

There are approximately twenty major components which make up a turbine, including blades, hub, low-speed-shaft, tower, generator and gearbox. The WindPACT studies take a baseline wind turbine and project how the mass of each component has to scale when blades become longer, hubs increase in height, and capacity grows. Hence, the WindPACT studies build component-mass scaling models which represent the mass of each turbine component as a function of the key turbine characteristics.

A WindPACT model first simulates wind turbines of various sizes and parameters. Second, it calculates the stress on turbine components under certain wind distributions and parameters. The underlying stress has to be within predetermined limits for the wind turbine to withstand the wind forces for a desired period of time.

For many component-mass scaling models, the arguments have power functions with exponents ranging from 2 to 3. This implies a non-linear increase in turbine mass with turbine characteristics. Certainly, technological innovation can reduce the exponents on the power functions. Some of this type of innovation may be anticipated by the engineering model, while others may not. For this reason, the engineering

[4] In this paper we estimate AEP for each vintage using the Plant-EnergySE plug-in of the WISDEM software by NREL available on GitHub (NREL, 2015a). Specifically, we use the nrel-csm-aep script.

component-mass-scaling models may become outdated. The WindPACT studies were conducted between 2000 and 2002. During that time, turbines were significantly smaller than today. As the large-size turbines entered the market, a discrepancy arose between the predicted and the actual mass of these turbines. To account for this, NREL produced new component mass-scaling models[5] in 2015. In the rest of the paper we frequently refer to the engineering component-mass-scaling models presented in the WindPACT studies as the 'old model' and the new component-mass-scaling models as the 'new model'.

A different approach is used to project the mass of turbine components in the new model. The authors first collect data about various wind turbines, their key characteristics and the mass of their components. Then they regress the values of the turbine characteristics on the mass of turbine components and identify a polynomial fit to the data. The resulting polynomial functions are the new component-mass-scaling models. Although, the new model does not rely on a pure engineering estimation technique, it is based on the engineering parameters of turbines.

According to equation 2, $CapEx$ includes turbine cost and BOS cost. We will first derive turbine cost based on each model:

Turbine Cost - Old Model

Fingersh et al. (2006) uses the old component-mass-scaling models, the material composition of components and material prices to offer component-cost-scaling models. Component cost-scaling models express the costs of turbine components as a function of its key characteristics. The procedure that the authors use to derive these models is the following:

step 1: Convert the turbine component-mass vector into the component-material-mass vector. For most turbine components only one material is used and they do not require assembly[6]. For the components that consist of several materials, the WindPACT studies assume that the proportion of materials in the component remains the same when turbine components scale.

[5]The new model has not been published officially (Stehly, Beiter, Heimiller, & Scott, 2018), however, the Turbine-CostsSE plug-in is available on GitHub (Dykes, 2015) as a part of WISDEM software, which is programmed to calculate the mass of each turbine component based on key turbine characteristics. Specifically, we use the nrel-csm-tcc-2015 and the turbine-costsse-2015 scripts.

[6]These components are readily available in the market and turbine manufacturers do not produce them separately

step 2: Apply material prices to compute the component-material-cost vector. Material prices in Fingersh et al. (2006) are given as producer price indices of these materials (PPIs). We are flexible to choose material prices of a particular year and to express all the costs in that year.

step 3: Compute labor costs for turbine components. As mentioned, most turbine components consists of only one material and do not require assembly by the manufacturer. Labor costs are already reflected in the PPI of such materials. The same is true for several more complex components, such as generators. In Fingersh et al. (2006), a generator is treated as a single material to which a single PPI applies, which includes the labor costs. Only three turbine components: blades, nacelle cover, and the electrical connections require labor by manufacturers, according to Fingersh et al. (2006). The labor costs are assumed to amount to fifteen percent of the total cost of the nacelle cover and the electrical connections. For the blade, labor costs are scaling with the rotor radius. Certainly, there are labor costs associated with the assembly and installation of a turbine itself. However, these are included in the balance of system (BOS) cost.

step 4: Summing material and labor costs of components yields the component costs. Component costs can be expressed in 2015 US dollars by applying the PPIs of 2015.

We use the component-cost-scaling models in Fingersh et al. (2006) to derive the turbine cost for each vintage. To do this, we plug the key vintage characteristics from table A1 and the PPIs[7] of 2015 into the component-cost-scaling models and calculate component costs in 2015 dollars[8] for each vintage. The sum of component costs yields the turbine cost in 2015 dollars for each vintage.

[7] Producer price indices can be selected based on the NAICS codes suggested in Fingersh et al. (2006). PPIs are available from the Bureau of Labor Statistics web-page.

[8] Using the PPIs of 2015 for materials would be wrong if the material composition of vintages changed frequently; however, Fingersh et al. (2006) assumes a fixed proportion of materials in each component based on WindPACT studies. This can be explained by the fact that the industry has significantly converged to three-bladed tubular horizontal axes wind turbines due to their efficiency and, therefore, material composition usually does not substantially differ across vintages (Hemami, 2012).

Turbine Cost - New Model

The new model does not explicitly provide either the composition or the proportion of materials in each component. Therefore, we cannot apply producer price indices in order to calculate the cost of each turbine component as we did based on the old model. However, Dykes (2015) provides the costs per kilogram of each component in 2015 dollars. These costs are likely computed with similar steps as in Fingersh et al. (2006). In order to compare the old and the new $LECOE$ series, we express both in 2015 dollars.

To calculate the turbine cost for each vintage based on the new model we use *nrel-csm-tcc-2015* and *turbine-costsse-2015* python scripts, which contain the turbine component-mass-scaling models[9]. The calculation procedure is the following:

step 1: Calculate the mass of each wind turbine component for each vintage given the key vintage characteristics from table A1. The new model offers four alternative component-mass-scaling functions for blade mass depending on the type of blade used. Hence, blade type is an additional input variable for the blade-scaling model. Blades differ based on whether they have carbon content, and whether the turbine is class I or class II/III. Carbon content makes blade lighter, however, according to Fingersh et al. (2006), carbon should not be used for blades with rotor diameters of less than 100 meters in size. The average rotor diameter for the vintages 1998-2014 is less than 100 meters (See table A1). Hence, we calculate the blade mass for these vintages using 'no carbon' as input. For all other vintages we assume carbon content.

The prevailing wind conditions in a location determine which class of turbine should be installed. The literature distinguishes at least five classes of turbines (Wiser & Bolinger, 2018), however, the new model divides these classes in two groups: class I and class II/III turbines. The reason for division into two groups is that the second group is designed for particularly low-wind-speed areas. The first group includes turbine classes up to class II/III, these are: class I, class I/II and class II. The second group includes turbine classes II/III and III. According to Wiser and Bolinger (2018), since 2012 there has been a greater tendency to install group two turbines (II/III and III) although wind conditions have not changed (See figure A1). Because more of the second

[9]These scripts are available as a part of Turbine-CostsSE plug-in on GitHub (Dykes, 2015).

group turbines have been installed since 2012, we calculate the blade mass by using 'class I' group as input in the blade-scaling model for vintages 1998-2011. We calculate the blade mass by using 'class II/III' group as input for vintages installed in 2012 and afterwards.

step 2: Calculate cost per component in 2015 dollars for each vintage. As we mentioned, we are given the cost per kilogram of each component in 2015 dollars. Therefore, we multiply the cost per kilogram of a particular component by its mass calculated in the previous step.

step 3: The sum of all turbine component costs is the turbine cost for each vintage in 2015 dollars.

Balance of System Costs

Both, the old and the new models offer models for BOS cost-scaling with turbine characteristics. The old BOS cost-scaling models are linear in the number of turbines. This implies that installing a second turbine in an existing wind farm adds exactly the same amount of BOS cost as the first turbine. The new BOS model takes the number of turbines as an additional input variable. This implies that adding a turbine to an existing wind farm saves some part of the BOS costs. However, there is a trade-off between the number and the size of turbines. With larger turbines, fewer can be installed per area for efficiency and security reasons (Hemami, 2012).

We plug the key turbine characteristics from table A1 and 2015 PPIs into the BOS cost-scaling models documented in Fingersh et al. (2006) to generate the old BOS cost series for each vintage in 2015 dollars.

As we mentioned, in the new BOS model[10], the number of turbines is an additional input variable. The number of turbines multiplied by turbine capacity is referred to as farm size. A common practice is to fix farm size and calculate the number of turbines installed per wind farm. We follow this practice and fix farm size for each vintage at 200 MW, which is a typical farm size according to Mone et al. (2017). Subsequently, together with the number of turbines, we input the key vintage characteristics in the new BOS model, which is expressed in 2015 dollars, to compute the new BOS cost series for each vintage in 2015 dollars.

[10] The new BOS model is available as a part of the Plant-CostsSE plug-in on Github (NREL, 2015b).

The sum of turbine and BOS cost divided by turbine capacity is $CapEx$ in 2015 US \$/MW for each vintage. The estimated $CapEx$ for each vintage using both models is documented in table A2.

Operations and Maintenance Costs (O&M). $O\&M$ costs can also be modeled as a function of turbine characteristics. However, the $O\&M$ cost-scaling-models which the old model proposes are not accurate, partly because there are insufficient empirical observations of the frequency at which the turbine parts are replaced in order to validate the model. Public data on $O\&M$ costs that wind electricity producers incur is typically unavailable. Wiser and Bolinger (2008-2018) collect limited and mostly confidential empirical data about $O\&M$ costs annually. This data may not be representative but could be informative of the trend of $O\&M$ costs across the vintages. According to the plot of $O\&M$ data in Wiser and Bolinger (2018), long-run $O\&M$ costs are generally declining.

Since 2010, NREL has published Costs of Wind Energy Reviews (2011-2018), in which $O\&M$ costs are reported in nominal values. They infer $O\&M$ costs from expert opinions combined with the $O\&M$ data from Wiser and Bolinger (2008-2018). For vintages installed between 2010 and 2017, we use their reported values of $O\&M$ cost and convert them to 2015 dollars using the GDP deflator[11] (Fingersh et al., 2006). In addition, Wiser and Bolinger (2018) reports the value of $O\&M$ costs for vintage 1998 at 80 \$/kW/year in 2017 dollars based on expert opinions. We take this value, convert it to 2015 dollars and use linear interpolation to proxy the $O\&M$ costs for vintages 1998-2009. When we calculate $LECOE$ based on the old and the new engineering models, we use this $O\&M$ data in both calculations. The estimated $O\&M$ costs for each vintage are documented in table A2.

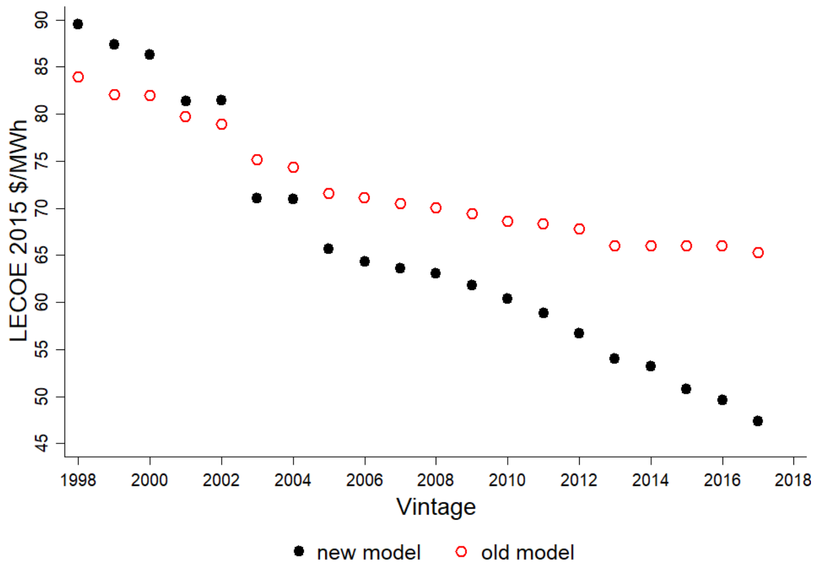
The $O\&M$ cost component is the weakest in our estimation of $LECOE$. However, its share of the total costs is not significant and it is also unlikely to vary significantly with engineering improvements and hence, across vintages. As a result, we do not expect that it would markedly influence the trend of the $LECOE$ data.

[11] we extracted the GDP deflator from the U.S. Bureau of Economic Analysis

2.4 Comparing the Results from the New and the Old Engineering Models and the Lessons Learned

According to the procedure described above, we derived the *LECOE* components for vintages 1998-2017 using the old and the new engineering models (see table A2 in the appendix). Figure 3 shows the *LECOE* derived using the two alternative models. The new model produces a steeper series. The series start to significantly diverge from the 2005 vintage. We can suggest several explanations for these differences: an unanticipated technological innovation occurred, the old model required a correction, or both. If the old model was correct, then an unanticipated technological innovation alone would deliver a different picture: the new series would precisely follow the old series until the technological switch occurred. Figure 3 rules out that the old model was correct, since the series follow different paths from the beginning of the period.

Figure 3: *Levelized Engineering Cost of Energy*



Notes. The figure plots our *LECOE* series calculated based on the old and the new engineering models. We use a 7% discount rate. The figure illustrates the margin of error that using the engineering method may produce.

To repeat, in the old model, the component-mass-scaling relationships are derived based on simulated conceptual wind turbines. In contrast, in the new model, the same relationships are fitted curves given the data on the actual key characteristics of the turbines and the mass of their components.

Hence, the old model identifies technological trends from simulated wind turbines, while the new model uses actual wind turbine data on units installed in the

US. When the original engineering study was undertaken, the turbines on the market were small in size. Figure 3 implies that the old model significantly mismeasured the mass of the turbines that were not available on the market at the time.

The comparison of the two $LECOE$ series provides information on the margin of error that an application of the engineering estimation method can produce. The new engineering model may require further improvement as new turbines enter the market. Therefore, caution must be taken when predicting $LECOE$ for future wind turbine vintages using this model. Nevertheless, we can rely on the new model to calculate $LECOE$ for the vintages installed during the period under review. This is due to the fact that the new engineering model already incorporates the data of turbines installed in this period.

Hence, in the rest of the paper, we consider our $LECOE$ series generated based on the new model as the innovation measure. We argue that our innovation measure reflects the engineering improvement of the vintages and is not influenced by interest rates, material prices or wind resource variations. In order to illustrate how the influence of these factors can impair innovation measures, in what follows, we compare our $LECOE$ series to an alternative measure.

2.5 Comparing our Innovation Data with Alternative Series

We compare our $LECOE$ data with alternative series from Wiser and Bolinger (2018). The procedure for calculating $LCOE$ in Wiser and Bolinger (2018) is the following:

step 1: Calculate $CapEx$ for each vintage based on the empirical data about capital expenditures of wind farms installed in the US. Wiser and Bolinger (2018) have compiled capital expenditure and performance data on approximately 86% of such wind farms. The $CapEx$ data typically includes turbine and BOS cost. The authors note that, due to the diversity of sources, the available data is not of equal quality, therefore, they warn readers to rely only on the general trends in the data, not on the individual. Using empirical $CapEx$ data to measure innovation is problematic in several ways. First, its major component is the price of a turbine. Turbine prices may vary due to temporary shocks such as fluctuations in the exchange rates, material prices or interest rates. We do not consider that these temporary shocks contribute to technological innovation. Second, $CapEx$ represents the largest part of the lifetime cost of a wind farm. Investors are likely to react to the temporary market shocks or technology-related policy changes and shift their investment decision to a different period. Therefore, using empirical $CapEx$ data may represent a distorted view of the actual trend of the capital cost. In contrast, using engineering properties of newly installed turbines to measure the $CapEx$ avoids these issues.

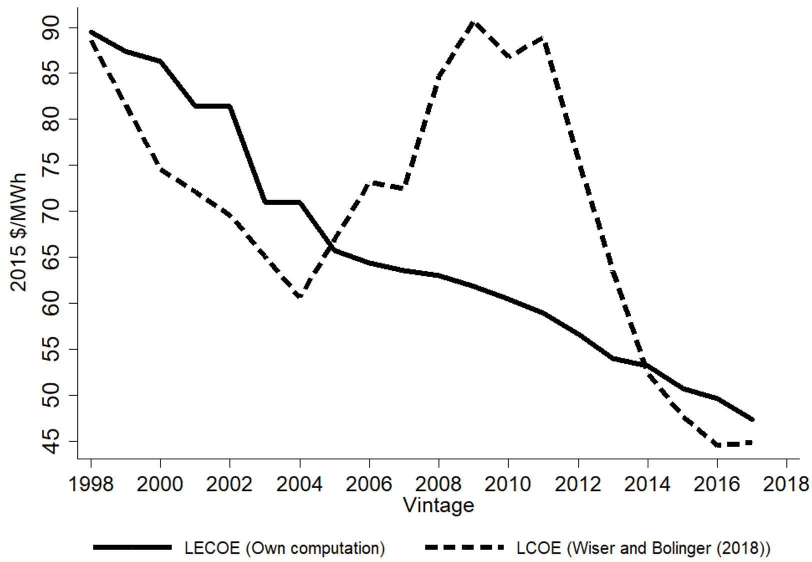
step 2: Unlike this study, the authors do not fix the value of the discount rate across vintages when calculating CRF. In particular, they vary the interest on debt throughout the period with respect to the changes in the twenty-year swap rate and bank spread. The fact that two vintages are charged different interest rates should not be the reason for the difference in the production costs if our goal is to measure changes in the production costs due to innovation.

step 3: The authors calculate AEP based on the actual performance of the vintages installed. AEP estimated in this manner will reflect annual, seasonal and locational wind resource variations. We instead calculate AEP for each vintage using an engineering model and by fixing wind resource parameters across the vintages.

step 4: For $O\&M$ costs Wiser and Bolinger (2018) rely on their own compiled data and the expert opinions to assign the value in 1998 \$80/kW/year, in 2003 - \$60/kW/year, in 2010 - \$51/kW/year and in 2017 \$44/kW/year.

Figure 4 compares our $LECOE$ data with the series from Wiser and Bolinger (2018). First we notice that the Wiser and Bolinger (2018) data is very volatile. Our $LECOE$ measure represents the production costs of energy, which is free from market driven temporary shocks such as, material costs, interest rates, and exchange rate fluctuations, while, the Wiser and Bolinger (2018) data reflects such fluctuations. For example, their data reflects an abnormal period between 2006 and 2011 when the production cost was rising. Certainly, this was not due to technological decay but because $CapEx$ largely reflected increases in turbine prices during this period. Bolinger and Wiser (2012) explained the rise of turbine prices in this period: first, many turbines were imported into the US from abroad, and during this period, the US currency was depreciating against the importing country currencies. Second, demand for turbines increased significantly and the supply side could not catch up with this trend immediately. For this reason, manufacturers started to face labor supply issues, which increased labor costs. In addition, manufacturers increased their profit margins, given the supply deficit. Finally, the rise in the wind turbine material prices also contributed to the increase in turbine prices.

Figure 4: *Visualizing the Advantage of Our Innovation data*



Notes. The figure contrasts our innovation data with the alternative series from Wiser and Bolinger (2018). Because the alternative *LCOE* data was not directly accessible, we measured it from the bar-chart produced in the 2017 Wind Technologies Market Report (Wiser & Bolinger, 2018). We used the WebPlotDigitizer tool to measure the bars.

If we omit the abnormal period, we notice that both series show similar trends and that our data series are slightly above the ones from Wiser and Bolinger (2018). This is a good indicator that the engineering costs quite realistically reflect the empirical cost of the turbines. One reason our *LECOE* series is slightly above the alternative ones, omitting the abnormal period, is that we may be using a higher discount rate on average. Another reason could be that we fix wind resource parameters and distribution to calculate turbine productivity, while actual productivity might have been higher on average during this period.

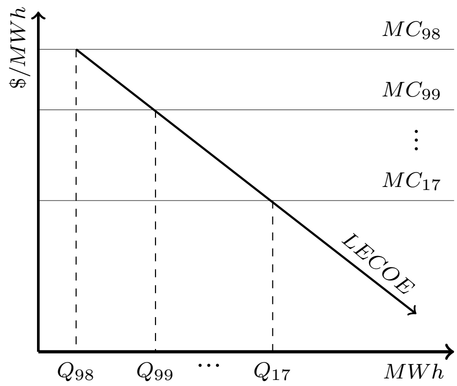
Hence, in this section we have illustrated the advantage of using the engineering method to calculate the production costs of wind turbines. The engineering model more realistically reflects production cost reductions driven by innovation.

3 The US Wind Energy Policy Environment

In order to discuss potential applications of our measure of innovation, we first study the current wind technology market structure and policy environment in the US. For this reason, we explore the supply and demand sides of wind electricity producers and the prevailing equilibrium outcomes given the current government policy instruments.

3.1 The Cost Side of Wind Electricity Producers

Figure 5: *Long-run and Short-run Electricity Supply Curves*



Notes. The LECOE curve represents the long-run marginal cost curve of wind electricity producers, while MC curves illustrate short-run marginal costs of electricity production by each vintage 1998-2017. Q denotes cumulative production.

In the previous section we found that long-run marginal cost curve (the supply curve) of wind electricity is downward sloping due to innovation. We now observe that the electricity supply curve for each vintage is horizontal (see figure 5). On the maps in figure A2 in the appendix, we see that the majority of wind farms have been built in densely populated areas and close to one another. This indicates that geographic constraints have not crowded out the wind farms to less windy areas. The crowding out of wind farms would imply an upward sloping electricity supply curve for each vintage. The upward sloping curve would reflect an increase in the marginal costs due to poorer wind resources, which electricity producers would face in remaining wind farm sites. To reinforce the claim that geographic constraints have not yet become binding in the US, we check the changes in the average wind speed across various vintages at the wind farm cluster level. Figure A3 in the appendix shows that wind quality has not worsened for newer vintages at the location level.

3.2 The Revenue Side of Wind Electricity Producers

Wind electricity producers receive income from selling electricity and from subsidies. Electricity sales are usually established through long-term power purchasing agreements (PPAs). The most significant subsidies producers receive are federal production tax credits and depreciation benefits. Before we summarize these sources of income and provide some statistical data, it is crucial to introduce the market players and to review the US electricity market structure. What follows is mostly based on the handbook of Federal Energy Regulatory Commission (2015).

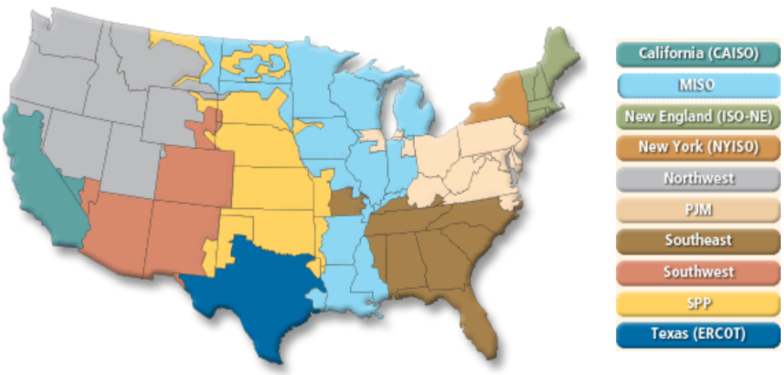
Many types of players participate in the complex electricity markets, so we introduce only the core players. Electricity producers, electricity generators and wind farm owners own a generation facility and produce electricity. Utilities own transmission and distribution lines and are regulated by the government. Electricity suppliers deliver electricity to the final consumers. A supplier may be a utility or a non-utility company. We will frequently refer to a non-utility electricity supplier as a retail electricity provider (REP). Electricity suppliers, unless they own generation facilities, purchase electricity from generators, therefore, we will also refer to them as wholesale electricity purchasers when needed.

Utilities have interconnected their transmission lines in the US, and this has formed several electricity markets. Transmission capacity between these markets is usually limited. Figure 6 displays the markets. Market structure determines the predominant nature of trade in these markets - bilateral or wholesale. Independent system operators (ISO) run the wholesale markets. The ISOs are non-profit organizations and they enforce efficient and non-discriminatory trade between participants.

Three types of market structures are prevalent in the US: vertically integrated markets (VIM), partially deregulated markets (PDM) and fully deregulated markets (FDM). In VIMs utilities own generation facilities and also supply electricity to final consumers. Utilities enter into bilateral trade in VIMs. In PDMs utilities are unlikely to own generation facilities, but they still supply electricity to final consumers. Electricity producers participate in the wholesale markets and compete to sell electricity to utilities.

FDMs are similar to PDM, however, competition is established not only at the generation level but also at the supply level. By default, in FDMs utilities purchase electricity in the wholesale market and supply electricity to consumers in the areas where they own transmission and distribution lines. Nevertheless, final electricity consumers have the option to switch to REPs. The reason for the switch could be due to a cheaper electricity package or a green electricity option. If consumer chooses

Figure 6: *US Electric Power Markets*



Notes. The figure shows deregulated and vertically integrated electricity markets in the US. The Northwest, Southeast and Southwest regions are vertically integrated, while the rest is operated as wholesale markets by independent system operators. Source. Federal Energy Regulatory Commission (2019).

a REP as a supplier, then the REP is responsible for purchasing electricity from generators and scheduling it for transmission and distribution. Transmission and distribution fees will be included in final electricity bills. The fees are very small in comparison to the cost of energy.

Figure 6 shows that the markets referred to as Southeast, Southwest and Northwest are VIMs (Federal Energy Regulatory Commission, 2019). The rest of the markets are either PDM or FDM. Comparing figures A2 and 6 suggests that the majority of wind farms operate in the interior region of the US where electricity markets are at least partially deregulated. This implies that utilities in these regions are unlikely to own wind farms and that most wind farms operate in the wholesale markets. However, participation in the wholesale markets is not mandatory for wind electricity producers. To hedge against market price fluctuations, they can enter into long-term power-purchasing agreements (PPAs) with electricity suppliers.

Statistically, utilities own only fifteen percent of the cumulative wind generation capacity installed between 1998 and 2017. In addition, only 23% of the cumulative capacity participates in the wholesale markets (Wiser & Bolinger, 2018). Therefore, we argue that PPAs are the most common source of revenue for wind electricity producers in the US. Hence, PPA is the best measure of the revenue. We summarize the average PPA rates across vintages below as the revenue source, and judge whether they are set competitively. Assessing the degree of competitiveness between wind farms is necessary for analyzing wind technology support policies.

Income From Power Purchasing Agreements

A power purchasing agreement is the negotiated price per unit of electricity between a wind electricity producer and an electricity supplier. A typical PPA specifies the price of unit electricity, annual escalation of this tariff, and the duration of the contract. The duration of approximately 60% of contracts is 20 years and about 90% of contracts is 15-25 years (Wiser & Bolinger, 2018). Therefore, the vast majority of wind electricity generators are locked-in at a specified price throughout the useful life of a wind farm project. As a result, electricity producers are protected from wholesale market price fluctuations.

The wholesale markets are competitive because all technology generators compete with each other. However, it may not always be the case that PPAs are set competitively. If there are too few wind farms and the utilities or REPs have an obligation to supply a certain portion of electricity from renewable sources[12], then wind electricity generators will have incentives to set premiums on their electricity prices.

We investigated the number of wind electricity generating firms that have entered each electricity market annually to assess potential competition levels between them. We first obtained data on all operating wind farms since 1998 in the US. The US Geological Survey, the Berkeley Lab, and the American Wind Energy Association (2016) compile such data in the United States Wind Turbine Database. The database provides the names of each wind farm, the years the farms were installed, and the locations and technical parameters of installed turbines. We then identified the wind farm owners and the electricity suppliers which purchase electricity from these wind farms[13]

We removed all observations when a wind farm owner and a corresponding electricity purchaser was the same entity, or one was a subsidiary of the other. Such firms would not be appropriate to analyze competition. Furthermore, we disregarded the Southeast market because there are few wind farms and the majority are owned

[12]Renewable portfolio standards represent state-specific targets for the share of electricity that suppliers are obliged to procure from renewable sources cumulatively in a particular state by a certain date. Some states may have high targets and implement penalties for non-compliers, while others require only goals and apply no penalties. The targets can be subject to change. (DSIRE, 2019b)

[13]Information on wind farm owners and corresponding electricity purchasers was mostly taken from the American Wind Energy Association (2013-2017), the Open Energy Information Database (2019) and The Wind Power database (2019). Information on electricity purchasers was confidential in only about one percent of cases.

by utilities (refer to the map in figure A2)

Using the locations of wind farms, we assigned each of them to the electricity markets in figure 6, where they most likely sell electricity. Table A3 in the appendix shows the cumulative number of wind farm owners in each market each year. The table suggests that there has been a reasonable level of competition between wind farms since the mid- 2000s. However, in the beginning of the period under review, wind farms were less competitive. To verify whether there is sufficient competition between probable electricity purchasers, we found information on the number of utilities and REPs participating in each electricity market. Table A4 demonstrates a reasonable level of competition between probable electricity purchasers as well.

Data series regarding the levelized PPA are documented by Wiser and Bolinger (2018). We convert the values into 2015 dollars using the GDP deflator[14] The authors generate levelized PPA series using the steps described below. The unit of measurement of levelized PPA is $/MWh:

step 1: Group individual power purchasing agreements by their execution date. PPAs are usually executed one or two years before wind farms are installed. Therefore, the PPA execution date and vintage launching date are different.

step 2: If an individual PPA involves annual price escalation, levelize it using a 7% discount rate, which implies making the negotiated price constant each year.

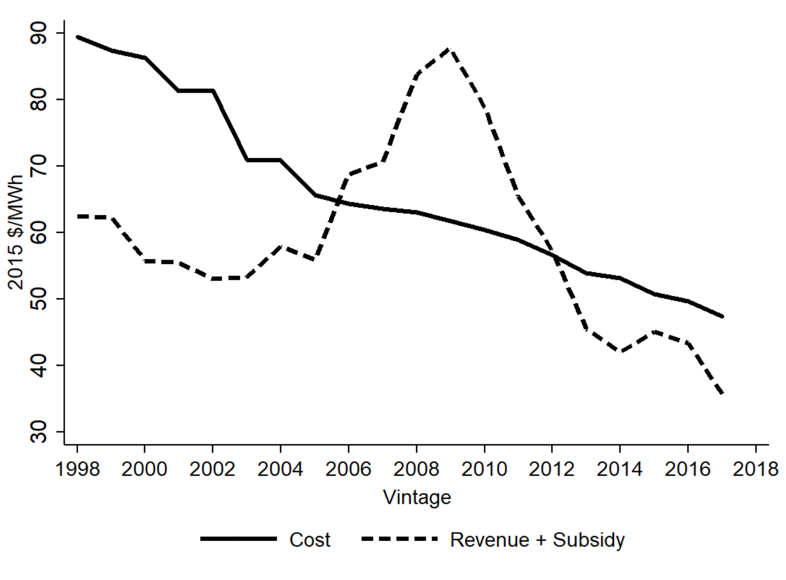
step 3: Assign weights to individual PPAs based on the generation capability of wind farms by PPA execution date. This implies that the authors assign bigger weights to wind farm projects which produce more, instead of simply averaging individual PPA prices by their execution date.

step 4: Derive levelized PPA by their execution date, i.e. sum the generation-weighted individual PPAs by their execution date.

The 'Revenue + Subsidy' curve in figure 7 is the sum of levelized PPA prices and levelized subsidies. Levelized PPA represents approximately 70% of the total income of the vintages. We should note that wind farm investors negotiate PPAs one or two years before installing the wind farms. Levelized PPA data is grouped by the year when these PPAs were executed, not by the year when the corresponding wind

[14] The data can be extracted from Wiser and Bolinger's (2018) data file.

Figure 7: *Costs and Revenues*



Notes. The figure plots the cost and income sides of each vintage, where income includes revenues from PPAs and subsidies. The cost side is calculated using an engineering model, while the income data is primarily empirical. Therefore, caution should be taken when inferring information from these curves.

farms were installed (Wiser & Bolinger, 2018). For example, PPAs executed in 2010 primarily denotes the vintages installed between 2011 and 2012. According to Wiser and Bolinger (2018), PPAs that are executed in a particular year effectively reflects the market conditions for the vintage that was installed in the same year. Following this argument, when we plot figure 7, we assign to each vintage the levelized PPA which was executed in the year of installation.

The revenue side of the wind electricity producers can be affected by the integration costs as well. Integration costs are those that wind technology brings to the power system due to the intermittent nature of wind resources (Milligan & Kirby, 2009). When the share of intermittent generation rises in the system, it becomes more challenging to balance electricity supply and demand. In many cases, oversupply incidences rise, which is sometimes addressed by forced curtailment of wind technologies, which in turn implies lost producer revenues (unless losses are compensated). Figure A4 in the appendix shows the estimated average capacity factors of wind generation in the US if curtailment had not occurred and compares it with the actual average capacity factors. The figure shows no curtailment before 2007. After 2007, capacity factors declined by 0.1-1 percent due to curtailment[15].

[15]Only in 2009 did the average capacity factor decline by two percent due to curtailment.

This reduction in capacity factors and hence, wind electricity generation, would not significantly affect the levelized PPAs. Therefore, we omit the curtailment factor from our discussion. Moreover, we use only the revenue side of the wind electricity producers for qualitative analysis, and slight reduction in levelized PPA after 2007 will not impact our results.

Production Tax Credits

Wind electricity producers receive subsidies per MWh of production in their first 10 years of operation as a production tax credit (PTC). The amount of PTC is determined at 15 $/MWh, which is the value in 1993 dollars and needs to be adjusted for inflation using the adjustment factor released annually by the US Internal Revenue Service[16] (Internal Revenue Code, Sec.45(e)). The adjustment factor for each year is the ratio of the most recently revised GDP implicit price deflator for the preceding year and the GDP implicit price deflator for 1993.

We derived the levelized value of PTC received for twenty years instead of ten years in order to distribute its value throughout the useful life of the wind farms. The process of calculating levelized 20-year PTC is written out in steps below. The brackets indicate the units of measure in each step:

step 1: Find the value of a ten-year PTC subsidy in 2015 dollars. To be consistent with our cost data, we want to convert everything into 2015 dollars. The value of a PTC subsidy in 2015 dollars is the ratio of the GDP deflator in 2015 and 1993 multiplied by 15 $/MWh. As the result, we obtain the value of a ten-year PTC subsidy in 2015 dollars 21.5$/MWh. ($/MWh).

step 2: Derive the annual PTC subsidy per vintage capacity. The value of PTC is independent of the productivity of a vintage as it is calculated per unit of electricity. Therefore, we imagine a wind turbine that works effectively only one hour per year. In addition, we assume that the annual productivity of vintages does not change through their useful life. Given these assumptions, the calculation is simple: we multiply the value of a ten-year PTC subsidy 21.5$/MWh by 1 h/year. ($/MW/year).

step 3: Derive the present value of annual PTC subsidy calculated in the previous

[16] The PTC policy has been stated to expire 10 times since its implementation but has been extended retroactively each time. Currently, wind energy technologies that were in construction prior to 2019 will still receive PTC.

step. We use a 7% discount rate to be consistent with our innovation data. ($/MW).

step 4: Given the present value of a ten-year PTC subsidy, the annual amount of PTC subsidy per vintage capacity for 20 years would be a constant annuity. The constant annuity is the product of the present value calculated in the previous step and the fraction $\frac{i(1+i)^n}{(1+i)^n-1}$, where $i = 7\%$ and $n = 20$. ($/MW/year).

step 5: Find the levelized value of a twenty-year PTC subsidy for each vintage by dividing the annuity calculated in the previous step by 1 h/year. We obtain a levelized value of twenty-year PTC subsidy in 2015 dollars to be 15 $/MWh. ($/MWh).

Depreciation Benefits

The Modified Accelerated Cost Recovery System (MACRS) allows wind generators to depreciate their turbines within 5 years[17] (Internal Revenue Code, Sec.168 (e)(3)(B)). The Federal Economic Stimulus Act of 2008 added a 50% bonus depreciation for wind technologies placed in operation in 2008 (Internal Revenue Code, Sec.168 (k)), which was retroactively extended several times and included all later vintages including 2014. In addition, the Tax Relief, Unemployment Insurance Reauthorization, and Job Creation Act of 2010 allowed a 100% bonus depreciation for the 2011 vintage (DSIRE, 2019a). The depreciation rates are listed in table 1.

Table 1: *Depreciation Schedule*

Year	1	2	3	4	5	6
MACRS	20%	32%	19.20%	11.52%	11.52%	5.76%
MACRS+50% bonus	60%	16%	9.60%	5.75%	5.75%	2.90%

Notes. We use a 12 year linear depreciation schedule as a counterfactual. The schedule depreciates 4.17% of the capital expenditure in the first and the last years of operation and 8.33% in the remaining years.

In a similar manner as we derived PTC, we calculate the levelized value of net depreciation benefit per MWh. Net depreciation benefit refers to the amount that is obtained after subtracting the benefit that wind electricity producers would have

[17]The depreciation schedule actually extends six years because of the so-called 'half-year convention' (Internal Revenue Code, Sec.168(d)). This means that the law treats properties as being placed into operation in the middle of a year. Hence, in the first year, taxpayers are only allowed six months of depreciation and any remaining amount is transferred to the sixth year.

received if their capital were not treated as a five-year property. For simplicity, we assume that the 5-year depreciation schedule applies to full capital expenditures because a wind turbine represents the most significant part of the capital expenditure, and because most of the *BOS* costs are also depreciated based on the 5-year depreciation schedule. The derivation steps follow:

step 1: Calculate the annual depreciation expense of each vintage. This will be the product of the *CapEx* of a vintage and the MACRS depreciation schedule from table 1. For vintages 2008-2014 the fifty percent bonus depreciation schedule applies, except for the 2011 vintage, for which a 100% bonus depreciation applies. ($/MW/year)

step 2: Calculate the annual depreciation benefit for each vintage by multiplying the depreciation expense above by the federal corporate income tax rate - 0.35% (Mone et al., 2017). This is the amount that would have been paid in taxes if the depreciation expense was not available. ($/MW/year).

step 3: Compute the present value of the five-year depreciation benefit for each vintage using a 7% discount rate. ($/MW)

step 4: Calculate the annual depreciation benefit for each vintage for 20 years, which is constant annuity. Constant annuity is the product of the present value calculated in the previous step and the fraction $\frac{i(1+i)^n}{(1+i)^n-1}$, where $i = 7\%$ and $n = 20$. ($/MW/year).

step 5: Find the levelized depreciation benefit for each vintage by dividing the annuity calculated in the previous step with the *AEP* of each vintage from table A2. ($/MWh).

step 6: Calculate the levelized net depreciation benefit. We need to subtract the levelized depreciation benefit that each vintage would have obtained if it was not treated as a 5-year property from the previous step. Bolinger (2014) suggests using a 12 year linear depreciation schedule as the counterfactual. Hence, we also compute the levelized value of linear depreciation benefit for each vintage following the previous steps, and subtract it from the levelized depreciation benefit in *step 5*. ($/MW).

Thus, we have calculated the levelized PTC and levelized net depreciation benefit for each vintage. The sum of these two values we refer to as the subsidies per MWh of electricity. We add these subsidies to the levelized PPA price data and plot it as the 'Revenue + Subsidy' curve in figure 7.

3.3 Analysis of the US Wind Energy Sector

In figure 7 we present historical income and cost figures for vintages. We emphasize that we calculate the cost side using an engineering model as described in the previous section. In contrast, the income side is primarily based on the empirical data. However, we can still compare the trends in the data.

In figure 7, we first notice an abnormal increase in the income side between 2004 and 2009. This abnormality is primarily caused by increased turbine prices and is well-documented by Bolinger and Wiser (2012). Certainly, wind farm investors take the capital costs into account when negotiating PPAs. According to Bolinger and Wiser (2012), the US imports most wind turbines from abroad and the US dollar was becoming weaker in relation to the largest importing country currencies during this abnormal period. Furthermore, the US substantially increased wind turbine installation, and high demand increased turbine prices. Hence, wind electricity producers required higher PPAs to compensate for rises in capital costs. Finally, in order to fully monetize production tax credits, wind farm investors typically cooperate with tax equity investors. During the 2008-09 global financial crises, access to tax equity substantially declined and raised the discount rate in equation 1. In contrast, we fix the discount rate across vintages in our computation. Similar factors on a smaller scale could explain other minor variability in the income side.

We also notice that, omitting the abnormal period, the cost curve is above the income curve. This is due to the fact that when calculating the engineering cost, we fix the wind resource parameters and distribution nationwide and compute production using only the key turbine characteristics as inputs. In contrast, levelized PPAs are based on the expected production estimated by the wind farm investors. We know that PPAs are not negotiated for all wind farms installed each year and that most PPA contracts are signed for farms in the interior of the US because these markets are deregulated[18] (Federal Energy Regulatory Commission, 2019). The interior region

[18]In the vertically integrated markets utilities typically own the wind farms, and hence, do not

has the most favorable wind resources (Wiser & Bolinger, 2018), hence, PPAs in this region should be lower on average than nationwide. In addition, a smaller discount rate in 1 would shift the $LECOE$ curve down.

If we omit the abnormal period, we can argue that costs and income follow similar patterns. However, the ratio between costs and revenues is larger in the beginning of the period under review. This is consistent with our earlier observation that competition between wind farm owners before the mid 2000s may have been low. This does not imply that the firms were monopolistic, but they were probably obtaining more markups, possibly as a return for the risk that they were taking for entering a relatively immature industry.

Based on the observations above, we developed an intuition into how wind energy support policies function in the US. The government first determines wind technology deployment targets. Then, it anticipates the average wholesale market price of electricity[19], which in turn determines the demand for wind electricity. The wind electricity demand curve is horizontal for each vintage, as is the marginal cost curve. In order to achieve an equilibrium, the government provides sufficient production subsidies to align the demand and supply curves: producers cover their production costs and obtain some markups using PPAs and subsidies. This provides investors sufficient incentives to enter the market. However, due to the fact that both demand and supply curves are horizontal given the vintages, multiple equilibrium outcomes are possible. To avoid this, the government applies quantity instruments to promote the deployment of sufficient wind turbines to reach the targeted capacity.

According to this logic, government deployment targets, combined with subsidies, determine the wind technology deployment rate. Government subsidies alone would not determine the deployment rate because of the horizontal marginal cost curves that wind electricity producers face. In addition, if the wind farm owners were monopolistic, and the demand for wind electricity were not horizontal, the firms would choose sub-optimal production. This would imply deployment below the targeted amount. Therefore, given sufficient competition, the government can determine deployment rates using quantity-based policies.

The ability of the government to determine deployment rates may translate into

make PPA contracts.

[19]Wind energy currently satisfies only seven percent of the total market demand in the US, therefore, it cannot influence the average market price of electricity

its ability to influence the rate of wind technology innovation. A simple guess would be that wind turbine manufacturers would innovate as a response to anticipated deployment rates. The relationship between increased deployment and production cost reduction is the subject of learning curve literature (e.g. Ibenholt, 2002; Junginger, Faaij, & Turkenburg, 2005; Kobos, Erickson, & Drennen, 2006). In the following section, we will briefly summarize the learning curve method and evaluate it using our innovation measure. Later, we will also discuss a possible causal relationship between government deployment targets and innovation.

4 Outcomes of the Learning Curve

In this section we illustrate the use of our innovation measure in the learning curve analysis. Analysis of learning curve is the most widely applied method in the energy literature of predicting future unit cost reductions. An accurate innovation measure, would make learning curve analysis more reliable, which we will show by comparing the performance of our data with alternatives.

The traditional meaning of 'learning curve' in this sense is that electricity production costs are reduced with increased production because of learning by production (Arrow, 1962). However, learning can be a result of innovative activities not related to production. For example, R&D investments in wind technology may lead to innovation, but this innovation is not related to production. We refer to this type of learning as learning by investing. Our analysis of the learning curve combines both types of learning.

To obtain the learning curve, we express the unit cost of energy at time t as C_t, cumulative installed wind generation capacity at time t as Y_t^C, the cost of energy at initial capacity as C_0, and learning elasticity as α in the equation below. We treat the year 1998 as period zero in our data-set. In addition, since cumulative installed generating capacity before 1998 was very small, we assume it to be zero:

$$C_t = C_0(1 + AY_{t-1}^C)^{-\alpha} \quad \text{for} \quad t = (0, ..., T) \tag{3}$$

The majority of the learning curve papers use *CapEx* or turbine prices per MW as the measure of unit cost (e.g., Hayward & Graham, 2013; Grafström & Lindman, 2017; Yu et al., 2017; Wiebe & Lutz, 2016). We consider that this approach underestimates the learning effect. As turbines become larger, $CapEx$ per MW may rise, however, effective hours of operation also rise, which compensates for the increase in $CapEx$. Therefore, if we measure innovation using $CapEx$ only, it is highly likely to underestimate the learning effect. In contrast, measuring the unit cost using $LECOE$ takes into account increases in effective operating hours. For these reasons, in our learning curve analysis, $LECOE$ data represents the unit cost of electricity for each vintage.

The time lag on the cumulative capacity in equation 3 takes into account the fact that learning does not occur instantly, given the deployed capacity. Figure A5 in the appendix plots our $LECOE$ and wind capacity deployment data. The following observations help us verify that the learning curve can deliver an unbiased measure of correlation between deployment targets and innovation:

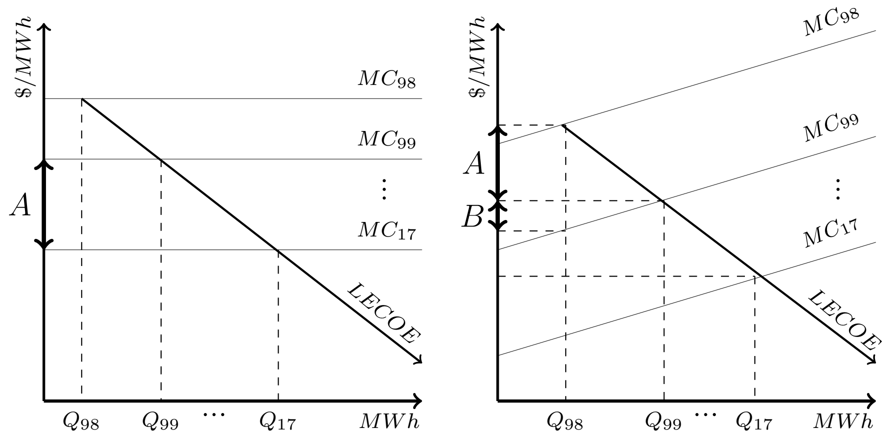
Observation 1 - Wind electricity producers face horizontal marginal cost curves

If the marginal cost curves were not horizontal, then applying the learning curve method would deliver a biased measure of correlation without further assumptions. The bias would be present due to omission of the geographic factor. Figure 8 illustrates the point: when the marginal cost curves are horizontal, the entire cost reduction is attributed to increased deployment (the segment A on the left graph); when the marginal cost curves are upward sloping, some cost reduction is not achieved due to geographic constraints, i.e. due to crowding out of new wind farms from high-wind-speed areas (the segment B on the right graph). Therefore, the correlation between increased deployment and technological innovation would be underestimated.

Observation 2 - Cumulative production may be a better explanatory variable than cumulative capacity.

We argued in the previous section that government deployment targets influence the deployment rates. If the manufacturing sector anticipates deployment rates and innovates as a response, then we may wonder why the government would not set higher targets in order to increase their incentive to innovate. On one hand, the required subsidy budget increases with installed generation capacity, which might become unaffordable. On the other hand, short-run marginal costs of innovating

Figure 8: *Illustration of Potential Supply Curves*



Notes. The left graph shows that when short-run electricity supply curves given each vintage are horizontal, we should attribute all reductions in production costs to increased deployment (segment A). However, if the curves are upward sloping, we cannot attribute all reductions in production costs to increased deployment, otherwise, we will miss the impact of geographic factors (segment B on the right graph).

increase with R&D. This implies that it is costly to speed up the innovation process.

For these reasons, we use cumulative production instead of cumulative capacity as an explanatory variable in the learning curve. A substantial increase in generation capacity in a particular year will substantially increase cumulative capacity, while it will not increase cumulative production as much. Therefore, cumulative production will have a smoother reaction to changes in the installed generation capacity, and this will justify the slower response of innovation.

4.1 Learning Curve with Cumulative Production

In this subsection we conduct a learning curve analysis using cumulative production as an explanatory to the reductions in the production costs, and compare it with the original specification in equation 3. We run both specifications of the learning curve using three sets of alternative innovation data: our innovation data generated using the new and the old engineering models and the innovation data of Wiser and Bolinger (2018).

In order to derive the time-t cumulative production variable, we first derive time-t production Q_t^N. Not all turbines that are installed in a particular year start production immediately. In fact, some turbines may be installed at the end of each period. To account for this, we assume that only half of the newly installed wind generation capacity in year t produces electricity in year t. The rest starts in the next period. Taking this into account and denoting time-t capacity by Y_t^N delivers:

$$Q_t^N = \sum_{s=0}^{t} Y_s^N AEP_s + \frac{1}{2} Y_t^N AEP_t \quad \text{for} \quad t = (0, ..., T) \tag{4}$$

Where AEP_t is the effective annual hours in operation for each vintage installed in year t from table A2. Cumulative production Q_t^C will simply be:

$$Q_t^C = \sum_{s=0}^{t} Q_s^N \quad \text{for} \quad t = (0, ..., T) \tag{5}$$

Therefore, learning curve model with cumulative production is the following:

$$C_t = C_0(1 + AQ_{t-1}^C)^{-\alpha} \quad \text{for} \quad t = (0, ..., T) \tag{6}$$

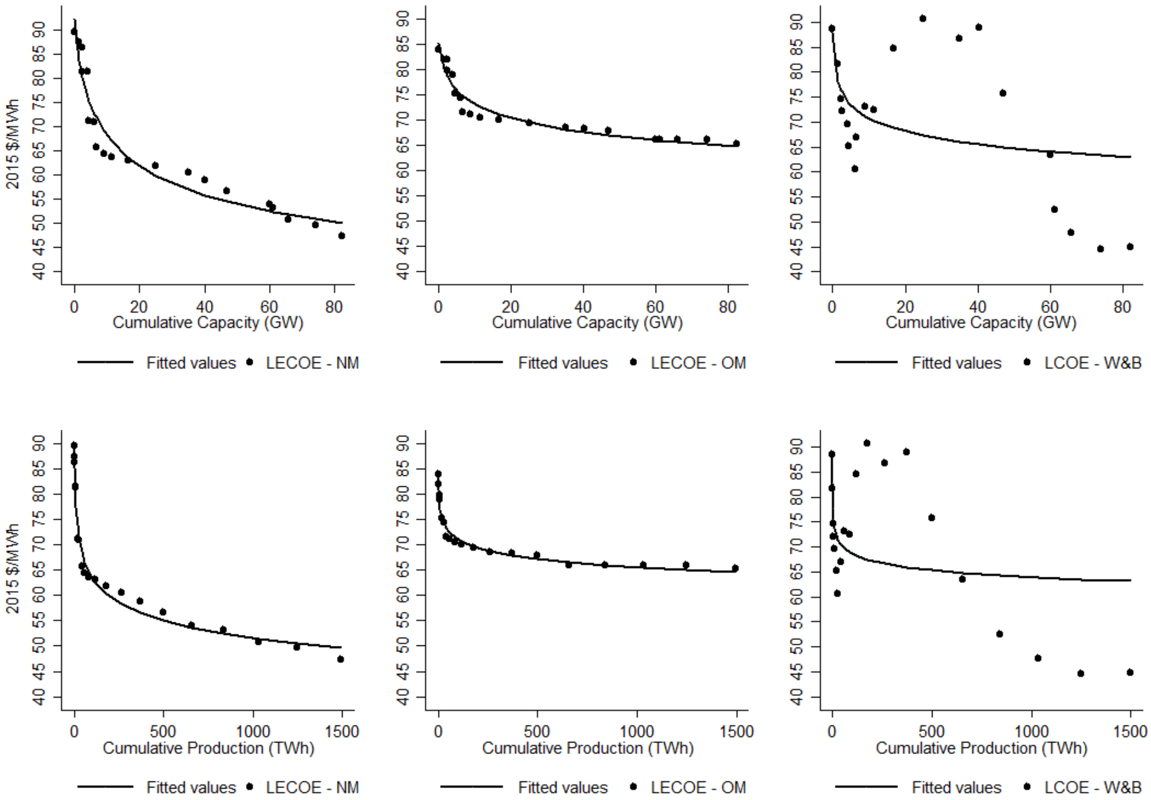
Production before 1998 is assumed to be zero because it is relatively insignificant. We run a non-linear regression on both equations 3 and 6 to find the parameters C_0, A, and α. We consider three time series to input as the production cost. The first and second are our innovation measure generated based on the new and old engineering models, respectively, and the third is the $LCOE$ data of Wiser and Bolinger (2018).

Regression tables A5 and A6 can be found in the Appendix. In figure 9 we notice that using cumulative production instead of cumulative capacity in the learning curve estimation arranges the data cloud more smoothly. However, it does not deliver significantly different estimation results (compare tables A5 and A6).

A noticeable difference arises when different innovation data are used. The learning curve is steeper when an innovation measure based on the new model is used instead of the measure based on the old model. A steeper learning curve implies a higher rate of learning. Both innovation measures confirm a correlation between cumulative production and production cost reductions, since the estimated parameters are statistically significant. In contrast, for the $LCOE$ data of Wiser and Bolinger (2018), the learning parameter is very small and statistically insignificant.

Also notice that data cloud is not smooth for Wiser and Bolinger (2018) and deviation from the fitted line is substantial. In tables A5 and A6 we can see that innovation data of Wiser and Bolinger (2018) delivers a larger root mean square error in comparison to our data. This indicates a weak fit. Hence, we have illustrated how we could improve the fit of the learning curve by supplying our improved measure

Figure 9: Estimation of the Learning Curve



Notes. Abbreviations NM, OM and W&B, refer to the innovation measures obtained from the new model, old model, and Wiser and Bolinger (2018), respectively.

of innovation. Our measure of innovation shows a strong correlation between wind technology deployment and innovation.

4.2 Effects of Policy on Innovation

In the above learning curve analysis, we show a strong correlation between the wind technology deployment rate and innovation in the US. In this section we discuss possible causality. In particular, it is not unreasonable to conjecture that when the government sets wind technology deployment targets, which determine the deployment rate, the incentive of wind turbine manufacturers to innovate is likely to increase.

Certainly, we cannot not rule out reverse causality, i.e., increased deployment of wind turbines as a response to reduced production costs. In addition, we do not argue that the US wind technology deployment targets are the only instruments that could influence wind technology innovation. For example, R&D spending in wind technology and other countries' wind technology support policies also contribute to innovation. However, it is still our conjecture that the US deployment targets influence innovation.

It is a fact that most countries aim to support clean technologies, particularly, solar and wind, in order to reduce greenhouse gas emissions and to limit climate change. For this reason, we consider that innovation is not the main driver of government policies, or at least policy is an important factor affecting innovation.

Suppose that the US deployment target does not drive innovation. Instead, suppose that costs would decline regardless of any intervention. We construct a simple optimization problem to show optimal wind technology deployment in this case. The government tries to maximize the social surplus. A positive surplus is delivered by exploiting a cheaper technology, i.e. a technology with lower marginal costs. We can assume that the long-run marginal cost curve of an alternative technology is horizontal, because conventional technologies do not experience technological innovation. The long-run marginal cost curve of wind technology is downward sloping, according to figure 2.

In equation 7 below, MC_t is the marginal cost of production using wind turbines at time t, MC^A is the marginal cost of production using an alternative source, Q_t is wind electricity production at time t and Q_T is the final deployment target:

$$\max_{Q_t} \quad \sum_{t=0}^{T} Q_t(MC^A - MC_t) \qquad \text{s.t.} \quad \begin{array}{l} Q_0 \ \leq \ Q_t \ \leq \ Q_T \\ Q_T \quad \text{given} \end{array} \tag{7}$$

The solution to the optimization problem is:

$$Q_t = \begin{cases} Q_0 & \text{if} \quad MC^A < MC_t \quad \text{for} \quad t \in [0, T-1] \\ \text{Any } Q \in [Q_{t-1}, Q_T] & \text{if} \quad MC^A = MC_t \quad \text{for} \quad t \in [1, T-1] \\ Q_T & \text{if} \quad MC^A > MC_t \quad \text{for} \quad t \in [1, T] \end{cases}$$

The logic of this result is quite simple: the government will obtain the maximum social surplus if conventional sources produce electricity until innovation in wind technology makes it competitive with conventional sources. Once the wind farm investors do not require subsidies, they will install the needed amount of generation capacity without government intervention. This is not, however, what we observe in the data. The US government has been supporting wind technologies for decades, and as a result, it has deployed the second largest amount of capacity in the world after China (Global Wind Energy Council, 2019).

The fact that the US government deploys a significant amount of wind technology implies that by supporting wind technology either it delivers social benefits different from least-cost generation, or it actually tries to impact the pace of innovation. Other benefits of promoting wind technology may include environmental benefits, developing the domestic wind technology manufacturing sector and creating new jobs (EWEA, 2012).

5 Conclusion

Supporting faster innovation in wind energy technology requires an understanding of the drivers of technological innovation. However, this is not feasible without an accurate measure for innovation itself. This paper generates such data, and thus fills a gap in the wind energy technology innovation literature. Our innovation data represents production cost reductions of wind turbine vintages installed in the US between 1998 and 2017. Computations of production costs are based on an engineering model, which allows us to exclude factors that can change production costs, but which do not contribute to technological innovation.

After generating our more accurate innovation measure for wind energy technology, we illustrate its potential use. We analyze the learning curve which measures correlations between the wind energy technology deployment rate and innovation. Our innovation measure improves the fit of the learning curve in comparison to alternative measures. The results show strong correlations between the wind energy technology deployment rate and innovation.

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Abbreviations Used

AEP	Annual Energy Production
BOS	Balance of System
CRF	Capital Recovery Factor
FDM	Fully Deregulated Market
ISO	Independent System Operator
LCOE	Levelized Cost of Energy
LECOE	Levelized Engineering Cost of Energy
NREL	National Renewable Energy Laboratory
O&M	Operations and Maintenance
PDM	Partially Deregulated Market
PPA	Power Purchasing Agreement
PPI	Producer Price Index
PTC	Production Tax Credit
REP	Retail Electricity Provider
RPS	Renewable Portfolio Standards
VIM	Vertically Integrated Market

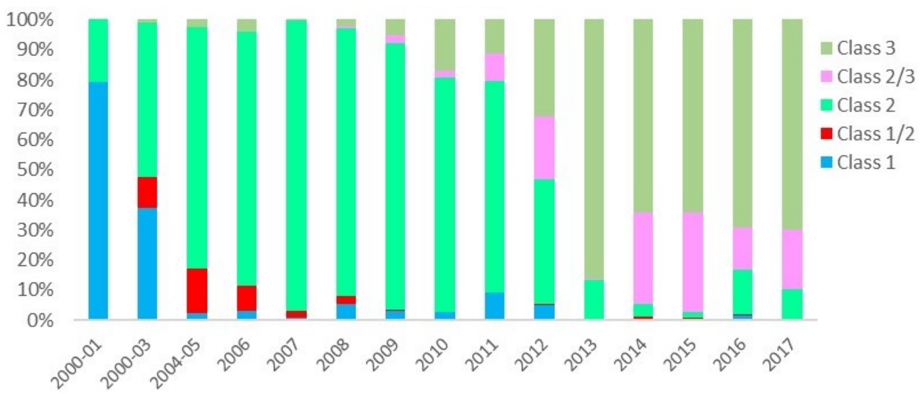
Appendix

Table A1: *Vintage Characteristics*

Vintage	CAP (kW)	RD (m)	HH (m)
1998	710	47.2	52.3
1999	720	48.2	56.6
2000	800	49.4	58.7
2001	890	53.1	58.2
2002	890	52.8	62.9
2003	1370	67.8	67.4
2004	1220	65.1	66
2005	1500	75.3	75.7
2006	1610	77.9	76.2
2007	1650	79	78.2
2008	1670	79.3	78.5
2009	1740	81.5	78.8
2010	1800	84.2	79.8
2011	1970	89	81
2012	1950	93.4	83.8
2013	1860	96.9	80.5
2014	1940	99.5	82.7
2015	2010	102.4	82.4
2016	2150	108.2	83
2017	2320	113	86

Notes. CAP - Turbine capacity; RD - Rotor diameter; HH - Hub height; all values are average characteristics of newly installed turbines. Units in the brackets. The data are borrowed from (Wiser & Bolinger, 2018) data-file.

Figure A1: *Distribution of Turbine Class*



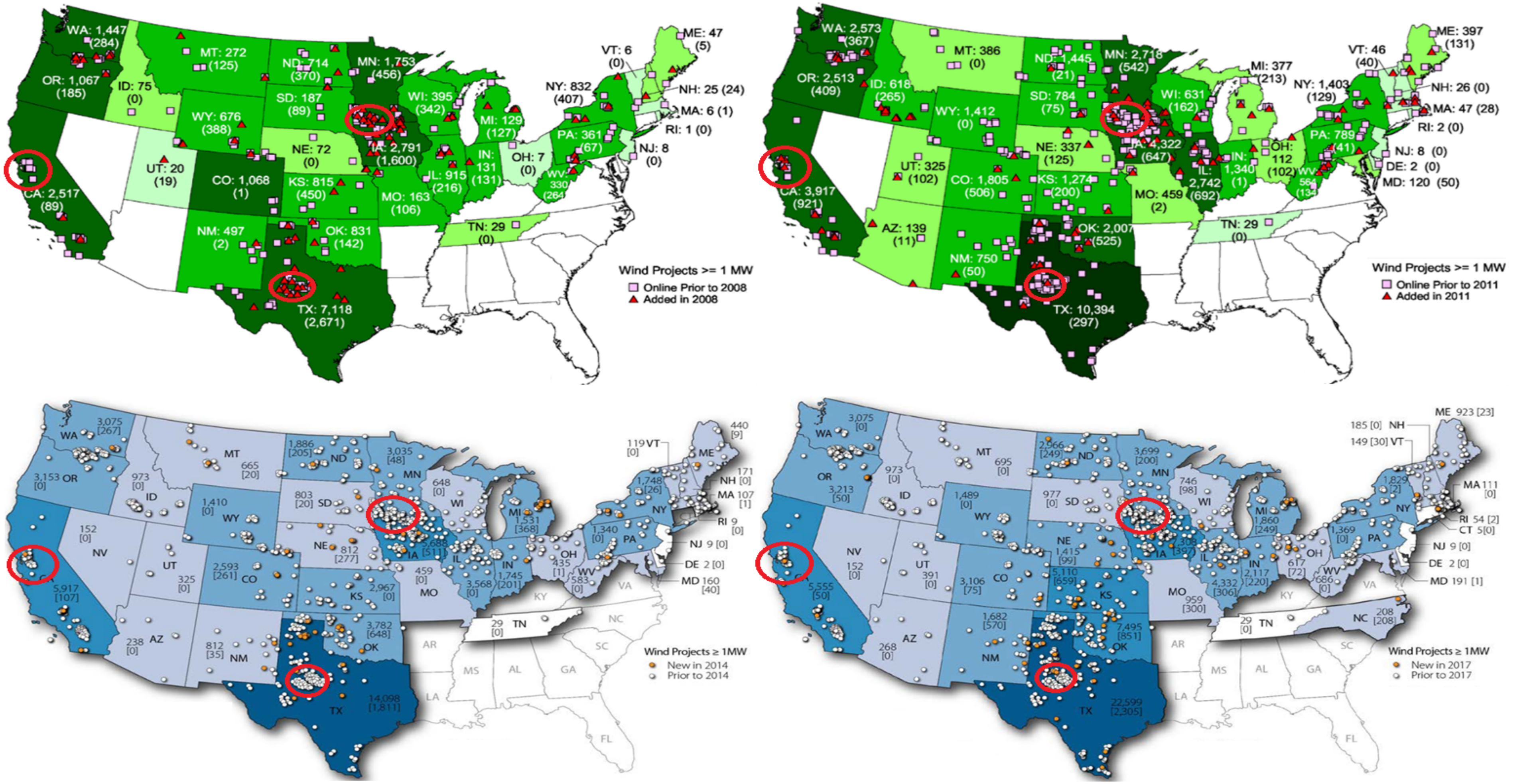
Notes. The figure shows that wind electricity producers have increasingly favored class 2/3 and 3 turbines, which are more suitable for lower wind-speed areas since 2012. Source. The data are borrowed from Wiser and Bolinger (2018).

Table A2: *LECOE and its Components*

Vintage	**Turbine Cost^{new} (\$/kW)**	**BOS^{new} (\$/kW)**	**Turbine Cost^{old} (\$/kW)**	**BOS^{old} (\$/kW)**	**O&M (\$/kW/yr)**	**AEP (h/yr)**	**LECOE^{new} (\$/MWh)**	**LECOE^{old} (\$/MWh)**
1998	985	584	922	498	77	2520	89	84
1999	1030	579	943	506	76	2608	87	82
2000	994	537	922	493	75	2538	86	82
2001	962	502	938	481	73	2596	81	80
2002	1001	501	943	488	72	2620	81	79
2003	927	391	1007	449	70	2762	71	75
2004	959	419	1016	462	69	2801	71	74
2005	1005	378	1111	458	67	3009	66	72
2006	990	365	1118	452	66	3008	64	71
2007	998	361	1128	452	64	3028	64	70
2008	995	358	1127	451	63	3023	63	70
2009	994	352	1143	449	61	3047	62	69
2010	1006	348	1173	450	60	3106	60	69
2011	1004	336	1205	447	59	3143	59	68
2012	1032	343	1306	458	58	3305	57	68
2013	1084	353	1409	465	51	3466	54	66
2014	1074	350	1437	466	52	3498	53	66
2015	1011	344	1468	465	51	3527	51	66
2016	1025	339	1537	466	49	3581	50	66
2017	1033	331	1581	470	42	3611	47	65

Notes. Costs are expressed in 2015 US dollars. Source. Author's own computations.

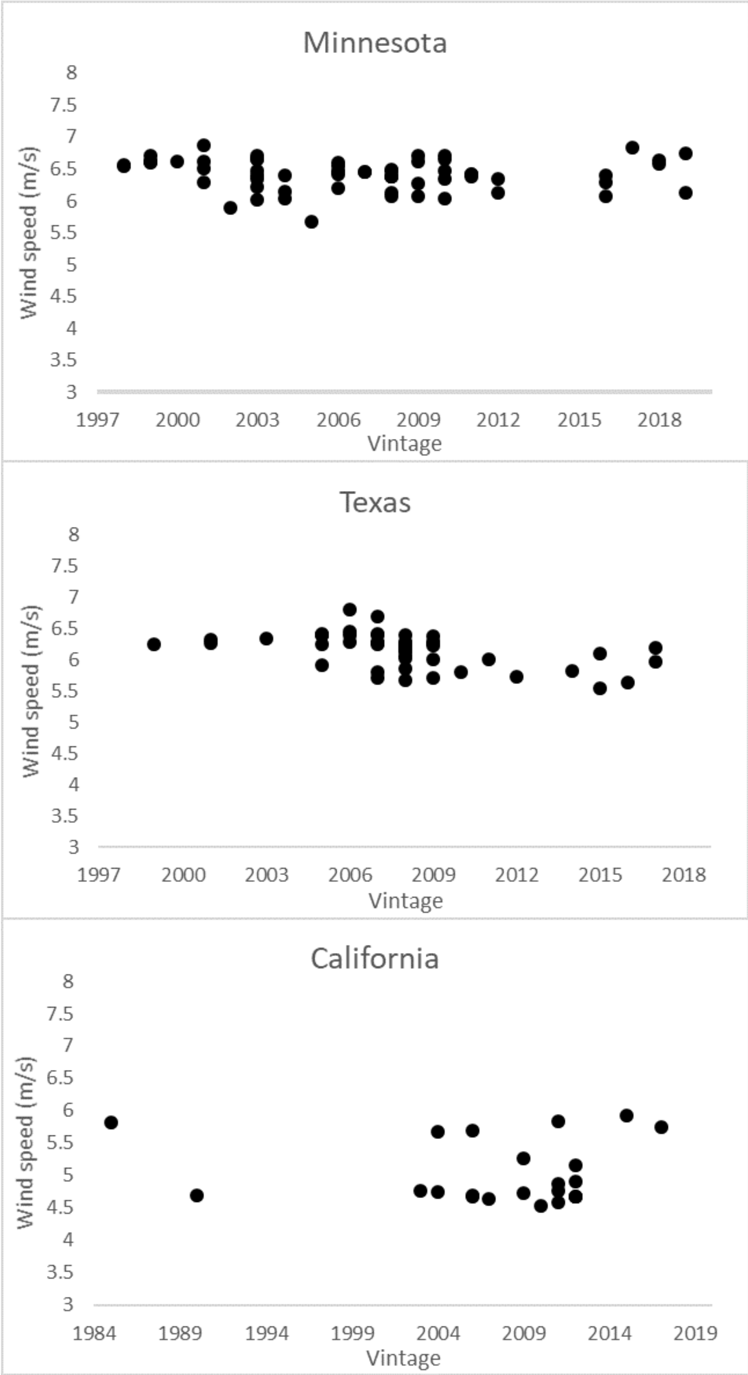
Figure A2: *Deployment of the Wind Technology in the US*



Notes. The numbers displayed within states with and without brackets represent cumulative and annual installed wind capacities, respectively in megawatts. The figure shows that new wind turbines has mostly been installed near exploited wind farm areas and in the densely populated locations. This implies that geographic constraints has not crowded out new wind vintages to worse wind resource areas. The red circles shows clusters of wind farms, for which we analyzed the changes in the wind quality in the following figure.

Source. The maps are borrowed from (Wiser & Bolinger, 2008-2018)

Figure A3: *Distribution of Wind Speed across Vintages*



The following figure shows the wind speed distribution across various vintages for three clusters of wind farms in Minnesota, Texas and California. The wind speed data is taken from the global wind atlas (Technical University of Denmark, 2017) at 50 meters altitude in the exact location of chosen wind farms. For the analysis we picked a reference wind farm in each of the three states and collected the wind speed information for all operational wind farms in the hundred kilometer distance from the reference wind farms. The reference wind farms are stoneray wind farm in Minnesota, loraine wind farm in Texas and solano wind project in California. The clusters of wind farms are circled on maps in figure A2. We chose hundred kilometer distance in order to have sufficient wind farms to reveal any trend in the wind speed distributions across vintages. The graphs do not reveal downward trend in wind speed at the cluster level. This indicates that the marginal costs have not been increasing due to crowding out of wind farms to less windy areas, given location.

Table A3: *Cumulative Number of Wind Electricity Generating Firms on the US Electricity Markets*

Year	CAISO	ERCOT	ISO-NE	MISO	NYISO	Northwest	PJM	SPP	Southwest
1998	0	0	0	2	0	1	0	0	0
1999	5	2	0	6	0	2	0	4	0
2000	5	2	0	7	2	2	1	4	0
2001	6	4	1	13	2	5	1	6	1
2002	8	4	1	16	2	5	1	6	1
2003	9	8	1	20	2	7	2	7	4
2004	10	8	1	22	2	7	2	7	6
2005	13	10	1	24	3	11	3	9	6
2006	13	11	2	27	3	17	4	11	8
2007	13	18	3	35	6	19	5	11	10
2008	15	27	4	45	7	23	8	15	11
2009	16	31	6	53	9	24	14	21	14
2010	17	33	8	60	10	28	16	23	14
2011	19	36	12	69	11	32	19	27	17
2012	24	44	24	89	13	42	29	35	20
2013	24	44	24	89	13	42	29	36	21
2014	26	47	24	93	13	45	31	40	21
2015	26	55	27	96	14	45	33	48	22
2016	26	59	33	100	14	48	36	50	23
2017	26	62	34	107	14	53	37	53	23

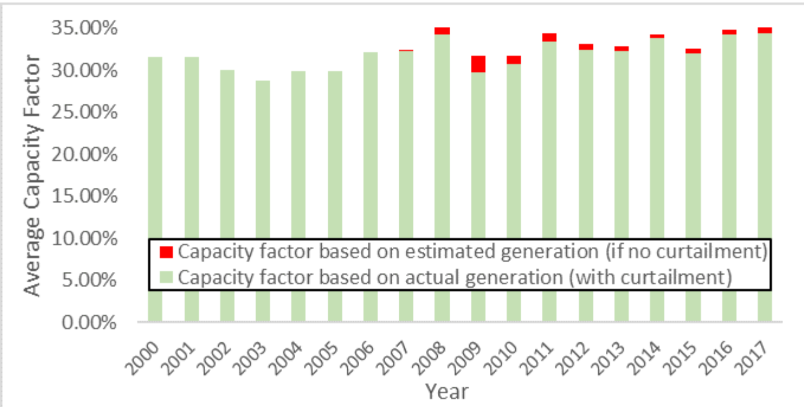
Notes. The table shows the number of wind electricity generating firms which has entered each US electricity market in 1998-2017. Since we have counted the number of firms based on the owners of the operating wind farms, the table may be omitting those wind farm owners, who installed turbines during this period, decommissioned them and exited the market. However, such cases are extremely small, because expected useful life of wind farms is at least twenty years. Therefore, the proportion of decommissioned farms is very small (U.S. Energy Information Administration, 1998-2017). In addition, it is highly likely that such firms owned some other operating wind farms, and hence, they are still included in the table.

Table A4: *Number of Potential Power Purchasers in US Electricity Markets*

Markets	Purchasers	Covered States	Source
CAISO	About 60 utilities	Covers California	https://www.energy.ca.gov/almanac/electricity_data/utilities.html#iou
ERCOT	More than 100 utilities. At least 40 REPs	Texas	https://callmepower.com/tx/utility
ISO-NE	More than 15 utilities	Connecticut, Maine, New Hampshire, Massachusetts, Rhode Island and Vermont	http://www.bestenergynews.com/solar/utility_co/utility_companies.php
MISO	More than 80 utilities. More than 50 REPs	Arkansas, Luisiana, Michigan, Minnesota, Wisconsin, parts of Illinois, Indiana, Iowa, Mississippi and Missouri	https://www.misoenergy.org/stakeholder-engagement/members/
NYISO	7 large utilities and many small ones	New-York	http://www.bestenergynews.com/solar/utility_co/utility_companies.php
Northwest	About 20 utilities	Idaho, Nevada, Oregon, Washington, Parts of Montana and Wyoming	http://www.bestenergynews.com/solar/utility_co/utility_companies.php
PJM	About 50 utilities and about 85 REPs.	Delaware, Meriland, New Jersey, Ohio, Pennsilvania, Virginia, West Virginia, Part of Indiana and part of Kentucky	https://www.pjm.com/about-pjm/member-services/member-list.aspx
SPP	More than 60 utilities	Kansas, Nebraska, Oklahoma, South Dakota, and small parts of contiguous states	https://www.spp.org/about-us/members-market-participants/
Southwest	About 10 utilities	Arizona, New Mexico, Colorado and small parts of contiguous states	http://www.bestenergynews.com/solar/utility_co/utility_companies.php

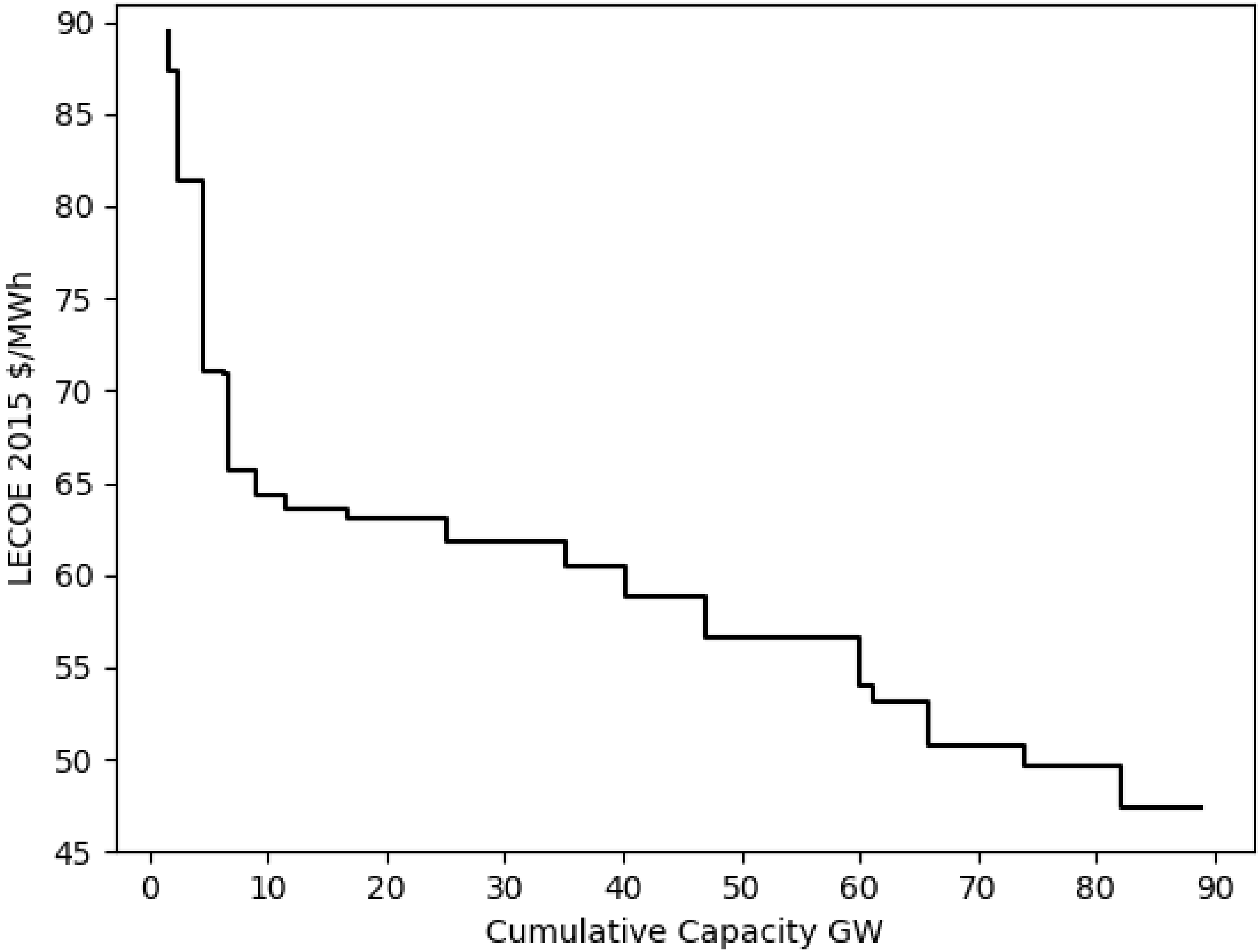
Notes. The table shows the number of potential electricity purchasers: utilities and REPs in each electricity market. The list omits some of the potential electricity purchasers, such as end-use consumers who directly purchase electricity and the power marketers who engage in the resale of electricity.

Figure A4: *Impact of Curtailment on Capacity Factors*



Notes. The figure shows the impact of curtailment on average capacity factors of wind generation in the US. Since curtailment has affected 0.1-1 percent of total generation each year, the revenues of the producers are unlikely to be significantly affected. In addition, forced curtailment is usually compensated. Source. Wiser and Bolinger (2018) data file.

Figure A5: *Relationship Between LECOE and Cumulative Capacity*



Source. LECOE - Author's own computations; cumulative capacity - Wiser and Bolinger (2018) data file

Table A5: *Estimation of Learning Curve with Cumulative Capacity*

Parameters	(1) LECOE - NM	(2) LECOE - OM	(3) LCOE - W&B
c_0	92.274***	85.114***	88.082***
	(3.40)	(1.66)	(13.89)
A	0.584	1.146	5.242
	(0.32)	(0.68)	(24.31)
α	0.157***	0.060***	0.055
	(0.02)	(0.01)	(0.04)
Root MSE	3.626	1.710	13.908

Notes. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports estimation results of the learning curve model in equation 6 using three alternative sets of innovation measures. Abbreviations NM, OM and W&B, relate to the innovation measures obtained from the new model, old model, and Wiser and Bolinger (2018), respectively. Explanatory variable is cumulative capacity.

Table A6: *Estimation of Learning Curve with Cumulative Quantity*

Parameters	(1) LECOE - NM	(2) LECOE - OM	(3) LCOE - W&B
c_0	89.247***	83.626***	88.358***
	(1.37)	(0.74)	(13.69)
A	0.407*	0.986*	40.606
	(0.15)	(0.44)	(306.68)
α	0.091***	0.035***	0.030
	(0.01)	(0.00)	(0.02)
Root MSE	1.970	0.975	13.734

Notes. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The table reports estimation results of the learning curve model in equation 6 using three alternative sets of innovation measures. Abbreviations NM, OM and W&B, relate to the innovation measures obtained from the new model, old model, and Wiser and Bolinger (2018), respectively. Explanatory variable is cumulative quantity.

Abstrakt

Po implementaci inovací v odvětví větrné energie bychom měli pozorovat pokles produkčních nákladů elektrické energie. Nicméně úsudky o míře inovací založené na produkčních nákladech nejsou věrohodné, jelikož změny v nákladech mohou být způsobeny i faktory, které s inovacemi nesouvisí. Tato studie aplikuje inženýrský model k vygenerování časové řady produkčních nákladů větrné energie jakožto míry inovací. Tento přístup nám umožnuje vyloučit faktory, které nelze přisoudit technologickým inovacím. Pro ilustraci významu naší míry inovací provádíme analýzu křivky učení, která měří korelaci mezi instalovaným výkonem větrných elektráren a redukcí nákladů na produkci elektrické energie. Naše data poskytují lepší popis křivky učení v odvětví větrné energie než alternativní míry inovací, které lze nalézt v literatuře.

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