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MEASURING THE IMPACT OF OWN AND OTHERS' EXPERIENCE ON PROJECT COSTS IN THE U.S. WIND GENERATION INDUSTRY

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Abstract

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1 Introduction

Productivity growth due to accumulated experience with a production process or technology—the phenomenon now known as *learning-by-doing*—has long been of interest to academics, managers, and policymakers.[1] In recent years, amid growing concern about climate change and energy security, there has emerged a literature investigating whether learning-by-doing is characteristic of renewable energy technologies in general, and wind power in particular. The argument is that learning-by-doing on the part of wind power developers—the firms that design and build wind power projects—is in

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[1]Alchian (1963), Hirsch (1956), and Wright (1936) were among the first to empirically investigate this type of productivity change, while Arrow (1962) was first to propose a comprehensive theoretical framework. The Boston Consulting Group (1968) later encouraged its clients to leverage such productivity change for competitive advantage.

part responsible for the dramatic fall in average wind power project costs in the United States from the early 1980s to the early 2000s.[2] Indeed, this logic has been used to rationalize a number of policies to promote wind and other renewables in the United States, including production and investment tax credits at the federal level and renewable portfolio standards at the state level.

Advocates of such learning-based policy interventions, however, often fail to appreciate the importance of establishing precisely whose experience affects whose costs.[3] If, for instance, one firm's efforts to design and construct wind power projects yield cost-reducing knowledge that spills over to competitors, then the firm has a disincentive to invest in these activities. In this case, policies that subsidize investment can compensate the firm for the positive externality it bestows on its competitors. If, on the other hand, the cost-reducing knowledge that results from a wind development firm's activities remains entirely within the firm, then there is no market failure and subsidies are not justified by the existence of positive externality. Existing empirical research in the U.S. wind industry has done little to distinguish between these two types of learning (across-firm knowledge spillovers versus firm-specific learning-by-doing). Moreover, as shown in 1, during much of the 2000s, average dollar per installed kilowatt (KW) wind power project costs in the United States actually increased, despite unprecedented investments in new wind generating capacity facilitated by federal and state incentives.

The purpose of this paper is to investigate the extent to which there is empirical evidence of across-firm learning-by-doing and within-firm learning-by-doing in the design and construction of U.S. wind power projects after controlling all other potential sources of wind project cost differences over time. The existence of the former learning-by-doing implies a positive externality that warrants policy interventions in the renewable energy marketplace, whereas the existence of the latter form does not.

Econometric estimation of learning-by-doing in this or any other setting is challenging for two major reasons. First, it is necessary to define experience and explain how and to whom it accumulates. Most existing research defines experience in terms of firms' cumulative past output, and we consider two alternative measures of output for U.S. wind power developers: cumulative megawatts of installed capacity and cumulative number of installed projects. Because the U.S. wind energy industry consists of many competing developers, and because we have assembled a detailed project-level dataset, we quantify separately the accumulated experience of each individual developer. This approach, made popular by Irwin and Klenow (1994), makes it possible to distinguish between inter-firm knowledge spillovers and firm-specific learning-by-doing (i.e. learning that does and does not entail externalities). Because the U.S. wind energy industry has witnessed significant technological change and has endured several boom-bust cycles, we allow for the possibility that output from the distant past counts less towards experience than does output from the recent past — i.e. we allow for the possibility that experience depreciates, as is the case in Argote et al. (1990), Benkard (2000),

[2] According to Wiser and Bolinger (2010), average U.S. wind power project costs declined in real terms from about \$4,800/kW in 1984 to about \$1,300/kW in 2001.

[3] In his August 12, 2008 column, Thomas L. Friedman of the New York Times writes: "Tax credits [...] stimulate investments by many players in solar and wind so these technologies can quickly move down the learning curve and become competitive with coal and oil." In a February, 2012 interview, Minh Le of the U.S. Department of Energy states: "Renewable portfolio standards help drive down the learning curve and reduce solar energy cost in the long run."

Kellogg (2011), Nemet (2012), and Thompson (2007).[4] Further, because there is a history of joint ventures and acquisitions in the U.S. wind development business, we allow for the possibilities that developers can share experience with and purchase experience from one another. Finally, because past experience from nearby projects may be more applicable than distant projects, we allow the value of past experience to differ by distance to the current project.

The second challenge arises because accumulated experience is but one of many possible factors that determine costs. For instance, the increase in average U.S. wind power project costs during the 2000s is in large part attributable to higher prices for primary inputs like steel as well as technological changes like the advent of larger wind turbines (Bolinger and Wiser, 2011). Indeed, failure to account for other likely determinants of cost besides accumulated experience is a major shortcoming of much existing empirical work on learning-by-doing in wind and other renewable energy technologies (Nordhaus, 2014; Pillai, 2015). It is therefore necessary to have a sufficiently rich econometric modeling framework that can disentangle learning from other contemporaneous determinants of cost. In this paper, we estimate cost functions for installed wind generating capacity derived from an economic model of firm behavior in the U.S. wind energy industry. This approach allows us to estimate firm-specific learning-by-doing, across-firm knowledge spillovers, the rate at which experience depreciates, and the degrees to which experience is shareable and transferable while controlling for the effects on wind project costs of scale economies, changing input prices, and technical progress exogenous to the cumulative experience of wind project developers.

Using our estimated model, we find evidence consistent with internal firm-specific learning, but not inter-firm spillovers. This firm-specific learning is found in a variety of model specifications, with a doubling of a firm's own experience base estimated to decrease its cost to install a megawatt (MW) of wind generating capacity by 1.3-1.6 percent, all other things being equal. Altogether, these findings suggest that the cost-reducing benefits of experience in wind power project development are fully captured by the entity that undertakes the projects, rather than by other industry participants. These results suggest that the industry has matured beyond the point where firms receive cost-saving knowledge following the completion of projects by others in the industry.

Beyond separating experience stocks into own- and other-firm experience, we find that it may also be economically meaningful to allow for measures of experience stocks to depreciate, to weight local projects higher than more distant projects, and to accommodate joint ventures. These findings could in part explain why the largest U.S. wind power developers undertake new projects at fairly regular intervals: they may seek to prevent or at least slow the erosion of competitive advantages stemming from their comparatively large experience bases. At the same time, however, observing a large number of fringe developers could be due to rapid depreciation of incumbents' experience across time and space.

Finally, evidence regarding the degrees to which firm-specific experience can be shared and transferred is inconclusive but nonetheless informative. For example, the data cannot reject the hypothesis

[4] Baloff (1970) and Hirsch (1952) discuss how interruptions to production might adversely affect future productivity; Barradale (2010) discusses how unpredictability concerning the federal renewable electricity production tax credit (PTC) — the single most important government incentive available to U.S. wind power projects—has caused such interruptions in the U.S. wind energy industry.

that experience resulting from projects undertaken as joint ventures is equally as valuable as experience resulting from equivalent projects undertaken by just one firm. Likewise, the data cannot reject the hypothesis that acquired experience—experience gained from a merger or acquisition—is a perfect substitute for organic experience—a result borne out by the fact that most acquisitions in the U.S. wind development business involve the purchase of an experienced incumbent by an inexperienced entrant.

The remainder of the paper is organized as follows: section 2 discusses anecdotal evidence of learning-by-doing in the design and construction of U.S. wind power projects, the growth of the U.S. wind energy industry, and the policies in place to support wind and other renewables. Section 3 introduces notation and discusses the unique dataset assembled for this paper. In section 4, we derive minimum cost functions for installed wind generating capacity from an optimizing model of firm behavior in the U.S. wind energy industry. In section 5, we discuss the estimation strategy and estimation results. Section 6 concludes.

2 Learning mechanisms and policy in wind power installations

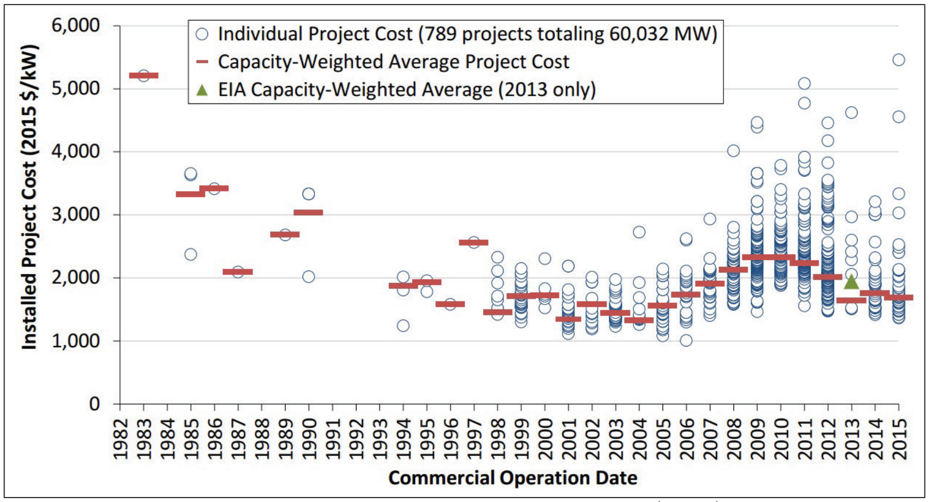
Figure 1 shows that average wind power project costs fell substantially in the United States from the early 1980s to the early 2000s, and there is much anecdotal evidence that this was due in part to learning-by-doing by wind power developers. As they accumulated design and construction experience, developers became adept at identifying sites well-suited for wind power projects—not just in terms of wind resource quality, but also proximity to transmission lines and other infrastructure.[5] Likewise, developers learned to navigate the myriad federal, state, and local regulations that govern the siting and construction of wind power projects.[6] Developers learned to optimize the logistics of transporting literally thousands of oversized cargo loads to remote project sites and the logistics of managing complex construction operations: for instance, how best to build foundations in different types of terrain, how to optimize large networks of access roads and electrical wiring, and even how best to move equipment around a project site. Developers' experience designing and building wind power projects also facilitated cost-reducing innovations upstream in the manufacturing of wind turbines: one example is the advent of modular tower sections, which are not only cheaper to manufacture but also to transport and install. Further anecdotal evidence of learning-by-doing in the design and construction of U.S. wind power projects is provided in Appendix A1.

Such anecdotal evidence, however, is silent as to precisely *whose* accumulated design and construction experience causes *whose* project completion costs to decrease. In other words, anecdotal evidence of learning-by-doing in the wind development business does not specify whether learning occurs solely within individual firms or whether learning spills over across rival firms. The cost reductions evident in figure 1 are consistent with either type of learning; in spite of this ambiguity—which empirical research has yet to resolve—the federal and state governments have enacted policies to promote wind

[5] Construction of new transmission infrastructure is an extremely time-consuming undertaking, especially for wind power projects, which are often located in environmentally sensitive areas far from major electricity demand centers.

[6] At just the federal level, a developer may need to secure project permits from each of the Environmental Protection Agency, Federal Aviation Administration, Federal Communications Commission, Fish & Wildlife Service, and Army Corps of Engineers.

Figure 1: Average U.S. wind power project costs



Source: Wiser and Bolinger (2016).

and other renewables that are economically justifiable only in the case of learning-related positive externalities.[7]

To further complicate matters, Figure 1 shows that for much of the 2000s average wind power project costs actually increased in the United States. This is despite unprecedented investment in new wind generating capacity—and hence potential for cost reductions due to learning-by-doing—facilitated by federal and state incentives (see Figure 2).

The federal renewable electricity production tax credit (PTC) awards a tax credit for electricity generated from eligible renewable resources. The PTC has been extended 10 times since 1999 (with lapses in 2001, 2003, 2013 and 2014 retroactively applied to projects). The most recent extension set the PTC at $24 per megawatt-hour of electrical energy generated by projects that were commenced in 2016, with a 20, 40, 60 and 100% phase out scheduled for the next 4 years, estimated by the Joint Committee on Taxation to cost $14.5 billion from 2016-2025.[8] In addition to the PTC, renewables portfolio standards (RPSs), state-level laws that require retailers of electricity to procure a certain percentage of their annual electricity sales to final consumers from qualified renewable resources, also effectively guarantee wind generators higher-than-market prices for their energy.[9,10] Accordingly, the primary goal of the present research is to investigate whether there is econometric evidence of learning-related externalities in the post-2000 time period that might substantiate learning-by-doing

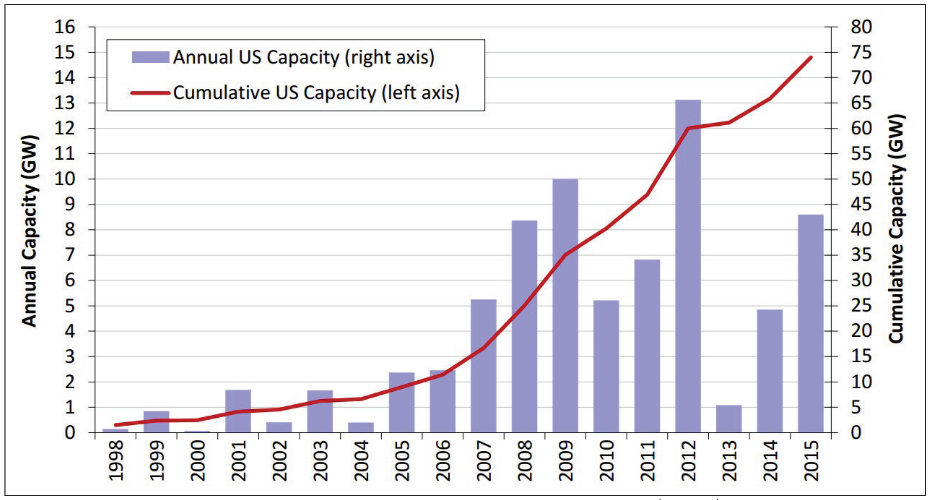
[7]To be sure: there are rationales for policies that support wind and other renewables in the United States besides learning-by-doing (e.g. environmental externalities). However, this paper is concerned exclusively with whether learning-by-doing ought to be one basis for such policies.

[8]See Sherlock (2017), which also contains a more detailed history of the PTC, including a discussion on the exclusions when claiming other tax credits such as the Investment Tax Credit (ITC) or the Section 1603 grant, part of the American Recovery and Reinvestment Act (ARRA) passed in the wake of the 2008 financial crisis.

[9]In practice, for the PTC and RPSs, "eligible renewable resources" more often than not means wind, which has accounted for the vast majority of additions to U.S. renewable generating capacity in each of year in our sample. See Sherlock (2017) for a breakdown renewable energy additions by technology.

[10]Strictly speaking, the PTC and RPSs incentivize production of wind-generated electricity; however, there is generally no excess wind generating capacity in the United States from which to squeeze additional output, so these policies strongly incentivize investment in new wind generating capacity.

Figure 2: Annual and cumulative growth in U.S. wind generating capacity



Source: Wiser and Bolinger (2016).

as a basis for public support of investments in wind capacity in the United States, despite the overall upward trend in the dollar per installed KW cost of U.S. wind power projects during this time period.

3 Data

According to the American Wind Energy Association (AWEA), 866 wind power projects had been completed in the United States by the end of the year 2015. For the purpose of this analysis, each project is classified by the following characteristics: the project's nameplate generating capacity, q; the state, s, city/region r, and coordinates l in which the project is situated; the developer(s), d, that designed and built the project; and the year, T, in which the project was completed.[11] Approximately ten percent of the projects completed through 2015 were undertaken as joint ventures between two or more developers, such that d, strictly speaking, is a set. For example, $d = \{\text{BP,Clipper}\}$ for the 60 MW Silver Star wind farm in Texas, whereas $d = \{\text{Iberdrola}\}$ for the 160 MW Barton wind farm in Iowa. The U.S. Energy Information Administration (EIA) Form EIA-860 database identifies the year-quarter, t, in which each project was completed (e.g. $t = 2008$:Q3 for Silver Star), and verifies the accuracy of the AWEA data.

Project cost estimates were identified for 408 of the 717 projects completed between 2002 and 2015,[12] and are from a variety of sources: Bloomberg New Energy Finance, business publications (in particular, Project Finance, Power Finance & Risk, and Global Power Report), state public utilities commissions' filings and testimony, corporate press releases, national and regional newspapers, and personal correspondence with wind power developers. A project's total completion cost, C, is the sum of its development, equipment purchase, and construction costs. Development costs include the

[11]All characteristics are made available by the AWEA with the exception of r. r is the geographically closest reference city in the RSMeans building construction cost data to a project within the same state.

[12]717 of the 866 projects were cross-validated in the EIA-860 database. Few project costs were found prior to 2002.

Table 1: Project-level data variables and definitions

Variable	Definition
q	Nameplate generating capacity (MW)
s	State
r	City/region
l	Latitude/longitude
d	Developer(s)
T	Year of completion
t	Quarter of completion
C	Total completion cost ($M)

costs of measuring and assessing the wind resource at a candidate project site, acquiring land usage rights, and completing environmental impact assessments. Equipment purchase costs are the costs of procuring the materials necessary to construct the wind power project, such as turbines, towers, and wires. Construction costs are the costs of erecting the wind turbines and connecting them and their attendant equipment to the electrical grid.

Table 1 summarizes the key project-level variables used throughout this paper. Appendix A2 presents annual summary statistics, while appendix A3 examines heterogeneity across developers in terms of number of projects completed, frequency with which projects are undertaken, market shares, and costs. Because reliable cost estimates could not be identified for all 717 projects completed from 2002 to 2015, appendix A4 makes a case that instances of missing cost data is unrelated to observable characteristics of the project.

4 Model

Econometric estimation of learning-by-doing is challenging for two main reasons: first, it is necessary to define experience and explain how and to whom it accumulates, and second, it is necessary to account for other determinants of cost besides accumulated experience. Section 4.1 develops a framework for quantifying experience in the U.S. wind development business that: (i) allows for alternative definitions of experience; (ii) differentiates between experience internal and external to firms; (iii) allows experience to depreciate over time; (iv) allows projects contributed nearer a planned site to contribute greater experience than projects completed further away; and (v) allows experience to accumulate through joint ventures and acquisitions. Section 4.2 derives a minimum cost function for installed wind generating capacity that integrates the experience measures into a coherent econometric model. This model estimates firm-specific learning-by-doing, inter-firm knowledge spillovers, the rate at which experience depreciates, a multiplier for the experience value of geographically distant projects, and the degrees to which experience is shareable and transferable while controlling for the effects on costs of scale economies, changing input prices, and exogenous technical progress.

4.1 Quantifying experience

This section constructs variables Q_{l_i,d_i,t_i} and $Q_{l_i,-d_i,t_i}$ that quantify two distinct stocks of accumulated experience available to the developer(s) of wind power project i at the time of the project's undertaking. The former quantifies experience *internal* to firm(s) d_i, i.e. experience useful to d_i that is the result of d_i's own design and construction activity. This measure will be used to estimate firm-specific learning-by-doing. The latter quantifies experience *external* to d_i, i.e. experience useful to d_i that is the result of d_i's competitors' design and construction activity, and will be used to estimate inter-firm knowledge spillovers.[13] Experience is typically measured in terms of cumulative past output, and here we consider two different measures of output for U.S. wind power developers: megawatts of installed wind generating capacity and number of installed wind power projects. If learning is thought to be proportional to project size, then megawatts of installed capacity is arguably the better measure of output: a 100 MW project counts twice as much as a 50 MW project. On the other hand, if learning is thought to be invariant to project size, then number of installed projects is arguably the better measure of output: two 50 MW projects count twice as much as one 100 MW project. The remainder of this section assumes megawatts of installed capacity is the measure of output; the exposition is analogous, however, for the case where number of installed projects is the measure of output (each occurrence of q is replaced with 1).

As a first step, define firm d's *organic* experience at time t relating to project i as:

$$Q^{O}_{l_i,d,t} = \sum_{j \in J} q_j \cdot \lambda_{|d_j|} \cdot M_{i,j} \cdot \mathbf{1}\left\{d \in d_j\right\} \cdot \mathbf{1}\left\{t_j < t\right\} \tag{1}$$

where J is the set of all U.S. wind power projects completed through 2015, $|d_j|$ is the cardinality of the set d_j (i.e. the number of firms that developed project j—in most cases just one) and $M_{i,j}$ is a multiplier that depreciates the experience gained from project j depending on its applicability to project i. The indicator functions ensure experience is only counted for projects completed before the current project and that included firm d. $M_{i,j}$ takes the form:

$$M_{l_i,d,t} = (1 - \delta_{own})^{t_j - 1} \cdot (1 - \rho_{own} \cdot \mathbf{1}\{dist(l_i, l_j) > 100\}) \tag{2}$$

where $dist(l_i, l_j)$ the distance between project i and j. δ_{own} measures the quarterly rate of depreciation of experience, such that all other things being equal, capacity installed in the distant past counts less towards experience than does capacity installed in the recent past. Modeling this feature is in keeping with recent work on organizational forgetting—the hypothesis that production experience depreciates over time—in settings as diverse as aircraft manufacturing (Benkard, 2000), oil drilling (Kellogg, 2011), shipbuilding (Argote et al., 1990; Thompson, 2007), and wind power production (Nemet, 2012). That experience accumulated by U.S. wind power developers should depreciate seems plausible for at least two reasons. First, wind turbine technology has evolved considerably (see figures A4 and A5) and experience with antiquated technology may not be as useful as experience with state-of-the-art technology. Second, the U.S. wind energy industry has endured

[13] This approach to identifying and estimating jointly firm-specific learning-by-doing and inter-firm knowledge spillovers (i.e. by quantifying separately the accumulated experience of each individual firm) was made popular by Irwin and Klenow (1994) and has since been employed by Kellogg (2011) and Nemet (2012), among others.

several boom-bust cycles on account of the pattern of repeated expiration and short-term renewal of the PTC (Barradale, 2010).

Periods of actual or anticipated unavailability of the PTC tend to result in significant labor force turnover—one of the most recognized explanations in the literature for organizational forgetting.[14] Related to the depreciation over time, ρ_{own} captures a depreciation of experience over distance, equaling the discounted value of experience obtained from a project greater than 100 miles away from i's location. This feature is intended to capture any extra relevance prior work in a local area may have toward a particular project, such as a connection to local contractors or a better understanding of the local physical and business environment.

Approximately ten percent of all wind power projects completed in the United States through 2015 were undertaken as joint ventures between two or more firms; accordingly, the λ parameters in equation (1) allow a project's relative contribution to developer d's organic experience base to depend on the number of co-developers. No project in the sample has more than three co-developers, i.e. $|d_j| \in \{1, 2, 3\}$ for all $j \in J$. λ_1 is normalized to $= 1$ such that capacity completed by a single firm is the numeraire against measuring the capacity completed by joint ventures between two or three firms. This specification allows testing hypotheses about the manner in which firms share experience. For instance, if $\lambda_2 = \lambda_3 = 1$, each partner in a joint venture is credited with having installed the total capacity of the project; alternatively, if $\lambda_2 = 1/2$ and $\lambda_3 = 1/3$, each partner is credited with having installed an equal proportion of the project's total capacity.

In addition to growing their experience bases organically as described by equation (1), it seems plausible that firms can accumulate experience by purchasing competitors. Table 2 reports eleven major acquisitions in the U.S. wind development business through 2015; notably, nine of these acquisitions involved the purchase of an experienced incumbent by an inexperienced entrant.[15] We might therefore define firm d's *acquired* experience at time t relevant to project i as follows:

$$Q^A_{l_i,d,t} = \mu \cdot \sum_{d' \in a(d,t)} Q^O_{l_i,d',t} \tag{3}$$

where $a(d, t)$ is the set of all firms acquired by d as of time t. Organic experience transfers from d' to d—that is, from first to second owner—at rate μ. If $\mu = 1$, for instance, then acquired experience is a perfect substitute for a firm's own organic experience. Table 2, however, shows two instances in which an acquiring firm later found itself the target of an acquisition (Enron in 2002 and PPM in 2007). Accordingly, equation (3) is generalized to allow for the possibility that experience can change owners twice:

$$Q^A_{l_i,d,t} = \mu \cdot \sum_{d' \in a(d,t)} \left(Q^O_{l_i,d',t} + \mu \cdot \sum_{d'' \in a(d',t)} Q^O_{l_i,d'',t} \right) \tag{4}$$

[14]Leading up to the scheduled expiration of the PTC on Dec. 31, 2012, the New York Times ran headlines such as "An Expiring Tax Credit Threatens the Wind Power Industry" (Sept. 13, 2012), and "Tax Credit in Doubt, Wind Power Industry Is Withering" (Sept. 20, 2012). The PTC was ultimately extended, however, as part of the Jan. 1, 2013 federal legislation to avert the so-called "fiscal cliff".

[15]According to a Nov. 1, 2008 article in Windpower Monthly magazine, new entrants to the U.S. wind development business may need six or more months to get their bearings; acquiring an incumbent could be a means of short-circuiting this process. Indeed, an executive at one of the acquiring firms listed in table 2 explained to us that the target firm's experience in the U.S. wind development business was an important motivation behind the acquisition.

Table 2: Major acquisitions in the U.S. wind development business

Date	Acquired Firm	Acquiring Firm	Acquisition Marks Entry
1997:Q1	Zond	Enron	Yes
2002:Q2	Enron	GE	Yes
2003:Q1	Navitas	Gamesa	No
2005:Q1	Atlantic	PPM	No
2005:Q1	SeaWest	AES	Yes
2006:Q1	PacifiCorp	MidAmerican	Yes
2006:Q3	Padoma	NRG	Yes
2006:Q4	Orion	BP	Yes
2007:Q2	PPM	Iberdrola	Yes
2008:Q3	Catamount	Duke	Yes
2014:Q4	SunEdison	First	Yes

In equation (4), organic experience transfers from d'' to d—that is, from first to third owner—at rate μ^2.

Firm d's total accumulated experience at time t relevant to project i is just the sum of its organic experience and its acquired experience:

$$Q_{l_i,d,t} = Q^O_{l_i,d,t} + Q^A_{l_i,d,t} \tag{5}$$

Then, for a given wind power project i, an adjustment for the amount of developers on the project is required. The stock of accumulated experience that is *internal* to developer(s) d_i at the time of the project's undertaking, t_i, is:

$$Q_{l_i,d_i,t_i}\left(\delta_{own},\rho_{own},\lambda_2,\lambda_3,\mu\right) = \lambda_{|d_i|}\cdot\sum_{d\in d_i} Q_{l_i,d,t_i} \tag{6}$$

where Q_{l_i,d_i,t_i} is dependent on the parameters δ_{own}, ρ_{own}, λ_2, λ_3, and μ. Notice that if project i has just one developer (i.e. $|d_i| = 1$) then (6) reduces to (5). If, on the other hand, project i is a joint venture between two or three developers (i.e. $|d_i| > 1$) then the interpretation of (6) hinges on the λ parameters. If $\lambda_{|d_i|} = 1$ then Q_{d_i,t_i} is the sum of the joint venture partners' individual experience bases, as given by (5); alternatively, if $\lambda_{|d_i|} = 1/|d_i|$ then Q_{d_i,t_i} is the mean of the partners' individual experience bases.

Finally, for a given project i, the stock of accumulated experience that is *external* to developer(s) d_i at time t_i is:

$$Q_{l_i,-d_i,t_i}\left(\delta_{oth},\rho_{oth}\right) = \sum_{j\in J} q_j\cdot M^{'}_{i,j}\cdot\mathbf{1}\left\{d_j\cap d_i=\emptyset\right\}\cdot\mathbf{1}\left\{t_j<t_i\right\}\cdot\mathbf{1}\left\{d_j\cap a\left(d,t_i\right)=\emptyset\ \forall d\in d_i\right\} \tag{7}$$

where $M^{'}_{i,j}$ is a multiplier that depreciates the experience gained from project j depending on its applicability to project i. The indicator functions ensure experience is only counted for projects completed before the current project and that did not include any firm in d_i (or a firm later acquired by these firms). $M'_{i,j}$ takes the form:

$$M'_{i,j} = \sum_{j \in J} (1-\delta_{oth})^{t-t_j-1} \cdot (1 - \rho_{oth}.\mathbf{1}\{dist(l_i, l_j) > 100\}) \tag{8}$$

Via this multiplier, $Q_{l_i,-d_i,t_i}$ is dependent on the parameters δ_{oth} and ρ_{oth} that depreciate experience over time and distance.

For concreteness, appendix A5 presents simple numerical examples of the computation of variables Q_{l_i,d_i,t_i} and $Q_{l_i,-d_i,t_i}$ for cases that include joint ventures and acquisitions.

4.2 Technology and behavior

The production function for installed wind generating capacity is assumed to be Cobb-Douglas:

$$q_i = f(z, A_{l_i,d_i,t_i}) = A_{l_i,d_i,t_i} \prod_{h=1}^{N_Z} z_h^{\alpha_h} \tag{9}$$

where z contains factor inputs K_i, L_i, E_i, and M_i which are, the quantities of capital, labor, energy, and materials used in installing project i, and A_{l_i,d_i,t_i} is total factor productivity of the developer(s) of project i at the time of the project's undertaking. Given the Cobb-Douglas functional form, $\gamma = \sum_{h=1}^{N_Z} \alpha_h$ measures returns to scale in the design and construction of wind power projects. Further, assume the following functional form for total factor productivity:[16]

$$\begin{aligned} A_{l_i,d_i,t_i} =& [Q_{l_i,d_i,t_i}(\delta_{own}, \rho_{own}, \lambda_2, \lambda_3, \mu)]^{\beta} [Q_{l_i,-d_i,t_i}(\delta_{oth}, \rho_{oth})]^{\theta} \cdot \\ & exp\left(\phi_{T_i}^{TFP} + \psi_{S_i}^{TFP} + \frac{1}{|d_i|} \sum_{d \in d_i} \kappa_d^{TFP} + \pi_{m_i}^{TFP} + \epsilon_i^{TFP} \right) \end{aligned} \tag{10}$$

In equation (10), the parameter β measures the extent to which productivity is enhanced by the stock of accumulated experience that is internal to developer(s) d_i (i.e. learning-by-doing), whereas the parameter θ measures the extent to which productivity is enhanced by the stock of accumulated experience that is external to d_i (i.e. knowledge spillovers). A fixed effect for the year in which project i was completed provides a means of controlling for technological advancements that, while exogenous to U.S. wind power developers, might nonetheless affect the costs of designing and building wind power projects. Likewise, a fixed effect for the state in which project i is situated provides a means of controlling for different policy environments that, all other things being equal, make the designing and building of wind power projects more costly in some states than in others.[17] Fixed effects for the developers constructing project i (weighted by the number of developers on the project) $\frac{1}{|d_i|} \sum_{d \in d_i} \kappa_d^{TFP}$ controls for any permanent, firm-level cost advantages in the designing and

[16]Equation (10) is based on Irwin and Klenow (1994), who use a similar specification in their study of learning-by-doing and knowledge spillovers in the semiconductor industry. The key differences are: (i) the experience variables in equation (10) are functions of unknown parameters (δ, ρ, λ_2, λ_3, and μ); and (ii) equation (10) includes deterministic terms (year, state, firm and manufacturer fixed effects) in addition to a stochastic term.

[17]Wiser and Bolinger (2012) present evidence that average wind power project costs in the United States vary by region. In particular, states in the interior of the country—the so-called "Wind Belt"—tend to have the lowest costs, whereas states in New England tend to have the highest costs.

Table 3: Assumed temporal and geographical variation in input prices

Input	Price	Description
Capital	$p_{K_i} = \phi^K_{T_i} + p_{C,T_i,r_i}$	Completion-year FE, crane rental prices
Labor	$p_{L_i} = p_{L,t_i,s_i}$	Average construction wage in quarter t_i in state s_i
Energy	$p_{E_i} = p_{E,t_i,s_i}$	Average refined gasoline price in quarter t_i in state s_i
Materials	$p_{M_i} = \phi^M_{T_i} + \psi^M_{s_i} + \pi^M_{m_i}$	Completion-year, state and manufacturer FE

building of wind power projects. Turbine manufacturer fixed effects $\pi^{TFP}_{m_i}$ allow for the design aspects of different turbine brands to allow for differential productivity multipliers. Finally, total factor productivity depends on a mean-zero, project-specific productivity shock, ϵ^{TFP}_i, the realization of which is observed by developer(s) d_i once work on project i is underway, but unobserved by the econometrician.

Our model assumes profit-maximizing wind power developers that minimize the total cost of completing wind power projects of predetermined capacities given prevailing input prices. Virtually all of the firms in the U.S. wind development business are publicly traded and, as such, have fiduciary obligations to maximize returns to their shareholders. Because virtually all projects are financed through power purchase agreements (PPAs) that set the project's future revenue stream independent of its construction cost, this logic implies a profit-maximizing developer would like to minimize the cost of building the project.[18] It also seems probable that other firms in the business will have to minimize costs in order to compete with the publicly-traded firms.

In the United States, developers generally build wind power projects to the specifications of other entities, typically the ultimate owner or operator of the project. Consequently, the sizes of U.S. wind power projects can be thought of as predetermined to the developers that build them. Finally, the prices of the inputs to the production function (9) are set in large markets in which wind power developers are relatively small actors. As such, these prices can be taken as exogenous to the input choice decisions of individual developers. Altogether, these assumptions lead to the following cost minimization problem for each wind power project i:

$$\begin{aligned} &\min_z z.p_i \text{ s.t } q_i \leq f(z, A_{l_i,d_i,t_i}) \\ \Rightarrow C(q_i, A_{d_i,t_i,S_i}) &= \kappa(\alpha) \left(\frac{q_i}{A_{d_i,t_i,S_i}} \prod_{h=1}^{N_Z} p_{h,r_i}^{\alpha_h} \right)^{\frac{1}{\gamma}} \end{aligned} \tag{11}$$

Where $\gamma = \sum_{h=1}^{N_Z} \alpha_h$.

[18] Renewable PPAs typically pay a fixed price per KWh of energy produced by the project over the life of the agreement.

Table 3 summarizes the assumptions made about temporal and geographical variation in input prices for purposes of solving the cost minimization problem (11). The prices of capital are assumed to vary only over time. This variation is captured with regional crane rental prices and completion-year fixed effects, sourced from the annual volumes of RSMeans building construction cost data.[19] Variation in materials prices across projects are captured in completion-year and state fixed effects. Labor and energy prices are assumed to vary by year and by state, with construction wage data sourced from the U.S. Bureau of Labor Statistics (BLS) and refined gasoline spot price data sourced from the U.S. Energy Information Administration (EIA).

Under the stated assumptions concerning variation in input prices, the solution to (11) yields the following econometric model:

$$\begin{aligned} logC_i =& \frac{\alpha_C}{\gamma} logp_{C,T_i,r_i} + \frac{\alpha_L}{\gamma} logp_{L,t_i,s_i} + \frac{\alpha_E}{\gamma} logp_{E,t_i,s_i} \\ &+ \frac{1}{\gamma} q_i - \frac{\beta}{\gamma} Q_{d_i,t_i}(\delta_{own}, \rho_{own}, \lambda_2, \lambda_3, \mu) - \frac{\theta}{\gamma} Q_{-d_i,t_i}(\delta_{oth}, \rho_{oth}) \\ &+ \phi_{T_i} + \psi_{S_i} + \frac{1}{|d_i|} \sum_{d \in d_i} \kappa_d + \pi_{m_i} + \epsilon_i \end{aligned} \tag{12}$$

The fixed effects ϕ_{T_i}, ψ_{s_i} and π_{m_i} in equation (12) now reflect both variation in input prices and (exogenous) variation in total factor productivity. Consequently, it is not possible to separately identify the effects on project costs of certain input prices, exogenous technical progress, and time-invariant state characteristics. More importantly for purposes of this paper, it is possible to identify from equation (12) firm-specific learning-by-doing, inter-firm knowledge spillovers, the rate at which experience depreciates, the transmission of experience over geographic distance and the degrees to which experience is shareable and transferable while *controlling* for the effects on cost of changing input prices, project scale, and technical progress exogenous to wind power developers. The goal of the next section is to estimate the parameters of equation (12).

5 Estimation

5.1 Estimation strategy

The assumption that capacity q_i is predetermined when developer(s) d_i undertakes project i means q_i and ϵ_i are uncorrelated in the cost function (12), such that the parameters in (12) are consistently estimated by a least squares estimation procedure. This assumption is in keeping with the manner in which most wind power projects are completed in the United States. Before construction of a wind power project begins, the project's owner (an IPP, for instance) typically negotiates a long-term, fixed-price power purchase agreement (PPA) with an electricity retailer; the revenue stream guaranteed by this PPA allows the owner to secure financing for the project from a commercial

[19] Each project is matched to a city in the RSMeans construction cost data. The Monthly tower crane rental static tower 130' high 106' jib 6300 pound capacity cost is multiplied by the city's multiplier for the year before the project was completed.

or investment bank.[20] The owner then hires a wind power developer to design and construct the project with sufficient generating capacity for the owner to meet its contractual obligations to the retailer. In preparation for construction of the project, orders are placed for the necessary wind turbines and their attendant equipment. The revelation at this point that the project will be either more or less costly to complete than anticipated has no bearing on the quantity of capacity the developer must install: the owner still requires the previously decided-upon quantity of capacity to fulfill its PPA obligations, and it may be costly to the developer to cancel or alter an outstanding order for wind turbines. So, the productivity shock ϵ_i affects the completion costs of project i, and hence the profits of developer(s) d_i, but does not affect the capacity q_i of project i, i.e. q_i and ϵ_i are uncorrelated in equation (12).

The explicit mechanism by which a given wind power project i is "assigned" to developer(s) d_i is not modeled, rather, it is implicitly assumed that the set d_i is determined exogenously. One could argue, therefore, that it is not the case that a firm has low costs because it has accumulated experience—the relationship posited by the cost function (12)—but instead that a firm has accumulated experience precisely because it has low costs (for reasons that the econometrician does not observe). However, as outlined in appendix A3 (as part of a broader investigation of heterogeneity among U.S. wind power developers), the evidence is not indicative of any low-cost firm or firms capturing more and more of the U.S. wind development business over time.

In the following section, a nonlinear least squares (NLS) procedure is used to estimate the parameters of the cost function (12). Write equation (12) compactly as follows:

$$\log C_i = h\left(\mathbf{x}_i, \boldsymbol{\xi}\right) + \epsilon_i \tag{13}$$

where $\boldsymbol{\xi} = \left(\alpha_C, \alpha_L, \alpha_G, \gamma, \beta, \theta, \delta_{own}, \delta_{oth}, \rho_{own}, \rho_{oth}, \lambda_2, \lambda_3, \mu, \boldsymbol{\phi}', \boldsymbol{\psi}', \boldsymbol{\kappa}', \boldsymbol{\pi}'\right)'$ is the vector of parameters — including 13 year, 30 state, 130 firm and 18 turbine manufacturer fixed effects — to be jointly estimated and $\mathbf{x}_i$ is the data used to construct the i^{th} observation. $\widehat{\boldsymbol{\xi}}$ is the value of $\boldsymbol{\xi}$ that minimizes the sum of the squared residuals:

$$\mathrm{SSR}\left(\boldsymbol{\xi}\right) = \sum_{i=1}^{N} \left[\log C_i - h\left(\mathbf{x}_i, \boldsymbol{\xi}\right)\right]^2 \tag{14}$$

Given that the gradient $\partial \mathrm{SSR}\left(\boldsymbol{\xi}\right)/\partial \boldsymbol{\xi}'$ can be computed analytically, a quasi-Newton algorithm is used to search for a solution to the above minimization problem, subject to fixed bounds on the parameters.[21]

Let $\widehat{\mathbf{X}}$ be the matrix with i^{th} row $\partial h\left(\mathbf{x}_i, \widehat{\boldsymbol{\xi}}\right)/\partial \boldsymbol{\xi}'$. A heteroskedasticity-consistent estimate of the covariance matrix of $\widehat{\boldsymbol{\xi}}$ is used in inference and is defined as:[22]

$$\mathrm{Var}\left(\widehat{\boldsymbol{\xi}}\right) = \left(\widehat{\mathbf{X}}'\widehat{\mathbf{X}}\right)^{-1} \widehat{\mathbf{X}}' \,\widehat{\boldsymbol{\Omega}}\, \widehat{\mathbf{X}} \left(\widehat{\mathbf{X}}'\widehat{\mathbf{X}}\right)^{-1} \tag{15}$$

[20] Barradale (2010), for instance, shows that long-term PPAs were the dominant offtake arrangement for U.S. wind power projects completed in the 2000s.

[21] Economically sensible restrictions are put on the parameters, such as depreciation rates being bounded between zero and one.

[22] See, for instance, chapter 16 of Davidson and MacKinnon (1993).

where

$$\widehat{\mathbf{\Omega}} = \operatorname{diag}\left(\widehat{\omega}_1, \ldots, \widehat{\omega}_N\right) \tag{16}$$

and

$$\widehat{\omega}_i = \frac{N}{N-k}\left[\log C_i - h\left(\mathbf{x}_i, \widehat{\boldsymbol{\xi}}\right)\right]^2 \tag{17}$$

N is the number of observations on equation (13), and k is the number of parameters estimated (i.e. $k = \dim(\boldsymbol{\xi})$).

5.2 Estimation results

Table 4 presents the results of NLS estimation of the cost function (12) for the case where megawatts of installed wind generating capacity is the measure of cumulative output (measure 1); table 5 does likewise for the case where number of installed wind power projects is the measure of cumulative output (measure 2). For each of experience measure 1 and 2, six models are estimated. We report these 12 specifications to examine if under any parameter restrictions we can identify evidence consistent with learning-based spillovers. The first three model variants do not allow depreciation rates for own-firm and other-firm projects to differ ($\delta_{own} = \delta_{oth}$). Model I further restricts the parameters by not allowing project distances to enter the model ($\rho = 0$), model II does not allow distance multipliers to differ for own- and other- firm projects ($\rho_{own} = \rho_{oth}$), whereas model III does not impose this restriction. Models IV-VI follow models I-III, with the restriction that ($\delta_{own} = \delta_{oth}$) relaxed. Model VI is the unconstrained model detailed in section 4. The price and scale estimates will be discussed briefly before a more in depth discussion of the experience function and multiplier results.

5.2.1 Price and scale estimates

Point estimates of the scale parameter γ range from 0.991 to 0.996, suggesting there are small diseconomies of scale in the construction of wind generating capacity in the United States. For all model variants, however, the hypothesis $\gamma = 1$, constant returns to scale, cannot be rejected. Similarly, Wiser and Bolinger (2012) present evidence of weak returns to scale among small U.S. wind power projects (i.e. less than 20 MW) and constant returns to scale among larger projects.

Estimates for the input price coefficients α, i.e. the parameters in the Cobb-Douglas production function (9) associated with those inputs whose prices are explicitly modeled in (12), are not detected to enter the model.[23] Although we expect project costs to vary with these input prices, it may be that the model has difficulty identifying such relationships due to the inclusion of the year, state, firm and turbine manufacturer fixed effects. Joint tests under the null that each set of fixed effects do not enter each model are rejected at a 5% level of significance.

[23] In the canonical Cobb-Douglas production function $f = \prod_i x_i^{\alpha_i}$, the fraction $\alpha_i / \sum_j \alpha_j$ has the interpretation of the share of total production costs that are attributable to input x_i. This interpretation does not hold in the present setting because of the use of fixed effects in equation (12) to model variation in the prices of certain inputs.

Table 4: NLS estimation results for cost function (12) (output measure 1: megawatts of installed capacity)

		I	II	III	IV	V	VI
Crane rental price	α_C	0.045	0.042	0.039	-0.002	-0.005	0.000
		(0.089)	(0.091)	(0.090)	(0.084)	(0.085)	(0.084)
Labor price	α_L	0.050	0.072	0.069	0.087	0.074	0.076
		(0.172)	(0.182)	(0.181)	(0.175)	(0.178)	(0.177)
Gasoline price	α_G	-0.019	-0.008	-0.011	-0.030	-0.012	-0.032
		(0.080)	(0.080)	(0.080)	(0.078)	(0.079)	(0.078)
Scale	γ	0.993	0.992	0.992	0.995	0.991	0.993
		(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.019)
Own experience multiplier	β	0.021	0.024	0.023	0.019	0.024	0.019
		(0.009)	(0.011)	(0.011)	(0.009)	(0.010)	(0.009)
Other experience multiplier	θ	0.088	0.117	0.111	0.030	0.028	0.033
		(0.074)	(0.104)	(0.096)	(0.018)	(0.017)	(0.018)
Depreciation	δ	0.418	0.318	0.339			
		(0.211)	(0.190)	(0.196)			
Depreciation (own exp.)	δ_{own}				0.470	0.162	0.458
					(0.263)	(0.214)	(0.262)
Depreciation (other exp.)	δ_{oth}				1.000	1.000	1.000
					(.)	(.)	(.)
Distance multiplier	ρ		0.684			0.925	
			(0.29)			(0.092)	
Distance multiplier (own exp.)	ρ_{own}			0.488			0.000
				(1.106)			(.)
Distance multiplier (other exp.)	ρ_{oth}			0.707			0.839
				(0.311)			(0.283)
2-firm multiplier	λ_2	0.500	0.500	0.500	0.500	0.500	0.500
3-firm multiplier	λ_3	0.333	0.333	0.333	0.333	0.333	0.333
Merger multiplier	μ	1.000	1.000	1.000	1.000	1.000	1.000

Each model contains year, state, firm and manufacturer fixed effects. Each model has 408 projects used in estimation. Models I and IV fix $\rho = 0$. When standard errors are not reported, a corner solution was obtained, and the standard errors for the remaining coefficients are constructed assuming that the corner solution coefficient is a fixed constant. Heteroskedasticity-consistent standard errors are reported in parentheses.

Table 5: NLS estimation results for cost function (12) (output measure 2: number of installed projects)

		I	II	III	IV	V	VI
Crane rental price	α_C	0.099	0.100	0.103	0.087	0.104	0.116
		(0.104)	(0.105)	(0.103)	(0.105)	(0.107)	(0.103)
Labor price	α_L	-0.077	-0.132	-0.104	-0.096	-0.138	-0.157
		(0.196)	(0.207)	(0.202)	(0.205)	(0.209)	(0.203)
Gasoline price	α_G	-0.057	-0.066	-0.058	-0.074	-0.063	-0.079
		(0.083)	(0.081)	(0.082)	(0.081)	(0.082)	(0.081)
Scale	γ	0.995	0.993	0.994	0.996	0.995	0.996
		(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Own experience multiplier	β	0.062	0.035	0.058	0.062	0.076	0.063
		(0.040)	(0.069)	(0.040)	(0.038)	(0.053)	(0.039)
Other experience multiplier	θ	0.177	0.115	0.209	0.091	0.125	0.136
		(0.133)	(0.063)	(0.135)	(0.052)	(0.066)	(0.071)
Depreciation	δ	0.432	0.876	0.433			
		(0.196)	(0.339)	(0.206)			
Depreciation (own exp.)	δ_{own}				0.250	0.130	0.234
					(0.240)	(0.196)	(0.230)
Depreciation (other exp.)	δ_{oth}				0.941	0.856	0.821
					(0.321)	(0.341)	(0.342)
Distance multiplier	ρ		0.649			0.656	
			(0.336)			(0.253)	
Distance multiplier (own exp.)	ρ_{own}			0.000			0.000
				(.)			(.)
Distance multiplier (other exp.)	ρ_{oth}			0.707			0.699
				(0.221)			(0.250)
2-firm multiplier	λ_2	0.500	0.500	0.500	0.500	0.500	0.500
3-firm multiplier	λ_3	0.333	0.333	0.333	0.333	0.333	0.333
Merger multiplier	μ	1.000	1.000	1.000	1.000	1.000	1.000

Each model contains year, state, firm and manufacturer fixed effects. Each model has 408 projects used in estimation. Models I and IV fix $\rho = 0$. When standard errors are not reported, a corner solution was obtained, and the standard errors for the remaining coefficients are constructed assuming that the corner solution coefficient is a fixed constant. Heteroskedasticity-consistent standard errors are reported in parentheses.

5.2.2 Internal and external experience multiplier estimates

No solution to the model could be identified when allowing the joint-venture and acquisition parameters $(\lambda_2, \lambda_3, \mu)$ to be freely estimated. An earlier version of this paper using data up to 2009 failed to reject tests that $(\lambda_2, \lambda_3, \mu) = (\frac{1}{2}, \frac{1}{3}, 1)$, implying that there are no scale benefits from joint ventures or mergers.[24] Therefore, each model is estimated with this restriction. Lagrange multiplier tests of the models estimated with these restrictions fail to reject the assertion that $(\lambda_2, \lambda_3, \mu) = (\frac{1}{2}, \frac{1}{3}, 1)$.[25] Therefore, there is no statistical evidence against the null hypothesis that experience is averaged over the firms in a joint venture.

Point estimates of β (relating to a firm's internal experience) are positive and precisely estimated for the model using the cumulative MW measure of experience. Point estimates of θ (relating to external experience), on the other hand, are imprecisely estimated and it can not be rejected that $\theta = 0$ for tests at a 5% level of significance for any model or experience measure. Thus, the evidence is consistent with firm-specific learning-by-doing, but we find no evidence to support the presence of inter-firm knowledge spillovers.[26] Note that from equation (12) that the elasticity of cost with respect to firm-specific experience is $-\beta/\gamma$. Estimates of this elasticity range from -0.019 to -0.024 in the case of the cumulative MW experience. All other things equal, then, doubling a firm's experience base decreases its per-megawatt costs of installed wind generating capacity by 1.3-1.6 percent.[27] The most optimistic point estimate for knowledge spillovers is in table 4 model II, where doubling the experience stock of other firms is predicted to lower its per-megawatt costs of installed wind generating capacity by 8.5 percent. However, in practice, given the much larger stock of other firm experience relative to own firm experience, the predicted cost multiplier reductions from adding an additional project are mostly localized to the firm undergoing the project. Using the estimates from model II, figure 3 displays the change in the cost multiplier from adding 50MW of depreciated experience to either the own- or other- firm experience measures, $Q_{d_i,t_i}(\delta, \rho, \lambda_2, \lambda_3, \mu)$ and $Q_{-d_i,t_i}(\delta, \rho)$ for every project used in the analysis. Here we see that for firms with limited within-firm experience, an additional 50MW of within-firm experience is predicted to drop their project costs by up to 9 percent. However, the impact of adding the same 50MW of experience to the stock of other-firm experience does not reduce costs by any economically meaningful amount, particularly post-2006.

Our estimation method has attempted to address the critique of many prior attempts to estimate industry cost reductions from accumulated experience that experience is correlated with time and common measures of industry experience can confound other time varying trends. The inclusion of input cost drivers and year-of-sample effects means that the measure of external experience $(Q_{l_i,-d_i,t_i})$ is

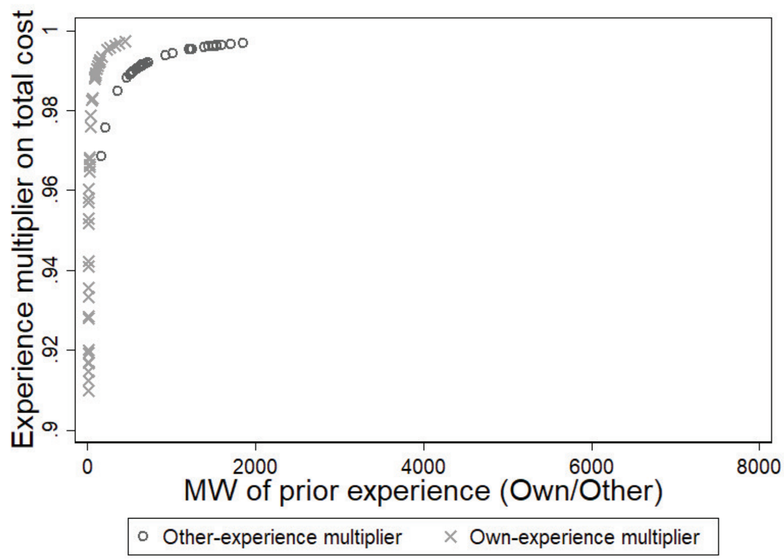
[24]See Anderson (2013). The model estimated in that paper did not include firm and manufacturer fixed effects and did not allow for parameters in the experience function to vary between own- and other-firm experience.

[25]In the notation from the previous section, the moment conditions for the full model (VI) are evaluated at the restricted model estimates to form $L = \tilde{X}\tilde{\epsilon}$. $N.L'.V^{-1}.L \sim \chi^2_3$ under the null that $(\lambda_2, \lambda_3, \mu) = (\frac{1}{2}, \frac{1}{3}, 1)$. Estimating V as either the variance of the moments (S), the numerical derivative of the moments (H, the Hessian of the objective function) or $HS^{-1}H$ returns score statistics of 0.09, 0.2 and 1.8, less than the 5% critical value of 7.82.

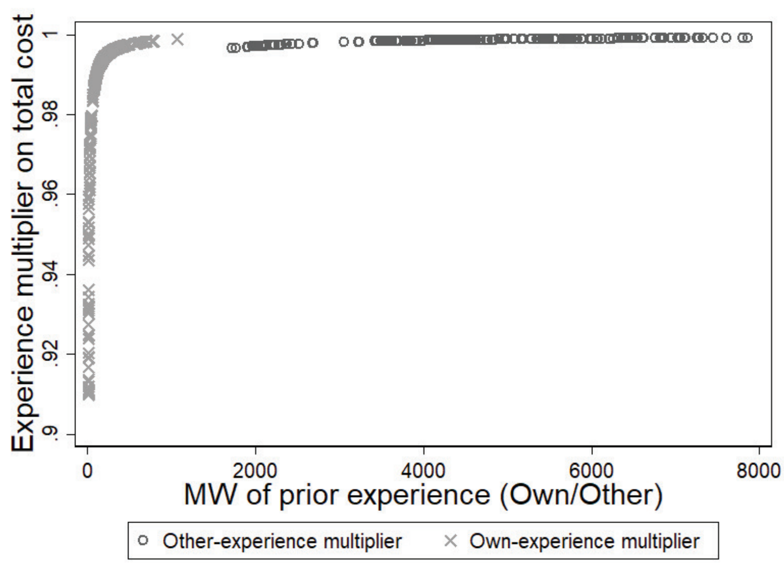
[26]This adds to the mixed evidence found in other studies of knowledge spillovers in electricity generation technologies: Joskow and Rose (1985) and Pillai (2015) do not find evidence of spillovers in the construction of coal power plants or solar panels, while Nemet (2012) and Zimmerman (1982) do find evidence of spillovers in the operation of wind power plants and the construction of nuclear power plants, respectively.

[27]The percentage change in per-megawatt cost from doubling a firm's experience base is $100 \times \left(2^{-\beta/\gamma} - 1\right)$.

Figure 3: Cost function multiplier from adding 50MW of experience



(a) Projects completed 2002-2006



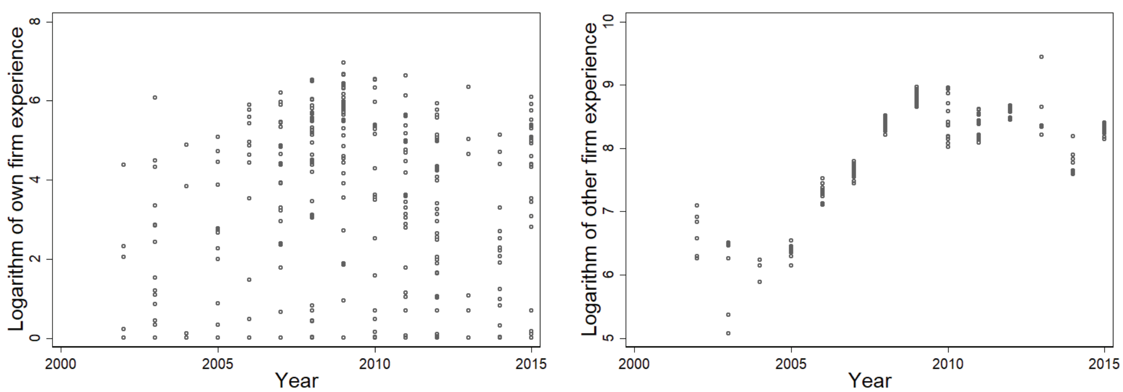
(b) Projects completed 2007-2015

Figures plot the predicted cost multiplier from of adding 50MW of experience to either own- or other firm experience. The scatter plot for own firm experience plots $\frac{(Q_{d_i,t_i}(\delta,\rho,\lambda_2,\lambda_3,\mu)+50)^{\beta}}{Q_{d_i,t_i}(\delta,\rho,\lambda_2,\lambda_3,\mu)^{\beta}}$ against $Q_{d_i,t_i}(\delta,\rho,\lambda_2,\lambda_3,\mu)$. The scatter plot for other firm experience plots $\frac{(Q_{-d_i,t_i}(\delta,\rho)+50)^{\beta}}{Q_{-d_i,t_i}(\delta,\rho)^{\beta}}$ against $Q_{-d_i,t_i}(\delta,\rho)$. All values calculated at parameter estimates reported in model II in table 4.

unlikely to be confounded with changes in input costs or Hicks neutral technical change. However, a practical consequence of controlling for these important cost drivers is the identifying variation of other firm experience stocks will diminish. In our case, variation in the measure of other firm experience that can identify knowledge spillovers must come from changes in the stock within a year (experience measures are re-calculated quarterly), across firms (more experienced firms have lower levels of other firm experience), and across locations (projects in locations close to where prior projects occurred will have greater other firm experience stocks than more isolated projects).

Figure 4 displays the estimated values of own- and other- experience stocks for every project in the sample. We see a large amount of variation in firm experience for all years of the sample due to the many firms that are observed to participate in the market. However, for other firm experience we also see substantial variation across projects, with the time path increasing from 2005-2009, and then the slowdown of completed projects in 2010 and the estimated depreciation rates of experience resulting in this stock flattening from 2010-2015.

Figure 4: Experience stocks for all projects included in sample, 2002-2015



(a) Own firm(s) experience on project

(b) Other firms' experience on project

Own firm experience plots the value of $log(Q_{d_i,t_i}(\delta, \rho, \lambda_2, \lambda_3, \mu))$ for each project i in the sample, and other firm experience plots the value of $log(Q_{-d_i,t_i}(\delta, \rho))$ using the parameter estimates of model II in table 4.

5.2.3 Time and distance depreciation experience multipliers

Point estimates for the rate of depreciation of experience are in general quite large, and less precise for the models with less parameter restrictions. In model I of the MW experience measure, fixing distance multipliers to zero and imposing that depreciation factors for own- and other- firm experience equal detects a non-zero discount rate with a point estimate of 0.418. This translates to just 11 percent of a firm's accumulated experience persisting after one full year of inactivity. For comparison, estimates elsewhere in the literature of the percentage of experience that persists after one year include: 51-61 percent in aircraft manufacturing (Benkard, 2000), 40 percent in oil drilling (Kellogg, 2011), 5-65 percent in shipbuilding (Argote et al., 1990; Thompson, 2007), and 3 percent in wind power production (Nemet, 2012). When allowing the separation of depreciation rates for own- and other- firm experience, the model does not identify an interior solution for other- firm experience, estimating full depreciation after one quarter. This further highlights that even if external knowledge spillovers occurred, they are not found to persist. The apparent speed with which wind power developers' experience depreciates is perhaps surprising; it is understandable, however, if one appreciates how disruptive the unpredictability of the PTC has been to the U.S. wind energy industry. Although employment data are not readily available, there is little disagreement among industry observers that actual or anticipated unavailability of the PTC renders many wind power projects unprofitable and leads to labor force downsizing at all levels of the industry — project development included.[28] Wind power developers employ engineers, lawyers, scientists, logisticians, and transportation and construction supervisors, all of whom develop knowledge over time that is specialized (to some extent or another) to the wind power industry (Hamilton and Liming, 2010). Consequently, if developers cannot make long-term commitments to their workers (e.g. because of PTC uncertainty), then specialized knowledge will be lost during industry downturns and replaced only slowly during industry upturns.[29]

Point estimates of ρ, the discount applied to the experience gained from distant projects, is detected to be non-zero under some specifications of the experience function. In model II of the MW experience model, previous projects built more than 100 miles away from a site are estimated to have 68.4 percent less experience value than an equivalent project within 100 miles of the site. However, when allowing this multiplier to differ for own- and other- firm projects, distance is found to have no impact on experience from internal projects but to reduce experience from external projects. Therefore, the estimates are consistent with firms gaining equal experience for all projects regardless of location, but that only local projects from competitor firms could possibly enter their experience stock, and even then the cost multiplier might not be affected given the values of θ estimated in the model. Ultimately, the time and depreciation results reinforces that any cost-reducing knowledge arising from the design and construction of wind power projects, slight as it may be, appear to remain entirely within the firm.

The depreciation and distance multiplier findings could in part explain why the largest U.S. wind power developers undertake new projects at fairly regular intervals. Table A2 in appendix A3 shows that from the 2005 to 2009 industry growth period where the model detects a large increase in the stock of industry experience, the average spell of inactivity among large developers lasted just two quarters; it is possible these developers seek to prevent or at least slow the erosion of competitive advantages stemming from their comparatively large experience bases. At the same time, however, the finding that experience depreciates rather quickly and over distance could explain why fringe developers are able to compete for business. See, for instance, the market share figures A9 and A10 in appendix A3.

6 Conclusion

If knowledge spillovers occur during the installation or operation of renewable generating capacity, then profit-maximizing firms will engage in these activities less than is socially desirable; public

[28] According to Wiser and Bolinger (2012), annual average wind power PPA prices ranged from about \$35/MWh to \$70/MWh over the 2001- 2009 period, which at the approximate PTC rate of \$22/MWh in 2009 suggests that the PTC accounted for about 24-39 percent of the average wind generator's total revenues ($\$22/(\$35 + \$22) = 0.39$; $\$22/(\$70 + \$22) = 0.24$).

[29] On this point that organizational forgetting in U.S. wind is reversed only slowly: an executive at a large wind power developer explained to us how difficult it has become for the industry to attract and retain talented workers. Evidently, potential workers regard their career prospects in this industry as uncertain because the fate of the PTC remains uncertain.

subsidies can overcome this market failure by compensating firms for the positive externalities their activities generate. For the particular case of the U.S. wind energy industry, however, we have found no empirical evidence of inter-firm knowledge spillovers in the design and construction of wind power projects. We have only found evidence of firm-specific learning-by-doing, which entails no externality. Thus, while federal and state policies like tax credits and renewable portfolio standards might accelerate reductions in wind power project costs, the empirical evidence presented in this paper suggests that cost reductions will occur even in the absence of government financial interventions.

We have presented evidence that experience accumulated by U.S. wind power developers depreciates over time and distance. This suggests that the boom/bust cycles in project development seen over the previous decade could result in higher incurred project costs than if a steady order book was maintained. Although our analysis does not speak to the exact mechanism behind experience depreciation, it could be that a stable industry trajectory decreases project costs insofar as it reduces labor force turnover and helps with retention of relevant institutional knowledge and experience. The empirical evidence presented here also suggests learning-related cost reductions might be achieved through greater consolidation in the U.S. wind development business. Such consolidation could be either temporary, as in the case of joint ventures, or permanent, as in the case of acquisitions. In the former, firms reap the full experience benefits of undertaking large or numerous projects without having to bear the full costs. In the latter, not only is existing experience consolidated in a single firm, but socially-wasteful, duplicative learning is potentially avoided in the future. Owing to the number of firms active in the U.S. wind development business, it seems unlikely that greater consolidation poses any significant threat to competition.

Finally, we have argued that the assumptions that give rise to our econometric model of firm behavior in the U.S. wind energy industry are consistent with the manners in which this industry is organized and operates. Importantly, the key empirical results in this paper are qualitatively, if not always quantitatively, robust to minor changes in these assumptions. Alternative assumptions concerning functional forms and the nature of uncertainty in the model are potential areas for future research. Likewise, it would be interesting to see if similar models can be derived (if the assumptions are plausible) and estimated (if data are available) for other technologies and countries. A better empirical understanding of the extent to which learning-by-doing is characteristic of renewable electricity generation technologies can help to ensure efficient use of public funds to support renewable energy.

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Appendix

A1 Further anecdotal evidence of learning-by-doing in U.S. wind

This appendix elaborates on the anecdotal evidence of learning-by-doing in the design and construction of U.S. wind power projects presented in section 2 with regard to: (i) transportation logistics; (ii) construction logistics; and (iii) induced wind turbine innovations.

The developers with whom we have spoken have all made clear that experience plays an important role in keeping transportation costs down. Completion of a wind power project can entail hundreds or even thousands of cargo loads delivered to the project site. Delivery of just a single wind turbine, for instance, can require up to eight oversize loads: one for the nacelle, three for the blades, and four for the tower sections. Developers have learned to schedule and route deliveries to make best use of existing roads without unduly disrupting local traffic patterns (due to road or bridge closures, for example). Moreover, they have learned to anticipate obstacles en route to a project site that could force the unloading and reloading of equipment or the complete rerouting of entire convoys of trucks. Consider the left-hand panel of figure A1: it was not left to chance that trucks hauling tower sections would ultimately fit across the bridge. Where unloading and reloading of equipment are unavoidable, however, as in the right-hand panel of figure A1, developers have learned how to do so quite effectively.

There is also anecdotal evidence that developer experience has lowered the construction costs of wind power projects. Wind turbine foundations, for instance, can require 20-40 tons of rebar and 250-450 cubic yards of concrete. See the left-hand panel of figure A2. Foundations can account for up to 16 percent of a project's capital costs (International Renewable Energy Agency (IRENA), 2012). Experienced developers have learned to adapt foundations to different turbine types and different ground and wind conditions so as to complete each foundation at low cost while (hopefully) avoiding the fate depicted in the right-hand panel of figure A2. Likewise, developers have learned how best to maneuver heavy equipment around a project site. For example, according to a contractor experienced in wind farm construction, the disassembling, transporting, and reassembling of a large crawler crane (e.g. the red cranes in figure A3) can take up to five days and cost as much as $70,000. Experienced developers therefore carefully sequence their construction activities so as to prevent or at least minimize such costly delays.

Finally, developers' experience designing and building wind power projects has also facilitated cost-reducing innovations upstream in the manufacturing of wind turbines. One example is the advent of modular tower sections, which as discussed in section 2 are cheaper not only to manufacture but also to transport and install. (According to IRENA (2012), towers make up about 17 percent of a wind power project's capital costs.) The left-hand panel of figure A1 shows a tower section in transit, while the left-hand panel of figure A3 shows tower sections being installed. A second example is rotors that can be assembled at ground level (left-hand panel of figure A3) and then lifted and installed in one piece (right-hand panel of figure A3).

Figure A1: Wind turbine transportation logistics

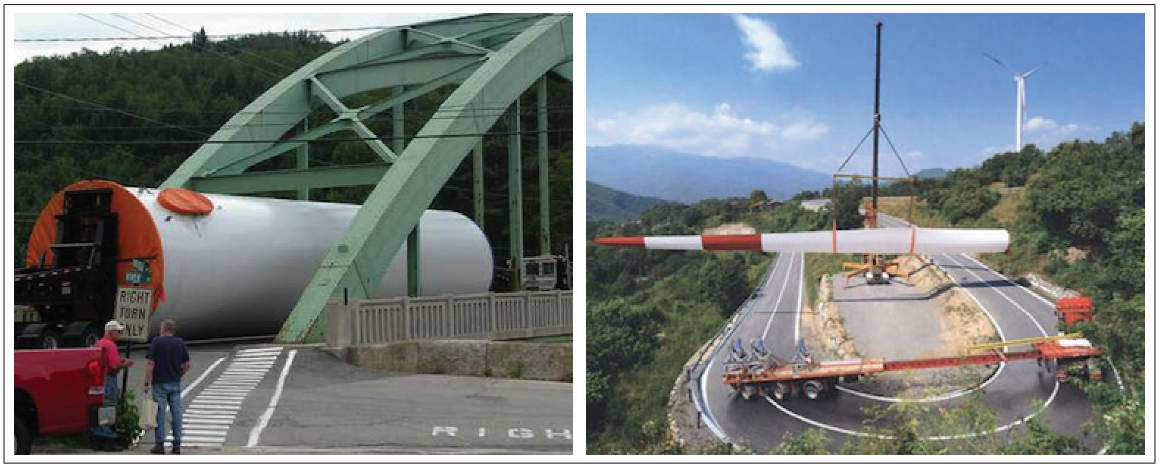


Figure A2: Wind turbine foundations (done right and done wrong)

Figure A3: Modular tower sections and ground-level rotor assembly

Figure A4: Antiquated vs. state-of-the-art wind turbine technology

A2 Annual summary statistics

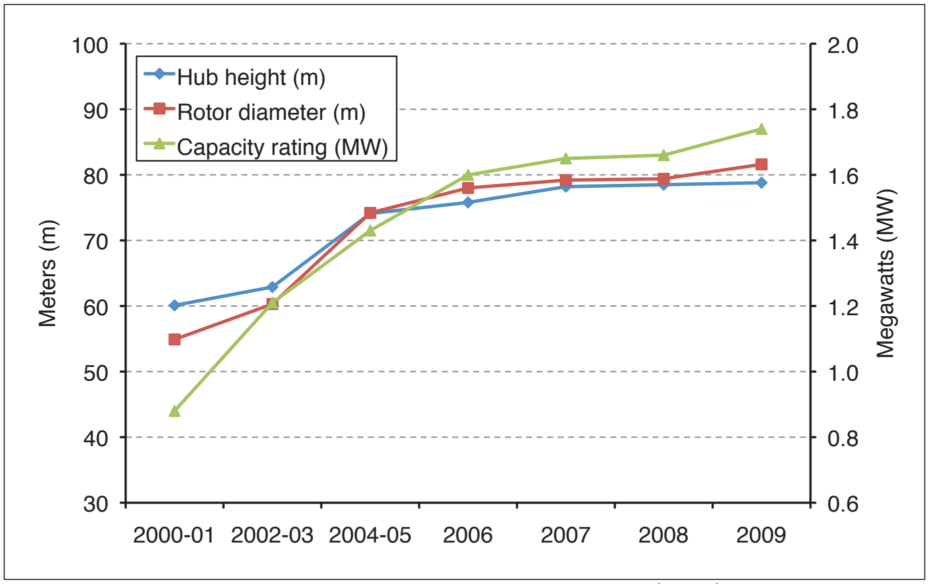
For the subset of 408 U.S. wind power projects completed from 2002 to 2015 and for which cost estimates are available, table A1 reports annual summary statistics for average cost of installed capacity (measured in millions of current-year dollars per megawatt) and nameplate generating capacity (measured in megawatts). As discussed elsewhere in this paper, average wind power project costs approximately doubled during the 2000s despite the completion of more and larger wind power projects than had ever previously been the case (i.e. despite potential for cost reductions due to learning-by-doing and economies of scale). Higher prices for primary inputs and the advent of larger wind turbines are two often-cited explanations for this period of rising costs (e.g. Bolinger and Wiser (2011)). Regarding the former, figure A6 plots four price indices for inputs important to the U.S. wind energy industry together with a GDP deflator; notably, all four price series increased at rates greater than the rate of overall inflation during the 2000s.[30] Regarding the latter, the hub height, rotor diameter, and capacity rating of the average wind turbine installed in the U.S. all increased significantly during the 2000s (see figures A4 and A5); larger turbines are generally more costly because they require disproportionately more materials to support their greater weight and withstand severe wind forces. Table A1 is also indicative of the importance of government intervention to the growth of the U.S. wind energy industry: fewer and smaller projects were completed in 2002 and 2004 when the PTC was unavailable to new projects, whereas more and larger projects were completed during the later years of the sample when the PTC was consistently available and many more states adopted RPSs.[31,32]

[30] The U.S. dollar-euro exchange rate is included because many wind turbine components are imported from Europe.

[31] Of the wind power projects completed in 2002 and 2004, some were ineligible for the PTC (e.g. those owned by rural electric cooperatives or municipal utilities), while others received the credit retroactively.

[32] According to the Database of State Incentives for Renewables and Efficiency (DSIRE), the total number of states to have adopted mandatory RPSs was 5 in 2001, 11 in 2005, and 26 in 2009.

Figure A5: Average U.S. wind turbine hub height, rotor diameter, and capacity rating

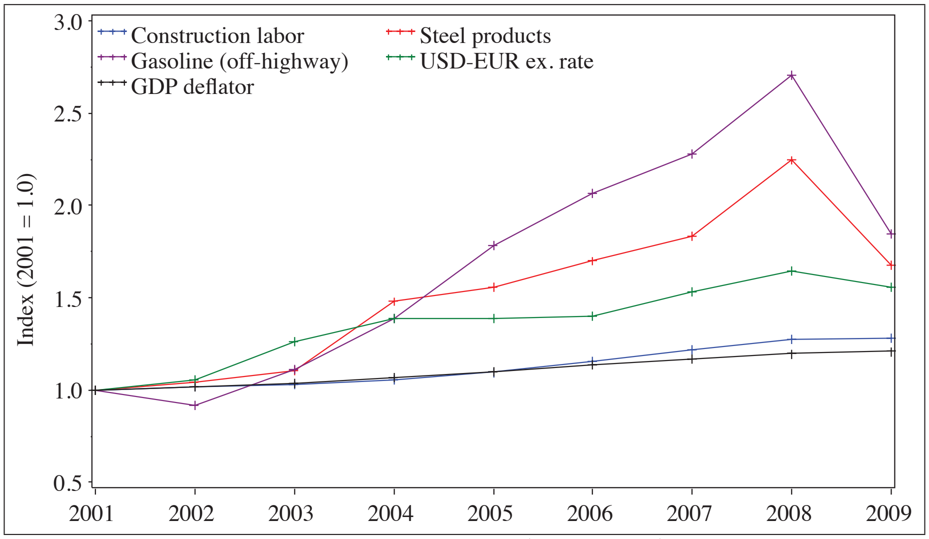


Source: Wiser and Bolinger (2010).

Table A1: Summary statistics, U.S. wind power project data, 2001-2009

		Average cost ($M/MW)			Capacity (MW)		
Year	Projects	Min	Med	Max	Min	Med	Max
2002	9	3.2	63.5	175	3.8	40.92	160.5
2003	19	2.9	55	210	2.6	50.4	204
2004	4	12.6	28	82	11.55	23.73	60
2005	15	10	120	220	10.5	114	213
2006	16	10	168.4	379	9	100.5	231
2007	30	20	191	700	14.7	113.03	400.5
2008	54	8	199.35	640	4.5	99	300.3
2009	59	3.87	212	612	2	100.5	400.3
2010	35	1.85	165	635	1	70	300
2011	50	3	105	600	1.5	49.95	304
2012	64	5	155	1900	1.5	89.5	845
2013	9	2.6	9	600	.9	4	265.44
2014	19	1.8	110	900	.6	75	400
2015	35	4.8	200	820.2	1.1	110	502.04

Figure A6: Selected U.S. price indices of relevance to wind energy industry



Sources: BEA; BLS; EIA.

A3 Developer heterogeneity

68 different wind development firms completed at least one wind power project in the United States between 2001 and 2009. Figure A7 shows the distribution of these firms by total number of projects completed from 2001 to 2009. Evidently, there are a number of large, experienced actors in this business; however, there are also many fringe competitors. Figure A8 plots average costs of installed capacity by year for eight of the largest developers in the sample. These firm-specific cost figures show the same upward trend over time as the industrywide figures presented in table A1. Admittedly, figure A8 disregards potentially important heterogeneity across projects (in terms of size and location, for instance) that might explain within-year variance in average costs across firms. Nevertheless, it is telling that the firms' per-megawatt cost rankings change from year to year. No firm is lowest-cost for a significant span of the 2001-2009 period. Perhaps for this reason, no firm has seen its market share grow to the significant detriment of other large competitors (figures A9 and A10). Thus, while the literature in industrial organization (e.g. Cabral and Riordan (1994) and Spence (1981)) recognizes that learning-by-doing can increase industry concentration through the emergence of a low-cost dominant firm, the evidence suggests this is not a concern in the present setting. Finally, it is noteworthy that among large developers, spells of inactivity are of relatively short duration. Table A2 shows that for the 2005-2009 period, rarely did more than two consecutive quarters pass without a large developer completing a new wind power project.

Figure A7: Distribution of wind developers by number of projects completed 2001-2009

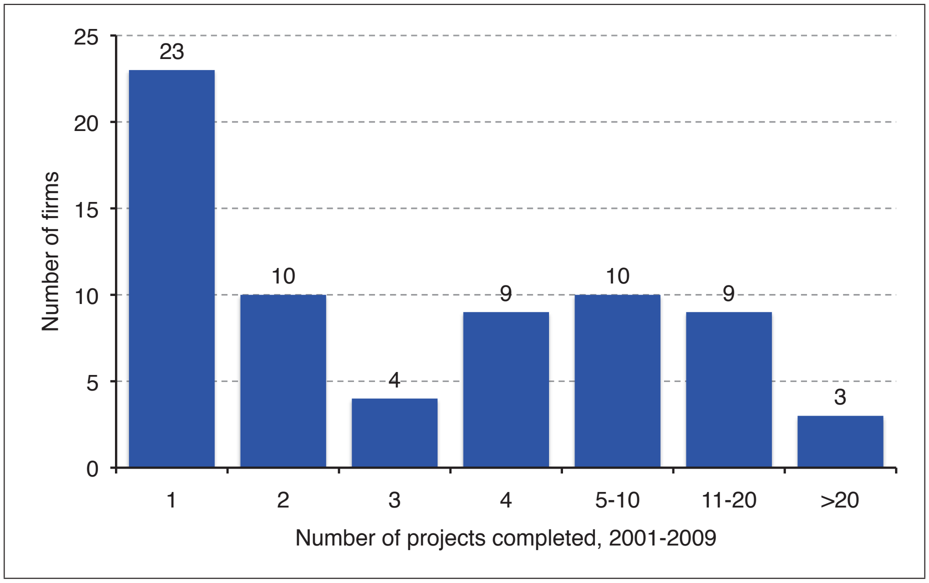


Figure A8: Average costs of installed capacity by year, selected developers

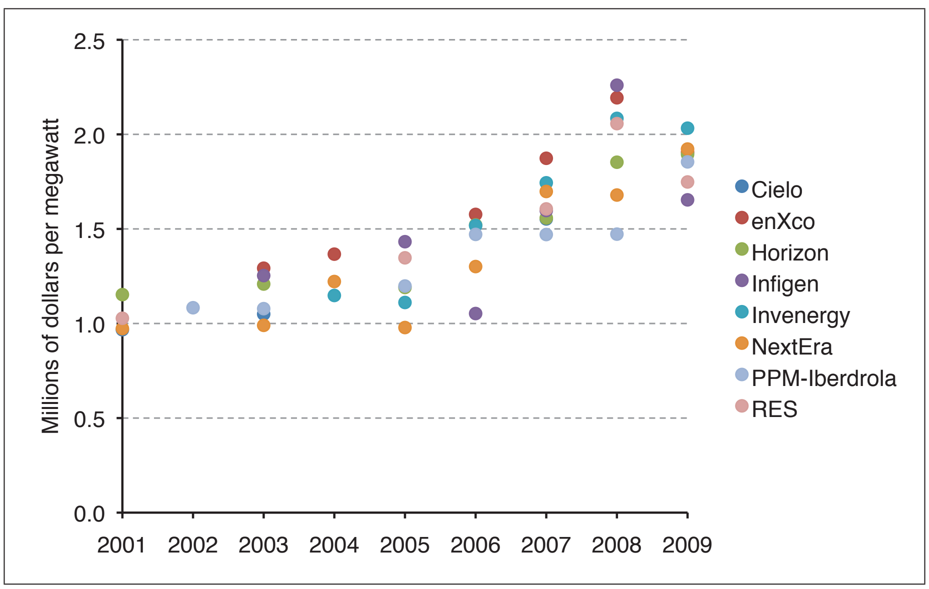


Figure A9: Market shares by year, selected developers (percent of installed MW)

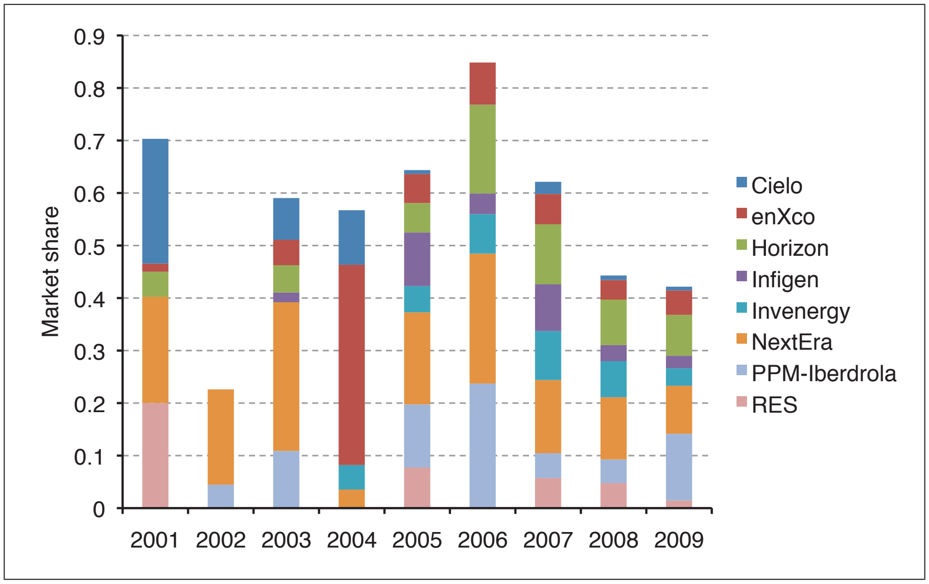


Figure A10: Market shares by year, selected developers (percent of completed projects)

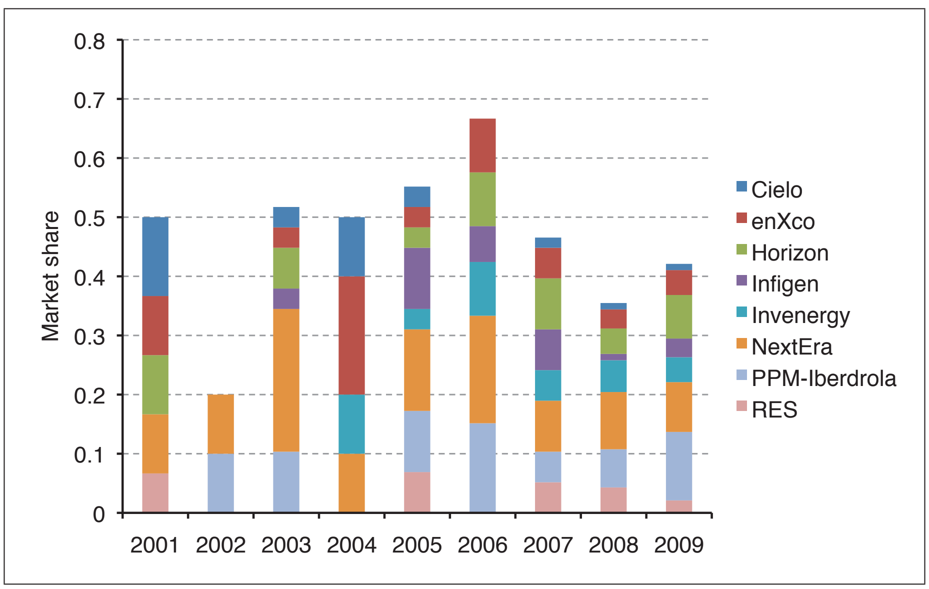


Table A2: Duration of spells of inactivity, selected developers, 2005-2009

Developer	N	Duration (quarters)			
	spells	Mean	SD	Min	Max
Cielo	5	3.2	2.3	1	7
enXco	7	1.7	0.8	1	3
Horizon	5	1.8	0.8	1	3
Infigen	6	2.2	1.0	1	3
Invenergy	5	1.6	0.9	1	3
NextEra	4	1.3	0.5	1	2
PPM-Iberdrola	4	1.5	0.6	1	2
RES	4	3.0	2.2	1	6

A4 Randomness of missing cost data

Here, we consider the econometric problems that could arise on account of my having cost data for only 408 of the 717 U.S. wind power projects completed between 2002 and 2015. It is well established in the economics literature that estimation based on nonrandomly selected samples can result in biased estimates of parameters of economic interest. Although Heckman (1976, 1979) proposed a two-step estimation procedure to overcome this selection bias, implementing his procedure requires additional modeling assumptions (a second equation explaining entrance into the sample) and data (to estimate the second equation). Because neither requirement is necessarily straightforward, it behooves the researcher to weigh the evidence for and against the randomness of his sample before abandoning least squares in favor of a more complicated estimation procedure.

Table A3 compares the subsample of 408 U.S. wind power projects for which cost data is non-missing to the subsample of 309 projects for which cost data is missing. If the proportion of projects sharing a particular attribute *within* each subsample does not differ significantly *across* the two subsamples, then there is evidence that the 114 instances of missing cost data occur at random. From the table, it is apparent that the biggest difference between the two subsamples concern geography. First, no relationship between missing data and project size is identified. Second, among projects with non-missing cost data, greater proportions are located in the NPCC and RFC reliability regions, and smaller proportions are located in the TRE regions, than is the case among projects with missing cost data. (Figure A11 presents a map of NERC reliability regions in the U.S.) This could reflect attitudes or policies towards the disclosure of project information that differ across states or regions.

With respect to the remaining attributes in table A3, the differences between the two subsamples of wind power projects are less pronounced. The proportion of projects completed in a given year or quarter does not appear to vary significantly across the two subsamples. Moreover, projects completed by multiple or foreign developers, and projects owned by independent power producers (IPPs), make up only slightly greater proportions of the subsample of projects with missing cost data than the subsample of projects with non-missing cost data — possibly because such projects are

Table A3: Attributes of wind power projects with and without cost data

Attribute	Non-missing cost data Count	Non-missing cost data Percent	Missing cost data Count	Missing cost data Percent	p-value*
Capacity (MW)					
q ∈ (0,10]	59	13.6%	55	18.3%	-1.7228
q ∈ (10,50]	99	22.8%	63	20.9%	.6049
q ∈ (50,100]	87	20%	69	22.9%	-.9382
q ∈ (100,200]	136	31.3%	85	28.2%	.9005
q > 200	53	12.2%	29	9.6%	1.0914
Completion year					
2002	9	2.1%	1	.3%	2.0041
2003	19	4.4%	4	1.3%	2.3347
2004	4	.9%	4	1.3%	-.5233
2005	15	3.5%	7	2.3%	.8846
2006	16	3.7%	14	4.7%	-.6499
2007	30	6.9%	19	6.3%	.3208
2008	54	12.4%	31	10.3%	.8935
2009	59	13.6%	36	12%	.6495
2010	35	8.1%	22	7.3%	.3766
2011	50	11.5%	40	13.3%	-.7192
2012	64	14.7%	61	20.3%	-1.9585
2013	9	2.1%	5	1.7%	.4024
2014	19	4.4%	23	7.6%	-1.8743
2015	35	8.1%	26	8.6%	-.2771
Completion quarter					
Q1	83	19.1%	45	15%	1.4674
Q2	59	13.6%	50	16.6%	-1.1317
Q3	57	13.1%	54	17.9%	-1.7896
Q4	235	54.1%	152	50.5%	.9744
NERC region					
ASCC	3	.7%	0	0%	1.4454
HICC	3	.7%	4	1.3%	-.8753
MRO	81	18.7%	64	21.3%	-.8707
NPCC	33	7.6%	10	3.3%	2.4321
RFC	58	13.4%	21	7%	2.7493
SERC	10	2.3%	3	1%	1.3224
SPP	35	8.1%	30	10%	-.8932
TRE	39	9%	42	14%	-2.1148
WECC	108	24.9%	70	23.3%	.5069
Industry sector					
Electric Utility (not IPP)	66	15.2%	32	10.6%	1.7947
Multiple developers					
Yes	45	10.4%	20	6.6%	1.7487

* z-statistic reported from a comparison of proportion equality test.
Some characteristics not available for each observation.

Figure A11: North American Electric Reliability Corporation (NERC) U.S. region map

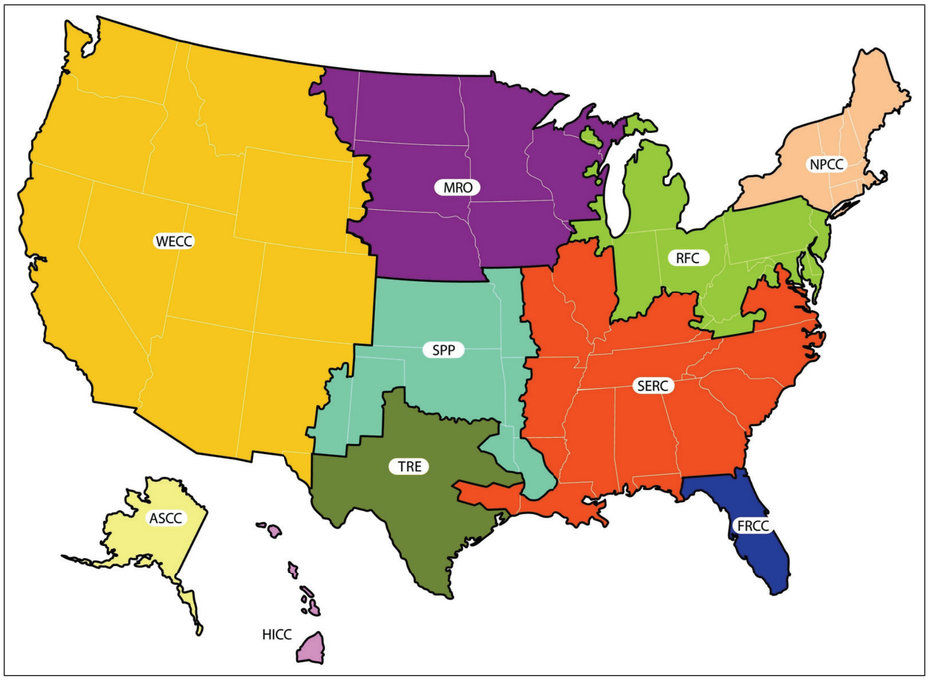


Table A4: Mean capacity and turbine rating of projects with and without cost data, by year

	Capacity (MW)			Turbine rating (MW)		
Year	Non-missing cost data	Missing cost data	p-value*	Non-missing cost data	Missing cost data	p-value*
2003	72.7	49.5	.7283	1.41	1.44	-.1618
2004	29.8	59.7	-.8035	1.28	1.45	-.556
2005	102	65.5	1.4349	1.5	1.29	1.5642
2006	100.9	83.5	.6057	1.69	1.53	.925
2007	126.3	86	1.6854	1.78	1.89	-.8334
2008	105.4	88.1	1.1284	1.82	1.78	.4423
2009	108.3	86.4	1.6234	1.84	1.86	-.1478
2010	77.7	75.6	.109	1.72	1.94	-2.0077
2011	78.9	69	.5589	1.86	1.97	-1.1685
2012	109.4	110.2	-.0383	1.89	2.03	-1.587
2013	67.9	65.6	.0422	1.76	1.38	1.1697
2014	115	91.8	.7068	1.75	1.84	-.6977
2015	134.4	154.1	-.7277	2.06	1.92	1.0242

* Pairwise t-test of equality of means. 2002 excluded because only one missing cost data exists.

Table A5: A hypothetical history of wind power project completions

	Installed capacity (MW)						
Project	Period	Firm 1	Firm 2	Firm 3	Dist(l_3, l_j)	Dist(l_4, l_j)	Notes
1	1	60	0	0	50	120	
2	2	0	40	0	2000	2070	
3	2	0	0	80	1000	1070	
4	3	100	100	0	.	70	JV between Firms 1 and 2
5	4	120	0	0	.	.	Firm 3 acquired by Firm 1

subject to less onerous disclosure requirements. No joint or pairwise test rejects the null hypothesis of within-subsample proportions that are equal across the two subsamples. Table A4 presents an additional comparison of project sizes across the two subsamples. Consistent with table A3, mean project capacity and turbine rating is not detected to differ among the missing and non-missing data. On balance, the evidence does not reject an assertion that cost data is missing at random; which helps support our decision to use a least squares estimation procedure in section 5 rather than a more complicated two-step procedure.

A5 Computation of experience variables: numerical examples

The purpose of this appendix is to demonstrate through numerical examples how to compute, for each wind power project i in the 2002-2015 sample, the accumulated experience variables Q_{l_i,d_i,t_i} and $Q_{l_i,-d_i,t_i}$ defined in section 4.1 as functions of data and parameters. Table A5 displays a simple and purely hypothetical history of wind power project completions for the case where there are three firms that install wind generating capacity over the course of four periods. Assume, without loss of generality, that the MW entries in table A5 constitute single wind power projects (rather than multiple projects whose capacities sum to these per-period totals). Furthermore, assume that Firms 1 and 2 completed the 100 MW project in period 3 as a joint venture, and that Firm 1 acquired Firm 3 at the start of period 4.

First, let $i = 4$ denote the 100 MW wind power project completed jointly by Firms 1 and 2 during period 3, such that $d_i = \{1, 2\}$, $t_i = 3$, $a(d_i, t_i) = \emptyset$, and $-d_i = \{3\}$. Then, by the definitions of section 4.1:

$$\begin{aligned} Q_{l_i,d_i,t_i} &= \lambda_2 \cdot [Q_{4,1,3} + Q_{4,2,3}] && \text{by equation (6)} \\ &= \lambda_2 \cdot \left[Q^O_{4,1,3} + Q^O_{4,2,3}\right] && \text{by equation (5)} \\ &= \lambda_2 \cdot [(\delta_{own} \cdot 60) + ((1 - \rho_{own}) \cdot 40)] && \text{by equation (1)} \end{aligned}$$

$$Q_{l_i,-d_i,t_i} = (1 - \rho_{oth}) \cdot 80 \qquad \text{by equation (7)}$$

Next, let $i = 5$ denote instead the 120 MW project completed by Firm 1 during period 4, such that $d_i = \{1\}$, $t_i = 4$, $a(d_i, t_i) = \{3\}$, and $-d_i = \{2\}$. Then, using the definitions of section 4.1:

$$
\begin{aligned}
Q_{l_i,d_i,t_i} &= Q^O_{5,1,4} + Q^A_{5,1,4} && \text{by equations (5) and (6)}\\
&= Q^O_{5,1,4} + \mu \cdot Q^O_{5,3,4} && \text{by equation (3)}\\
&= \big(\lambda_2 \cdot 100 + \delta^2_{own} \cdot (1-\rho_{own}) \cdot 60\big) + \mu \cdot (\delta_{own} \cdot (1-\rho_{own}) \cdot 80) && \text{by equation (1)}
\end{aligned}
$$

$$
Q_{l_i,-d_i,t_i} = \delta_{oth} \cdot (1-\rho_{oth}) \cdot 40 \qquad \text{by equation (7)}
$$

In the first example, accumulated experience that is "internal" to the consortium of Firms 1 and 2 is a linear combination of 1 and 2's organic experience bases, whereas Firm 3's organic experience base is "external" to the consortium. Projects 2 and 3 receive a distance multiplier for being greater than 100 miles from project 4. In the second example (i.e. after Firm 1's acquisition of Firm 3), Firm 3's organic experience base has become "internal" to Firm 1, whereas Firm 2's organic experience base, with the exception of the 100 MW that Firm 2 completed jointly with Firm 1, is now "external" to Firm 1. Now, projects 1,2 and 3 receive a distance multiplier for being more than 100 miles from project 5.