# Knowledge spillovers from learning by doing in wind power

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**Abstract**

This study empirically examines a prominent justification for public subsidies of emerging technologies: that stimulating demand for them provides opportunities for learning by doing. Even if firms learn from their experience, subsidies are still second-best to pricing negative externalities if firms can appropriate the benefits of learning. I construct a panel of electricity output from wind power projects, for a case involving $1 billion in public funds, to assess whether firms' performance benefited from the experience of other firms. I find evidence of learning by doing, knowledge spillovers, and improved incentives from productivity-oriented policies. However, knowledge gained from experience shows both diminishing returns and depreciating effectiveness.

*Keywords*: learning by doing; subsidies; spillovers.

# 1 Introduction

Stimulating the adoption of new technologies is appealing, in part, because it allows society to more fully realize the benefits of public investments in science. Governments have shown particular interest in new energy technologies as they have the potential to provide energy inexpensively, cleanly, and domestically. However, policy makers face a formidable set of decisions about how best to support innovation in the energy system. The cumulative cost of U.S. federal programs to subsidize demand for emerging energy technologies exceeds half a trillion dollars (Bezdek and Wendling, 2006). The societal challenges associated with energy production and use—including national security, macro-economic disruption, environmental impacts, and limited access for the impoverished—have led to higher public expenditures in recent years and to influential proposals for further subsidies, on the order of several trillion dollars (IEA, 2010).

## 1.1 Public goods problems in technology development

Government involvement in the development of environmentally beneficial energy technologies is necessary because of two well-established market failures (Jaffe et al., 2005). First, most current energy technologies impose negative externalities on society in the form of non-priced environmental damages. Second, firms under-invest in the development of new technologies in general because new knowledge "spills over" from one firm to another, (Nelson, 1959; Teece, 1986). The intellectual property system corrects for some of this second effect, but many new ideas are not patentable and firms can reverse-engineer the new products of others (Griliches, 1992; Jackson, 2003). Tax credits for R&D and direct government funding of R&D can

also address spillovers (Wu, 2005), but may not provide an adequate substitute for learning from real commercial experience (Mowery and Rosenberg, 1998). This paper focuses on the specific problem that some of the benefits obtained from experience in production, known as learning by doing, may not be fully appropriable—that is, these benefits may spillover from one firm to another.

Demand-pull policies, such as subsidies, increase demand for technologies and thus create opportunities for improvements through economies of scale and learning by doing. While policy debates include a wide array of justifications for demand side instruments (Lyon and Yin, 2010), subsidizing demand is generally more expensive and second best to pricing environmental, security, and other externalities directly—such as through taxes or emission permit systems (Fischer and Newell, 2008). However, subsidizing demand may be essential if knowledge externalities exist. Firms will underinvest in the development and deployment of nascent technologies if they are unable to fully appropriate the benefits that accrue to learning-by-doing and scale (Zimmerman, 1982). In contrast to laboratory and R&D settings, new technologies in real commercial use cannot be hidden from competitor firms. At least parts of their design—and crucially, their performance—can be observed and evaluated by others. Strong incentives may exist to learn from novelty, whether it is effective or flawed, without bearing the cost of producing that invention. These incentives discourage investment in the development and initial deployment of novel technologies.

Governments can address knowledge-based market failures by subsidizing demand for new technologies. But decisions about subsidies depend on whether, and to what extent, the gains from experience are appropriable. This study aims to inform these policy decisions by empirically estimat-

ing the extent of appropriability in the case of wind turbines installed in California from 1985–1995.

### 1.2 Paper organization

This paper continues with a review of previous work on learning by doing, the policy context for this particular case study, as well as the decisions facing firms in this case. Section 3 presents the hypotheses, the estimation approach to test them, and the data set developed. Section 4 shows the estimation results and is followed by a concluding section.

## 2 Technology policy and learning by doing

Learning by doing originates from observations that workers performing repeated tasks, especially those in manufacturing plants, become more efficient as they produce additional units (Bryan and Harter, 1899; Wright, 1936; Alchian, 1963; Rapping, 1965). Arrow (1962) formalized the notion more generally to characterize the processes of innovation and economic growth. Rosenberg (1982) described a related process of "learning by using" to describe experienced gained by users, as opposed to producers of a technology. Recent work has more carefully identified the role of experience in improving productivity amidst a large set of rival determinants, including the impacts of capital investment (Bahk and Gort, 1993), economies of scale (Gruber, 1996), and quality (Thompson, 2001). Of special relevance to this case, it has also been extended to encompass choices about which technology to adopt (Jovanovic and Nyarko, 1996).

A subset of this effort to identify the role of experience focuses on the role of experience that is external to the firm, or knowledge spillovers (Bahk and

Gort, 1993; Irwin and Klenow, 1994; Gruber, 1998; Thornton and Thompson, 2001; Kellogg, 2011). A central conclusion from this work is that spillovers are generally present, but have a smaller effect than learning from within-firm experience. Estimation of external learning effects can be sensitive to estimation approach (Barrios and Strobl, 2004), an important reason why this study employs multiple specifications and robustness tests.

This literature has also established two important limitations to learning from experience. Arrow (1962) found that learning by doing is subject to "sharply diminishing returns." Subsequent studies have made it clear that knowledge gained from experience is somewhat ephemeral; it depreciates, as observed in the cases of ship building (Argote et al., 1990; Thompson, 2007), delivery service (Darr et al., 1995) and aircraft manufacturing (Benkard, 2000). While Arrow's diminishing returns reduce the effectiveness of additional experience, knowledge depreciation increases the importance of recent experience relative to earlier experience.

As a result of this work, we know several characteristics of learning by doing: it remains significant even when other explanatory factors are accounted for; knowledge spillovers exist, but are less effective than internal experience; knowledge gained from experience depreciates rapidly, with a half-life of less than two years; it also is subject to diminishing returns; and methodologically, parameter values are sensitive to choices about assumptions and econometric specification.

## 2.1 Implications of LbD for technology policy

Experience that improves performance, flows across firms, and persists for a limited duration, has important implications for policy design, and for

energy technology policy in particular. Modeling studies show that the optimal selection of technology-oriented policy instruments to address energy and environmental concerns is highly sensitive to the rate of appropriability (Fischer and Newell, 2008; Benthem et al., 2008). However, these modeling exercises employ assumptions about levels of appropriability, e.g. 50%; they neither provide nor cite an empirically derived estimate of the level of appropriability. Nordhaus (2002) in particular has emphasized the need for more micro-scale empirical estimates of learning by doing and its appropriability. He and others have also raised concerns about incorrect policy implications resulting from biased specification of learning estimates (Nordhaus, 2009; Hendry and Harborne, 2011).

### 2.2 Dramatic improvement in California wind turbines

This paper assesses learning by doing for the case of wind turbines in California. The case is selected mainly because the state had a very active policy regime and experienced a dramatic improvement in the performance of its wind turbines. Fig. 1 shows that the most direct measure of performance, capacity factor, improved by a factor of 4 from 1985–2005.[1] Electricity production appears to have risen similarly. California wind power is an attractive case to study for several reasons: investment there dominated the world during the period of that improvement, avoiding most issues with international knowledge flows; a comprehensive, continuous, nonproprietary data set is available for 1985–1995, the period of interest; and government activity was central—roughly $1 billion of public funds were used to subsidize the

[1] Capacity factor is a measure of how much electricity was produced in a given period as a proportion of the electricity that would have been produced if that producer had operated at full capacity for the entire period. An increase by a factor of 4 is equivalent to generating 4 times as much electricity from the same set of turbines.

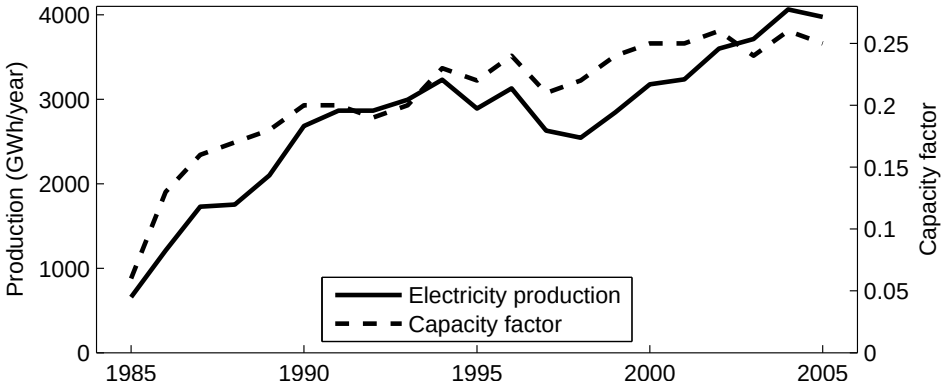


Figure 1: Annual electricity production and capacity factor for wind turbines in California.

$2b worth of wind turbines that were installed in the period of performance improvement. Further, qualitative assessments of this case point to specific mechanisms that resemble the processes observed in earlier studies of learning by doing (Lynette, 1989; Gipe, 1995; Thresher and Dodge, 1998; Taylor et al., 2006). For example, Braun and Smith (1992) noting the large dispersion in performance across firms point to the opportunity to achieve high performance "through incremental improvement of less material-intensive designs based on accumulated field experience."

### 2.3 Public policy and wind power in California

During the study period, the U.S. federal and California state governments implemented several programs that created incentives for the development of wind power projects. Table 1 shows the sequence and duration of these policies. A federal law passed in 1978, the Public Utility Regulatory Policy Act (PURPA), mandated that electric utilities offer power purchase agreements to small power generators at rates that reflect the cost to the utility

of obtaining additional power. This regulation was intended to encourage competition and new smaller-scale technology, such as wind power, which was generally opposed by large electric utilities. In effect, PURPA gave independent wind power producers access to a rudimentary wholesale power market. The remaining policies included four distinct types of policy instruments, which, while they all encouraged the development of wind power, created distinct incentives. Each of the next four policies included in Table 1 below PURPA provided an upfront subsidy to offset the cost of installing a wind power project. Governments delivered these subsidies in the form of a tax credit, which meant that firms could use this credit to offset tax liabilities from other businesses. The "Standard Offer Contracts," the state's implementation of PURPA's federal mandate, guaranteed that wind farm developers would receive a specified purchase price for the electricity they generated. The most common contract, Standard Offer #4 (SO4), was available for new projects from 1983–1985, lasted for 10 years, and provided a purchase price well above competitive wholesale purchase prices. The Production Tax Credit (PTC) gave producers of wind power a tax credit for each unit of electricity they produced. It guaranteed the credit for 10 years, but eligibility for new projects has been intermittent, as the program has expired three times. Finally, Renewable Portfolio Standard (RPS) mandate that electric utilities source a specified portion of the electricity they sell from renewable sources. There is no direct subsidy from the government, but public utility commissions generally allow utilities to pass on the full costs to their rate-payers. For incentives, an important distinction exists among these policy instruments. Under the set of four capital cost-based tax credits, wind farm developers had a strong and immediate incentive to install wind turbines. Under the SO4, PTC, and RPS, their incentives were

Table 1: Federal and state policies relevant to wind power in California

| Policy | Subsidy level | Begin | End |
|---|---|---|---|
| PURPA | none | 1978 | — |
| Federal Investment Tax Credit | 10% of capital cost | 1978 | 1985 |
| Energy Tax Act Credit | 10% of capital cost | 1978 | 1980 |
| Oil Windfall Profits Tax Credit | 15% of capital cost | 1980 | 1985 |
| CA Alt. Energy Tax Credit | 25% of capital cost | 1978 | 1986 |
| Standard Offer Contracts | Price = 14c/kWh | 1983 | 1995 |
| Production Tax Credit | 1.8c/kWh tax credit | 1994 | — |
| Renewable Portfolio Standard | — | 2003 | 2020 |

to produce electricity.

### 2.4 Decisions faced by wind power firms

This study is focused on the decisions that wind turbine operators made in maximizing profits for their firms. Wind power operators obtain revenue via electricity procurement contracts with electric utilities or other buyers of wholesale power. During the period of this study, the revenues operators obtained were directly proportional to the amount electricity they generated. Public policies in this case affected revenues, at certain times by raising purchase prices to above market rates and at other times by providing tax credits for each unit of electricity produced. Costs that operators faced included capital costs of installation, land rent, and operation and maintenance costs, with the costs of purchasing the turbine as the overwhelmingly dominant component of cost. Despite changing policies that affected the profitability of wind power over time, this structure of revenues and costs meant that wind power operators had a clear and consistent objective over the study period: to maximize output of electricity over the life of a turbine. As a result, this study uses electricity production to measure performance.

The amount of electricity a wind turbine can produce depends on three categories of activities: equipment purchase, site selection, and operations. Learning by doing plays a role in each. First, wind power operators must choose a wind turbine model to install. In the study period, 48 wind turbine manufacturers produced turbines, selling 102 distinct models. Key aspects of the technology selection decision in addition to cost include: the efficiency of the turbine in converting wind power to electricity, maintenance costs, and reliability. Since the area swept by the rotating blades increases with the square of the length of the blades and because materials costs increase at less than blade-length squared, larger units are preferable—provided a reasonable degree of reliability exists. Second, operators must select a site, on which to install turbines. Because the amount of energy available in the wind increases with the cube of the wind speed, selecting windy locations is crucial. Micro-scale wind dynamics caused by topography, Venturi effects, and turbulence created by upwind turbines are important and are not obvious ex ante, even today. Poor understanding of these latter "array effects" were considered an important source of problems with early California turbines (Braun and Smith, 1992). Third, operators minimize the costs of operating and maintaining their equipment (O&M). Because wind turbines typically rotate over a million times per year, poor maintenance can lead to expensive damage to components. Minimizing the share of time a unit is out of service for maintenance and repair, known in the industry as "availability", is important to electricity generation. Further, there are very large benefits to timing maintenance to coincide with non-windy periods.

Decisions in each of these three categories—technology selection, site selection, and O&M—directly affect electricity production for each turbine. A central premise of this paper is that there was substantial uncertainty

in each of these three areas: technology selection was difficult because the technology was new and changing rapidly; site selection was difficult due to the absence of meteorological records at micro-scale; and choices about the timing and level of maintenance had to be made with an unproven technology and with poor knowledge about when low-wind periods were likely to occur. In a study of the initial disappointing performance of California wind turbines, Lynette (1989) notes that "most companies had little experience with design, manufacturing, installation, and operation and maintenance." The general research question addressed in this study is thus: *did knowledge gained from experience improve operators' ability to make good decisions in these three areas?*

## 3 Approach

This study estimates the existence and appropriability of learning by doing by identifying the factors that account for changes in the performance of wind power projects. It tests two null hypotheses:

- $H_1$: a firm's *own experience* had no significant effect on the performance of that firm's wind projects (learning by doing).
- $H_2$: the *experience of other firms* had no significant effect on the performance of a firm's projects (appropriability).

Rejecting $H_1$ would establish the presence of learning by doing and rejecting $H_2$ would establish inter-firm knowledge spillovers. Following the preceding discussion, I separately assess the effect of experience on decisions made at the time of installation and those made on an on-going basis.

### 3.1 Estimation methodology

Estimation begins by adopting a modified production function employed in previous work on learning by doing (Bahk and Gort, 1993):

$$Y_{i,t} = f\left(L_{it}, M_{it}, K_{it}, X_{it}\right) \tag{1}$$

where $Y$ is the level of output for plant $i$ at time $t$. Output is a function of labor input $L$, material input $M$, the stock of capital $K$, and the stock of knowledge derived from experience $X$. Output in this case is the amount of electricity produced by wind turbines measured in kilowatt·hours during each 3-month period represented by $t$. The unit of analysis $i$ is the "project," which corresponds to a group of wind turbines of the same type installed at a single location. Each project $i$ is owned by a single operating firm $j$ in each period. Ownership of each project can change over the course of the study period. Material inputs once a project has been built, e.g. lubricants and replacement parts, are minimal so $M$ is dropped from the model as in Bahk and Gort (1993). Similarly, we employ the assumption from Benkard (2000) of zero returns to increasing labor inputs, so $L$ is also dropped. Note that changes in the skill-level of labor are picked up by the variable for experience $X$. Capital stock $K$ is determined by the cost of the turbine and ancillary equipment. In the particular case of wind power, the amount of electricity a project can produce also depends heavily on how much wind is available $W$ at the location of each project during each time period. To account for exogenous improvement in the *quality* of equipment that is not captured in higher purchase prices, e.g. via technological change, a measure of equipment quality $Q$ is added (Barrios and Strobl, 2004). The model used

here is thus:

$$Y_{i,t} = f\left(K_{it}, X_{it}, W_{it}, Q_i\right) \tag{2}$$

I identify the role of experience in informing the three types of decisions described above: technology selection, site selection, and O&M. The first two can be distinguished from the third because the first two are one-time decisions while the third involves continuous iterative decision-making over the life of the project. To assess the outcomes of O&M decisions, I apply a model with project fixed effects to a panel of wind power data to identify the change in performance within each project over time. To assess the outcomes of the combination of site and technology selection, I estimate the performance of each project immediately following installation using year of installation fixed effects.

### 3.2 Data and variables

The data include project characteristics and quarterly electricity production for every wind turbine project of at least 100kW installed in California from 1982–2003 (n=312 projects). The output data span the period from 1985 to 2003 (WPRS, 2006).[2] These data are unique for wind power worldwide in that they are comprehensive for the geography, consistently collected over two decades and publicly available, which is atypical as plant level performance data are often proprietary. That the data include every project installed since the beginning of the local industry is important because it avoids the survival bias present in many studies of learning by doing. Indeed, included here are many poorly performing projects that eventually went

[2]Because records are missing for the years 1996, 1997, 1998, and 2000 estimation is performed on the period, Q1-1985 to Q4-1995.

Table 2: Variables used

| Symbol | Description | Units |
|---|---|---|
| $t$ | Calendar time; $t = 1$ in Q1-1985 | quarters |
| $i$ | Project identifier (n=312) | category |
| $j$ | Operating firm (n=63) | category |
| $s$ | State of California | category |
| $w$ | The world | category |
| $Y_{it}$ | Electrical output by project $i$ in quarter $t$ | kWh/qtr |
| $\Upsilon_{i\tau}$ | Electricity produced in quarter $\tau$ by project $i$ | kWh |
| $\upsilon_{i\tau}$ | Turbines installed in quarter $\tau$ by project $i$ | turbines |
| $\lambda$ | Knowledge depreciation; remaining after 1 quarter | % |
| $\delta$ | Qtrly rate of knowledge depreciation; $= -ln(\lambda)$ | % |
| $E_{it}$ | Depreciated operating experience | kWh |
| $I_{it}$ | Depreciated installation experience | turbines |
| $V_{it}$ | Avg. wind speed in quarter $t$ at project $i$ | meters/second |
| $W_{it}$ | Wind energy available in quarter $t$ at project $i$ | kWh/m$^2$·qtr |
| $U_t$ | Dummy for windy season; 1=Q2 and Q3 | binary |
| $h$ | Number of hours per quarter | hours |
| $G_i$ | Generation capacity of each turbine at project $i$ | kW |
| $A_i$ | Blade swept area of each turbine at project $i$ | m$^2$ |
| $T_{it}$ | Number of turbines in quarter $t$ at project $i$ | turbines |
| $D_i$ | Dummy for imported turbines; 1=imported | binary |
| $c_t$ | Cost of wind turbine capacity in quarter $t$ | (2008$/kW) |
| $\gamma$ | Quarterly rate of capital depreciation | % |
| $C_{it}$ | Depreciated capital stock in quarter $t$ at project $i$ | (2008$) |
| $P_t$ | Value of policy dummies in quarter $t$ | binary |

bankrupt. Table 2 lists the variables used.

### 3.2.1 Wind project performance

Following the discussion on operator decisions above, I measure output $Y$ as the amount of electricity generated in each quarter $t$ by each wind power project $i$. This most straightforward measure of output was chosen over other measures of performance such as capacity factor and specific yield. Capacity factor is a value between 0 and 1 that measures the amount of

electricity generated as a portion of how much could be generated during the time period if the unit were operating at full capacity. As Fig. 1 shows, capacity factor is a useful measure of performance because it normalizes project capacity. Raw electricity production is preferable for estimation since capacity can be put on the right hand side. Another possible performance metric is *specific yield* (kWh/m$^2$), which normalized electricity production by the area swept by the turbine blades. This measure has the advantage of being insensitive to manufacturers' testing conditions and incentives to over-state the capacity rating to increase sales, although in this case the two have a correlation of over 0.98. Simple electricity production was ultimately chosen because it allows more direct comparison with previous work on LbD estimation, which derives from Cobb-Douglas and uses capital stock as a right hand side variable rather than in the denominator of the output measure. Assembling the database involved specifying which firms operated each project in each quarter. As befits a nascent industry, there was considerable churn over time as to which operators ran each project.

### 3.2.2 Knowledge stocks

Operators of wind farms acquire experience in two ways: by installing turbines and by operating them. While both activities produce experience, the knowledge acquired in each is likely to be useful for different purposes. The experience of installing a turbine can inform subsequent decisions about siting and technology choice. Installing many turbines in slightly different locations can reveal what aspects of topography, arrangement and height to consider in locating subsequent turbines. Multiple installations can also

show what design characteristics of available turbine models are important for extracting energy from the wind and minimizing downtime for maintenance. Because siting and technology selection are one-time decisions, the relevant indicator is the experience available at the time of installation.

In contrast, operating experience, measured by cumulative units of electricity produced, provides insight about how to maintain equipment and how to time maintenance to avoid being off-line during windy periods. The high volatility of wind speed over time, combined with the non-linear returns to high-wind periods, make selecting appropriate times for repairs important. I thus construct three types of knowledge stocks: (1) cumulative electricity produced $E_t$, (2) cumulative electricity produced at the time of installation $E_{t=0}$, and (3) cumulative turbines installed at the time of installation $I_{t=0}$. Operating and installation experience stocks were calculated using annual data back to 1982 when the first projects were installed; extending the experience calculation back in time before the quarterly performance data were available (1985) avoids truncation issues common to empirical assessments of experience and learning by doing.

### 3.2.3 Knowledge depreciation

Knowledge acquired from experience loses its value over time. For example, some of the knowledge may be tacit and leaves the firm due to employee attrition. Knowledge may also become less relevant due to changes in demand, technology, or industry structure. Following Thompson (2007), I assume that each unit of experience depreciates continuously at a rate $\delta$.

The depreciated experience available to project $i$ at time $t$ is:

$$E_{it} = \sum_{\tau=1}^{t} \Upsilon_{i\tau} e^{-\delta(t-\tau)} \tag{3}$$

where $\Upsilon$ is a measure of the experience generating activity for project $i$ in each time period $\tau$ from the beginning of the data set $\tau = 1$ until $\tau = t$. $\Upsilon$ is equal to electricity output to measure operating experience $E$. Similarly, $\upsilon$ is equal to new turbines installed to measure installation experience $I$.

Previous work provides a wide range of values for the depreciation of experience-derived knowledge, including quarterly rates of: 53% (Argote et al., 1990); 79% (Darr et al., 1995); 11% (Benkard, 2000); 10%–16% (Thompson, 2007); and 14% (Kellogg, 2011). To estimate the rate of depreciation in this case, I use the grid search procedure developed by (Argote et al., 1990) and later used in modified form by Darr et al. (1995) and Thompson (2007). In their approach, the value $\lambda$ can have a value from 0 to 1 and represents the amount of experience remaining at the end of a quarter. They re-estimate their equations at multiple levels of $\lambda$ and use the value for $\lambda$ that produces the highest likelihood value. I thus use eq. 3 to recalculate knowledge stocks $E$ at each level of $\lambda$ in the interval [0, 1] using increments of 0.01. In terms of eq. 3, $\delta = -ln(\lambda)$. The models described below are thus each estimated 101 times to determine the depreciation rate corresponding to the best fit.

### 3.2.4 Knowledge spillovers

If knowledge created in the process of learning by doing is not fully appropriable, then firms will have access to the knowledge created by the experience of other firms. To test this possibility, I calculate knowledge stocks at four

levels of aggregation, the project $i$, the firm $j$, the state of California $s$, and the entire world $w$. Since each stock is a subset of the subsequent stock as listed above, they are related to each other similar to the way that Irwin and Klenow (1994) characterized knowledge spillovers in the semi-conductor industry:

$$Y_{it} = a_i + \beta_1 E_{it} + \beta_2 (E_{jt} - E_{it}) + \beta_3 (E_{st} - E_{jt}) + \beta_4 (E_{wt} - E_{st}) \qquad (4)$$

Assuming no other determinants, $\beta_1$ would indicate learning from project $i$ itself, $\beta_2$ indicates learning from the firm's other projects, and $\beta_3$ and $\beta_4$ characterize "external learning." In this case, experience for California and the rest of the world may be collinear, so a fifth knowledge stock is created that combines the two, $(E_{wt} - E_{jt})$.

### 3.2.5 Diffusion of knowledge

Even if knowledge derived from experience spills over, it likely does so heterogeneously. For example distance, language and international borders affect the speed of knowledge transfer (Gort and Klepper, 1982; Keller, 2004; MacGarvie, 2005). I examine the sensitivity of the results to uneven knowledge diffusion by applying alternative lag structures to the experience stocks. Assuming that 1 year represents a reasonable lag for knowledge gained from experience to affect performance, I estimate performance in three ways: (1) with no lags on experience, (2) with lags on all experience stocks, and (3) with differential lags on experience; within-firm experience is not lagged and all other experience is lagged.

### 3.2.6 Wind energy available

Wind speed has a direct influence on turbine performance and varies considerably over time and space. Because the unit of analysis is a 3 month period, the minute-to-minute variation in wind speed is averaged away. Still because wind in California is driven by local thermal gradients between a cool ocean and hot areas in the interior, there is strong seasonality in the amount of wind energy available from which to produce electricity. Average wind speeds in the California spring and summer are a factor of 3–4 higher than in the fall and winter.

Following Rasmussen et al. (2011), I used satellite data from the North American Regional Reanalysis (NARR) (Mesinger et al., 2006) to estimate quarterly average wind speeds ($V_{it}$) for the location of each wind project $i$ from 1985–2003.[3] These satellite data are available as grid cells at a resolution of 32×32 km. Almost all of the wind farms in California are located in one of three sites—Altamont Pass (37.732°N, 121.652°W), Tehachapi Pass (35.102°N, 118.282°W), and San Gorgonio Pass (33.916°N, 116.600°W). Using the location of each of these passes I selected the NARR grid cell that contained that location (Fig. 4). To account for the various heights of the wind farms above sea level, the geometric heights of the wind farms were converted to isobaric pressure levels. An additional 50 meters was added to the surface elevation to estimate wind at the turbine hub height for the most advanced technology in this data set. Roughness parameters and stability parameters were chosen to account for the unusually steep terrain and large thermal gradients that characterize all three sites. Each wind power project was assigned a wind speed in each quarter based on the area in which it is

[3] Detail on the methodology used to calculate wind speeds is available here:`https://`...

located. As a result, all of the wind projects in an area are assumed to have the same wind speed. The wind speed variable created here $V$ is a measure of the *potential* wind energy available at each of the three sites. *By selecting windy sites within these areas, and by choosing technology that maximized conversion of moving air into electricity, firms could improve performance.*

Using these wind speeds, I then developed an estimate of the energy available at each site in each quarter. The physical equation for calculating the power available in the wind is: $P = 1/2\rho V^3$, where $\rho$ is the density of air. However, the cubic function tends to be highly sensitive to the windiest periods, which overstates the potential available because turbines typically have "cut-out" speeds, above which they no longer operate in order to protect the equipment. To calculate an estimate of the realistic potential energy available I estimate how much electricity could be extracted from the wind if using equipment at the technological frontier. As in Lu et al. (2009) I use a power curve for a General Electric 2.5 MW turbine that determines the relationship between wind speed and electrical output.[4]

Finally, I address the issue of quarterly averaging, which tends to underweight the importance of windy periods due to the cubic relationship between speed and power. I apply a Rayleigh distribution to the average wind speed calculated over the quarter to account for the non-linear relationship in the power curve and the observed frequency of above mean periods (Randolph and Masters, 2008). This measure of potential wind power available (in kWh/quarter) is calculated as:

$$W_{it} = F_{GE2.5}(R(V_{it})) \cdot h \tag{5}$$

[4]The GE power curve is essentially a truncated version of $P = 1/2\rho V^3$ and importantly retains the cubic relationship at medium speeds.

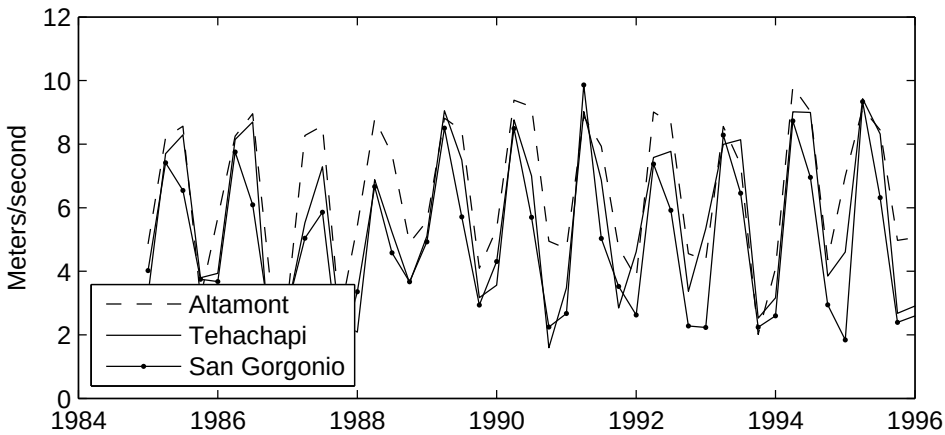


Figure 2: Wind power available at each quarter and location (kWh/m$^2$·quarter).

where $R$ is a Rayleigh distribution with mean, $V_{it}$, $h$ is the number of hours in a quarter, 2192, and $F_{GE_{2.5}}$ is the power curve for the wind turbine at the technological frontier. Fig. 2 shows the calculated values for $V$ for each quarter at the three locations. The strong seasonality that can be observed in the figure leads to the creation of a binary time variable for the windy season, $U = 1$ for quarters 2 and 3 (April–September). Because the returns to operating effectively when there is little wind are very low, I only include performance in these 2 windy quarters of each year.

### 3.2.7 Capital stock and equipment characteristics

I assemble data from WPRS (2006), Gipe (1995), and turbine manufacturers to include characteristics for each wind power project including: generation capacity $G_i$ (kW), blade swept area $A_i$ (m$^2$), and the number of turbines operating in each quarter $T_{it}$. I also code each turbine as one of 102 models made by one of 48 manufacturers.

Previous work has emphasized that identification of learning effects is sensitive to the vintage and quality of equipment (Bahk and Gort, 1993; Thompson, 2001). I use the date that a turbine was installed as a proxy for the vintage of the equipment. I proxy for quality using the size of the turbine in terms of the area swept by the blades ($A_i$). Bigger turbines are better because swept area increases with the square of the blade length, and costs are more closely related to blade length than to area. Building bigger turbines has been a non-trivial endeavor; it has taken two decades to scale up turbines to megawatt size. The history of the California wind experience suggests that a second proxy for quality is whether the turbine was manufactured in the U.S. or imported, $D_i$. Imported turbines, especially those from Denmark—thus the $D$—had substantially higher capacity factors than those made domestically (Gipe, 1995).

A measure of the capital stock was created for each project using a time series of the average cost of wind turbines $c_t$ sold in California in each year (Nemet, 2009). The price level at the time of installation was multiplied by the capacity installed ($T \cdot G$) and then depreciated at a rate $\gamma$ to estimate a capital stock $C_{it}$ for each project in each quarter.

$$C_{it} = \sum_{\tau=1}^{t} c_\tau T_{i\tau} G_{i\tau} e^{-\gamma(t-\tau)} \tag{6}$$

### 3.3 Policy variables

I define binary variables to account for the government actions that had important effects on incentives to build and operate wind power in California. With production data available from 1985–1995, the 8 policies included in Table 1 are used to create 3 binary policy variables: ($P1$) capital cost

tax credits from 1978–1986, ($P2$) the production tax credit of 1.8c/kWh from 1994-onwards, and ($P3$) guaranteed purchase price contracts from mid-1983–1995.

# 4 Results: the effects of experience on performance

The following analyses identify the effects of experience in influencing the dramatic improvement in wind power performance seen in Fig. 1. The first set of analyses assesses on-going operating performance and the second assesses decisions at the time of installation.

## 4.1 Experience and operating performance

To assess whether experience helped improve operating performance I use eq. 2, adding policy $P$ to account for incentives emerging during an active period of policy initiatives in California:

$$Y_{it} = f\left(K_{it}, W_{it}, X_{it}, Q_i, P_t\right) \tag{7}$$

I run linear regressions with robust standard errors on the panel of 312 wind power projects over 44 quarters (1985–1995). Project fixed effects are used to control for inter-project heterogeneity enabling identification of the improvement observed *within* each project. I use the following variables to operationalize eq. 7. Capital $K$ is measured using the variable for capital stock $C$. Availability of wind $W$ is measured using variables for wind energy $W_{it}$. Variables for quality $Q$ are dropped since they do not change over time. Policies $P$ are introduced as binary variables for the two wind power incentive programs, $P1$, and $P2$. I drop $P3$ since it is constant over the

period. For experience I use depreciated cumulative electricity output for each project $E_i$, each firm $E_j$, the entire state $E_s$, and the world $E_w$ where the latter three measures are increments above the previous measure (eq. 4). The resulting estimator is:

$$Y_{i,t} = f\left(K_{it}, W_{it}, E_{it}, E_{jt}, E_{st}, E_{wt}, P1_t, P2_t\right) \tag{8}$$

Table 3 shows descriptive statistics and Table 4 shows coefficient estimates for five versions of this regression. Model 1 estimates coefficients for eq. 8 assuming that experience affects performance linearly. Models 2–5 add quadratic terms for experience, following the description by Arrow (1962) of "rapidly diminishing returns" to learning by doing. In model 3, extra-firm experience is modified to include both California and the rest of the world as a single stock. These two knowledge stocks are highly correlated so are treated as a single stock. In models 4 and 5 extra-firm experience is lagged to simulate the differential diffusion of knowledge across firms and countries. In model 4, California experience is lagged 1 quarter. Assuming that lags increase with distance, the stock of state and rest of the world experience is lagged 4 quarters in model 5.

The results in Table 4 provide evidence of learning by doing, diminishing returns, knowledge spillovers, and public incentives for productivity. Each model is run 101 times over $\lambda$ [0,1]. The depreciation rate of best fit, $\lambda = 0.41$ to 0.43, appears rather high, but is actually quite close to that estimated by Argote et al. (1990) for ship-building. The controls act as expected; in every estimator, the coefficients for capital stock are positive and significant, as are those for wind energy available.

A first observation, robust to various estimators, is that wind turbine op-

Table 3: Descriptive statistics for variables in regressions shown in Table 4. Data are restricted to 2nd and 3rd quarters of each year; $\lambda = 0.42$.

| Variable | | n | Mean | Std.dev. | Min. | Max. |
|---|---|---|---|---|---|---|
| Electric output | $Y_{it}$ | 3062 | 6 | 21 | 0 | 331 |
| Capital stock | $C_{it}$ | 3062 | 7 | 23 | 0 | 335 |
| Wind resource | $W_{it}$ | 3062 | 395 | 87 | 167 | 505 |
| Op. exp. project | $E_{it}$ | 3062 | 9 | 30 | 0 | 520 |
| Op. exp. firm | $E_{jt}$ | 3062 | 113 | 146 | 0 | 634 |
| Op. exp. state | $E_{st}$ | 3062 | 1258 | 477 | 224 | 2083 |
| Op. exp. world | $E_{wt}$ | 3062 | 1825 | 1021 | 239 | 4409 |
| Policy: cap. cost | $P1_t$ | 3062 | 0.15 | 0.36 | 0 | 1 |
| Policy: production | $P2_t$ | 3062 | 0.18 | 0.39 | 0 | 1 |
| Time | $t$ | 3062 | 1991 | 3.07 | 1985 | 1996 |

erators do appear to learn from experience. One sees positive and significant coefficients on experience in every model shown in Table 4. A second robust observation is that the productivity of experience exhibits diminishing returns. In almost every case where experience takes a quadratic functional form, the linear term is positive and the squared term is negative. In several, but not all, cases the squared term is significant. A third observation is that project-level experience appears to be the most stable experience stock. It is always significant and its size does not vary much across the different assumptions employed in models 2–5. Interestingly, the effect of a firm's other projects appears to be less important than within-project experience. The sizes of the coefficients on firm experience are smaller than for projects and are not significant, although they are positive and do show diminishing returns. This may result from a high degree of customization within individual projects and poor knowledge transfer within firms.

A fourth observation is that extra-firm experience is generally significant and positive. This provides evidence that inter-firm spillovers do appear

Table 4: Coefficient estimates for project fixed effects models. Dependent variable is quarterly electricity production, $\ln(Y_{it})$.

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | $\exp^2$ | CA+row | lag 1q | lag 4q |
| $K$, Capital and $W$, wind resource | | | | | |
| Capital stock | 0.198*** | 0.179*** | 0.176*** | 0.204*** | 0.209*** |
| | (5.96) | (5.11) | (4.91) | (5.27) | (5.29) |
| Wind energy | 0.361*** | 0.316*** | 0.330*** | 0.398*** | 0.489*** |
| | (10.22) | (8.70) | (8.83) | (10.03) | (13.24) |
| $X$, Operating experience | | | | | |
| Project | 0.401*** | 0.489*** | 0.487*** | 0.407*** | 0.398*** |
| | (11.38) | (6.51) | (6.39) | (5.16) | (5.00) |
| Project$^2$ | | -0.0241 | -0.0254 | -0.0187 | -0.0236 |
| | | (-1.09) | (-1.13) | (-0.81) | (-1.00) |
| Firm | -0.00890 | 0.00326 | 0.0129 | -0.0325 | -0.00992 |
| | (-0.89) | (0.12) | (0.47) | (-1.15) | (-0.33) |
| Firm$^2$ | | -0.00292 | -0.00433 | 0.00609 | -0.00200 |
| | | (-0.75) | (-1.08) | (1.53) | (-0.47) |
| State | -0.240*** | 0.435*** | | -1.367*** | |
| | (-8.85) | (2.65) | | (-4.16) | |
| State$^2$ | | -0.0553*** | | 0.134*** | |
| [a] | | (-4.00) | | (4.59) | |
| World | | | 0.533*** | | -0.232 |
| | | | (3.58) | | (-1.33) |
| World$^2$ | | | -0.0664*** | | 0.0192 |
| | | | (-5.25) | | (1.40) |
| $P$, Policy | | | | | |
| Policy: cap. | -0.157*** | -0.115*** | -0.105*** | -0.00149 | -0.104*** |
| | (-7.02) | (-5.32) | (-4.56) | (-0.05) | (-3.52) |
| Policy: PTC | -0.0410** | -0.0480*** | 0.134*** | 0.0855*** | -0.00150 |
| | (-2.47) | (-2.81) | (6.62) | (4.81) | (-0.07) |
| Time | 70.25*** | 81.85*** | 152.7*** | -70.70*** | 2.844 |
| | (6.02) | (6.15) | (7.73) | (-4.21) | (0.15) |
| Constant | -533.8*** | -623.7*** | -1,162*** | 538.4*** | -23.33 |
| Depr., $\lambda$ | 0.41 | 0.42 | 0.42 | 0.43 | 0.43 |
| adj. $R^2$ within | 0.349 | 0.359 | 0.355 | 0.307 | 0.293 |
| overall $R^2$ | 0.874 | 0.878 | 0.877 | 0.847 | 0.833 |
| observations | 3,035 | 3,035 | 3,035 | 3,035 | 3,035 |
| projects | 262 | 262 | 262 | 262 | 262 |

[a] Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

to exist—and they show significant diminishing returns. The size of the effect of external knowledge is comparable to that of project experience; in some case it is smaller and in others it is larger. Some of the variation in the size of the external knowledge coefficients are attributable to whether external experience includes only California (2) or both California and the rest of the world (3). High correlation between the two (Table 6) implies we are not able to separate these effects. Note that this result does not hold in models 4 and 5, in which the external experience stocks are lagged. The lagged variables produce poorer goodness of fit and some unexpected results on external experience, i.e. increasing returns. The interpretation of delayed knowledge is complicated by the rapid depreciation of knowledge and the extreme seasonality of production (Fig. 2). It is likely that lagging experience offsets knowledge depreciation that would normally occur over time and especially from low-wind periods.

The policy variables have significant effects. The capital cost rebates from 1978-1986 had a negative effect across all models. This result is consistent with critiques, which argued that these credits were widely abused as tax shelters for unrelated activities. The production tax credit, which by design rewards productivity rather than investment, is positive in some, but not all, models. These results provide some support for the notion that productivity-oriented, rather than investment-oriented, incentives do encourage performance.

### 4.2 Experience and installation decisions

Decisions about location and technology choice also affect productivity. Indeed, Fig. 3 shows that the capacity factor of projects during their first year

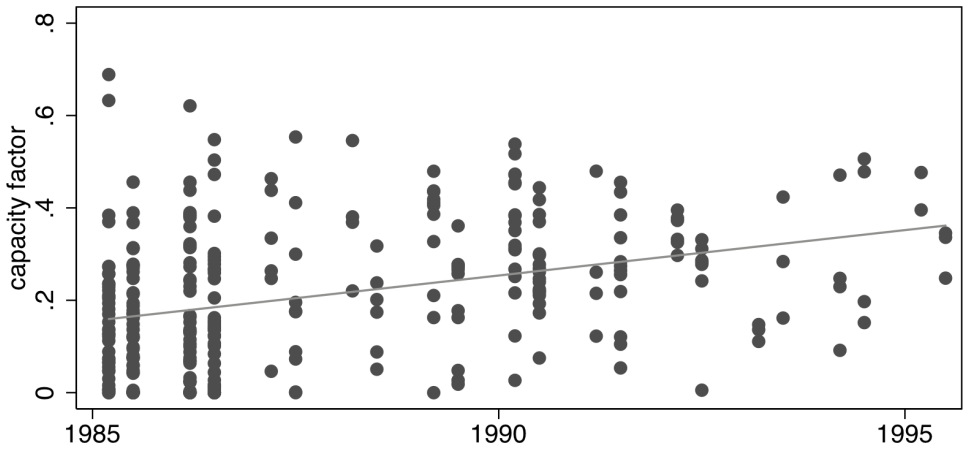


Figure 3: Capacity factor of projects during the first year of operation. Only high-wind quarters (Q2 and Q3 in each year) are shown to control for seasonality. The line is a linear fit of time to capacity factor.

of operation increased over time. The rest of this section seeks to identify the role of experience in enabling improvement in the choices made at the time of installation—rather than in ongoing operations as covered above.

Similarly to the previous section, I adapt eq. 7. Whereas the previous set of models estimated performance within projects over time, this set of models estimates performance across projects at the time that each was installed. This change in approach enables consideration of quality attributes, which were static in the previous section. Quality is represented using the size of a project's turbines $G$ and whether the turbines were imported $D$. Two types of experience are used. First, I use depreciated cumulative electricity production at the time of installation, $E_{t=0}$, for each firm, as well as for the state. Project experience is not used since all projects have zero experience at the time they begin. Second, I use depreciated cumulative turbines installed at the time of installation, $I_{t=0}$, for each firm and for the

state. The resulting estimator is:

$$Y_{i,t=1} = F\left(K_i, W_i, Q_i, E_j, E_s, I_j, I_s, P\right) \tag{9}$$

Coefficient estimates for six versions of eq. 9 are shown in Table 5. I run linear regressions with robust standard errors on the panel, restricting observations to the first windy quarter (Q2 or Q3) after the project was installed. I use year of installation fixed effects to account for exogenous changes in technology, other than size and imports, which I control for separately.

All models use the same variables for capital stock, quality, wind availability, and policy. Measures for experience vary. Model 1 uses installation experience ($I$), model 2 uses operating experience ($E$), and model 3 uses both. In these 3 models 'external' experience is that produced by the rest of California—outside the firm that owns project $i$. Model 4 is similar to model 1, but includes experience of the rest of the world in the external knowledge stock. Model 5 is similar to model 4 but lags external experience by 4 quarters to simulate delayed diffusion of knowledge over space. Model 6 is similar to model 1 but assesses performance 1 quarter after the installation quarter, to exclude the dynamics in the start-up quarter. All models use the depreciation rate estimated in models 2 and 3 of Table 4, $\lambda = 0.42$.

Controls are significant and as expected. Capital stock, wind available, as well as the quality attributes, turbine size and imported turbines, are almost always positive and significant. The influence of the experience stocks on performance in Table 5 is less significant and less robust than that found in the analysis of ongoing performance in Table 4. One reason for lower power is that the installation data include at most one observation for each project, rather than dozens of quarters for each. Still, some of the results

Table 5: Coefficient estimates for linear regression with year-of-installation fixed effects. Dependent variable is quarterly electricity production at time of installation. All ratio variables are in logs.

| | (1) inst exp | (2) oper exp | (3) both exp | (4) incl wld exp | (5) lag exp | (6) fwd 1 qtr |
|---|---|---|---|---|---|---|
| $K$ capital stock, $W$ wind resource, $Q$ quality, and $P$ policy | | | | | | |
| Capital stock | 0.698*** | 0.721*** | 0.706*** | 0.690*** | 0.702*** | 0.731*** |
| | (15.67) | (15.92) | (16.00) | (15.62) | (16.47) | (18.67) |
| Wind energy | 0.611** | 0.594** | 0.579** | 0.612** | 0.525* | 0.289 |
| | (2.24) | (2.09) | (2.06) | (2.28) | (1.85) | (0.91) |
| Turbine size | 0.323*** | 0.339*** | 0.349*** | 0.320*** | 0.323*** | 0.365*** |
| | (5.82) | (5.64) | (5.76) | (5.93) | (5.87) | (6.83) |
| Imported | 0.245*** | 0.264*** | 0.252*** | 0.259*** | 0.277*** | 0.276*** |
| | (3.38) | (3.50) | (3.33) | (3.52) | (3.80) | (3.80) |
| Policy: capital | -0.171 | -0.742** | -0.478 | -0.150 | -0.479** | -0.119 |
| | (-0.74) | (-2.39) | (-1.51) | (-0.62) | (-2.54) | (-0.47) |
| $X$, Experience at time of installation | | | | | | |
| Inst.exp, firm | 0.156* | | 0.104 | 0.155* | 0.101 | 0.117 |
| | (1.94) | | (1.29) | (1.93) | (1.27) | (1.56) |
| Inst.exp$^2$, firm | -0.0304** | | -0.0243 | -0.0296* | -0.0207 | -0.0233* |
| | (-1.98) | | (-1.61) | (-1.92) | (-1.35) | (-1.69) |
| Inst.exp, external | 0.953* | | 0.916 | 0.0731 | -1.976 | 0.549 |
| | (1.70) | | (1.58) | (0.05) | (-1.01) | (0.85) |
| Inst.exp$^2$, external | -0.0934** | | -0.0930* | -0.0332 | 0.118 | -0.0543 |
| | (-1.99) | | (-1.92) | (-0.34) | (0.83) | (-1.03) |
| Op.exp, firm | | 0.120 | 0.130 | | | |
| | | (1.46) | (1.39) | | | |
| Op.exp$^2$, firm | | -0.0282 | -0.0288 | | | |
| | | (-1.40) | (-1.39) | | | |
| Op.exp, external | | 1.876 | 2.000 | | | |
| | | (1.30) | (1.41) | | | |
| Op.exp$^2$, external | | -0.176 | -0.193 | | | |
| | | (-1.33) | (-1.48) | | | |
| constant | -7.385*** | -9.782** | -11.89*** | -4.135 | 3.406 | -4.744* |
| Depreciation ($\lambda$) | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 |
| adj. $R^2$ | 0.699 | 0.693 | 0.702 | 0.702 | 0.700 | 0.756 |
| observations | 195 | 195 | 195 | 195 | 195 | 192 |

[a] Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

are significant and a few indications emerge.

First, one can see some evidence of learning by doing. Moreover, it appears that experience in installing turbines (models 1, 3–6) is a significant predictor of initial performance but experience in generating electricity (model 2) is not. This finding fits with the intuition of this second set of results; we are looking at different types of decisions and thus would expect different types of experiences to inform them. Specifically, experience measured by counts of previous instances of selecting, siting, and installing turbines is helpful for informing future decisions involving those three activities. Conversely, experience measured by the amount of electricity produced does not appear to be applicable to those three activities. Second, there are again significant diminishing returns to experience. Third, one sees evidence of knowledge spillovers. External experience is positive in several cases and significant in some—again with significant diminishing returns. It is somewhat surprising that coefficients on external experience are larger than within firm experience, especially since the experience stocks are only weakly correlated (Table 9). This result may also reflect the rather weak effects of firm experience found in Table 4. Perhaps due to churn and employee turnover, firms again seem to have struggled to apply the knowledge gained in one project to decisions on another. It may also reflect the nature of the dependent variable in Table 5. Choices regarding equipment, location, and construction of a new turbine seem inherently more visible to competitors, than do decisions around maintenance and on-going operations. When installations in the rest of the world are included, the significance of external experience goes away.

As above, the investment tax credits have a negative, and sometimes significant, effect on performance. The production tax credit is dropped be-

cause no new projects are installed in the eight quarters that it is available. Lagging experience by 1 year (model 5) produces results on experience that are not significant. Moving assessment of performance forward one quarter (model 6) also produces insignificant effects, although the signs of the coefficients indicate spillovers and diminishing returns to experience.

I also add models that include 2 interaction terms (1) the combination of experience and wind power available, to assess the possibility that experience specifically enables siting in windy locations, and (2) the combination of experience and turbine size, to asses whether experience specifically enables firms to learn how to operate large scale equipment. I find neither interaction term is significant. The appendix table 11 provides these additional results. In that table, model 1, provided for comparison, is the same as model 1 in Table 5; models 2 and 3 add the two interaction terms; models 4 and 5 evaluate production one quarter later (like model 6 in Table 5); model 4 lags all experience by 4 quarters; and model 5 lags only external experience by 4 quarters.

# 5 Conclusions

This study addressed two questions: (1) *did firms learn from their own experience?* and (2) *did firms learn from the experience of others?* The results provide evidence of both, but with important qualifications. One is that both types of experience were subject to diminishing returns. Another is that knowledge gained from experience appears to depreciate rather rapidly. This paper concludes that the design of policy instruments to create incentives for learning depends not only on the existence of spillovers to learning by doing, but also on these important qualifiers.

## 5.1 Experience improved performance

The trends in the descriptive results show that the operating performance of wind power projects did improve over time—both when assessed initially (Fig. 3) and on an on-going basis (Fig. 1). These improvements involved location choices, equipment selection, installation, and operating decisions. The analyses described above identified a positive and significant role for experience in enabling improvements in these activities. This result was robust across several alternative specifications.

The benefits of experience, so clear within each project, do not appear to have been easily transferable across projects within firms. One possibility is that knowledge acquired through production was highly project-specific. Another is that this knowledge was retained tacitly among individuals who operated the equipment. It was not codified in a way that would have facilitated transfer to other projects. Finally, given the evidence of learning from other firms, gains from concentration may have influenced this result. Firms that were focused on a small number of projects may have been able to develop a deeper understanding of local conditions, especially of topography and meteorology. Experience at other sites may have distracted from this focus; it may actually have been easier to learn from other firms.

## 5.2 Knowledge spilled over across firms

The results provide evidence of knowledge spillovers across firms—the main innovation-related justification for subsidizing demand. Operating experience by other firms has a positive effect on on-going project performance. Similarly, installation experience by other firms at the time of installation of a new project has a positive effect on that project's performance.

It is not clear however, whether these spillovers are being generated primarily by experience within the state of California or from beyond, as there is collinearity in those two knowledge stocks. We also do not find clear results when the extra-firm knowledge stocks are lagged differentially, to simulate delay in knowledge transfer across firm and national borders. At first glance, the possibility of international knowledge spillovers does not seem to fit with the notion of learning that is tacit and highly project-specific. But perhaps some knowledge is more general and has been codified, e.g. via reports and industry conferences. Since equipment was sold internationally from early on, decisions about which turbine technology to select may have been particularly amenable to dispersion. Another interpretation is that the benefits of global experience became embedded in new equipment that allowed performance improvement. In this study, that is captured most directly in the coefficients on variables for quality in Table 5. The rapid diffusion of imported turbines with substantially improved performance characteristics supports a role for global experience. The complexities of policy design to address knowledge externalities are heightened when knowledge spills over across jurisdictions.

### 5.3 Limits to learning

The decreasing returns to newly acquired knowledge and the weak persistence of that knowledge over time are central features in this case study. Iterative estimation over a full range of possible depreciation rates led to the use of rates that seem high—although they are well within the range of estimates in previous work on learning by doing. Knowledge gained from experience may be inherently more susceptible to depreciation than other

types of knowledge. Scientific knowledge goes through a process of peer-review and dissemination; research and development activities are carefully monitored and often intentionally organized as experiments. In contrast, lessons about how to run wind farms were gained as a side-effect of trying to produce electricity. Careful codification of the outcomes of trials was unlikely to have been a high priority in the context of an investment boom for an infant industry. Bankruptcies were frequent and employee attrition was high. Even if important knowledge was gained in the process of installing and operating wind turbines, it dispersed and much of it was not available for future projects.

Similarly, diminishing returns show up in almost every model specification tested. This finding is consistent with much of the work on learning by doing. In this case, as in previous ones, the knowledge gained from experience is useful for the refinement of existing systems. It seems much less useful, at least on its own, to producing radically different designs that could lead to non-incremental changes in performance. Indeed, other work on this case shows that the period of rapid expansion coincided with a convergence on a dominant design and a decline in efforts to develop alternative configurations (Nemet, 2009). The extent to which policy makers rely on learning by doing as a mechanism for technology improvement probably depends on how much improvement is needed. With decreasing marginal returns to experience, other avenues may be required if non-incremental improvement is desired.

The strong results on depreciation and diminishing returns may be partly attributable to the fact that the data are comprehensive over the time period and not prone to survival bias, as acknowledged in other studies of learning by doing (Barrios and Strobl, 2004). These data include all projects

in the state during the period, not just those that remained at the end. For example, firms with poorly performing projects were more likely to suffer employee layoffs and bankruptcy, both of which were endemic in the California wind power industry—and both of which would have accelerated depreciation. One can learn from failure, but it is probably harder to do so when insolvency threatens as a consequence.

### 5.4 Policy incentives for performance

A first implication of the main result of this study—that inter-firm knowledge spillovers exist—is that we should expect firms to under-invest in, or at least delay, technology deployment investments. Firms can benefit at low cost by waiting to take advantage of the knowledge made available through the investment and experience of other firms. Policies that increase demand are thus needed to provide incentives for technology deployment to offset the private incentives to delay and to free-ride on the investments of others.

A second implication is that the characteristics of the policy instrument affect the production of experience-derived knowledge. The frequently opposing signs on the coefficients of the two policy dummies reflect the qualitatively different incentives they created. The capital cost rebates, which provided tax breaks proportional to the cost of newly installed equipment, have negative coefficients throughout the analysis. In contrast, the Production Tax Credit (PTC) has a mixed, and generally, a positive effect. The incentive under the PTC is to produce electricity. Even if it is being used as a tax shelter, a firm still needs to produce power to receive the credit. In contrast, the incentive under the capital cost program was to install equipment; a firm received the same tax benefit regardless of how much power it

produced.

The main incentive problem with the PTC, subsequent to the period studied here, is that it has been allowed to expire intermittently, leading to cycles of layoffs and rapid hiring in the industry (Barradale, 2010). With the finding that new knowledge is so vulnerable to depreciation, policy volatility is especially damaging to the effectiveness of policy in addressing knowledge externalities. A longer term policy that provided stable incentives, and rewarded production, not just capital investment, would improve incentives. Renewable portfolio standards have emerged as a promising way to combine these attributes. Still, longevity of knowledge is an issue. Tacit learning, obsolescence, and project-specific knowledge may heterogeneously limit the flow of the gains from experience. One avenue for enhancing the effectiveness of such policies is to emphasize codification and transfer of new knowledge. For example, the data analyzed in this study are only available because the California Energy Commission required, collected, and made publicly available performance data from each firm. However, they are no longer available and such information is now considered proprietary.

The amounts of public funds at stake add some urgency to improving understanding of the scale and characteristics of knowledge spillovers from learning by doing. It seems quite clear that policies that enhance demand are necessary to generate sufficient knowledge from experience. The insights from this case—specifically the observations of depreciation and decreasing returns—heighten the value of policy instruments with performance-oriented mechanisms, longevity, and perhaps even explicit support for codification and transfer of experience-derived knowledge. Otherwise, it is likely to be ephemeral despite even substantial public investment.

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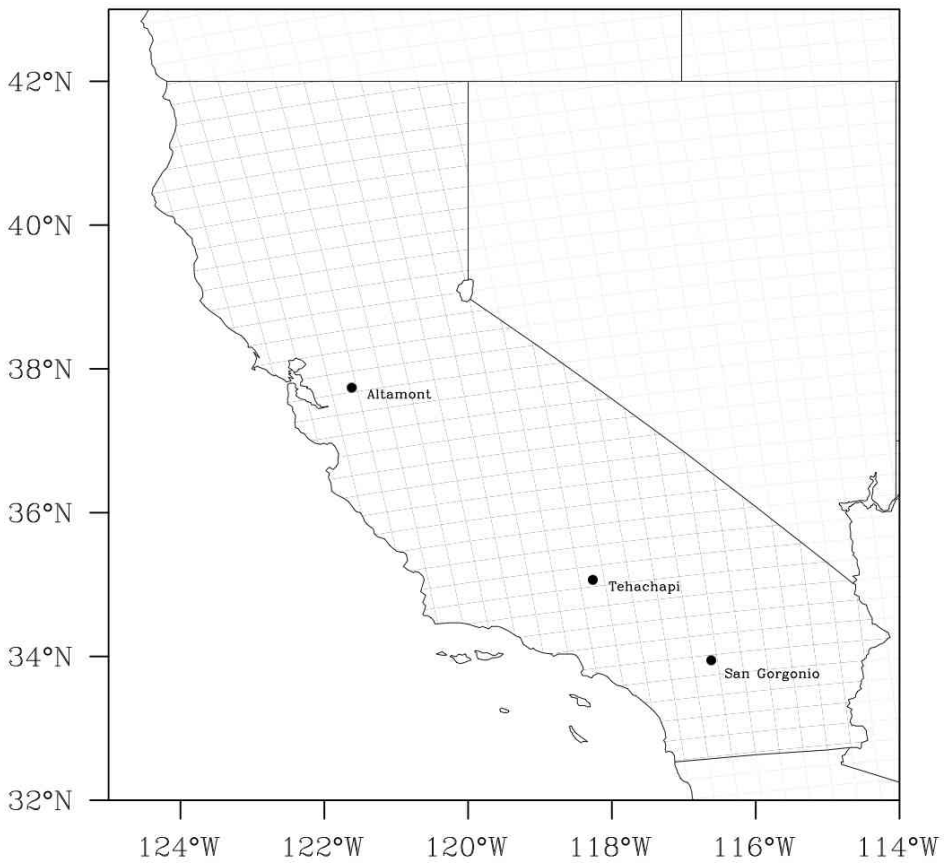


Figure 4: Locations of wind farms and of satellite data grid cells used to calculate quarterly average wind speeds.

# Appendix

The following figures and tables are included to describe the case study and provide additional descriptions of the data used. As noted earlier, detailed methodology on the calculation of wind power is available online.

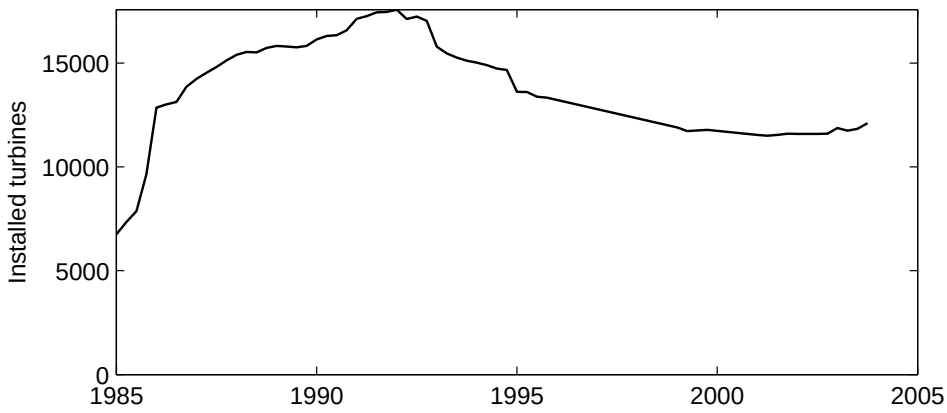


Figure 5: Wind turbines installed in California.

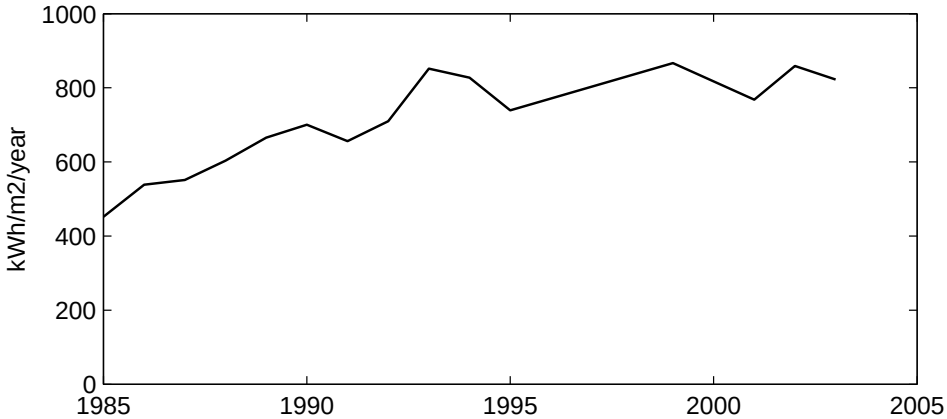


Figure 6: Example firm: annual specific yield (kWh/m$^2$/year) for Zond Energy (now G.E. Wind).

Table 6: Correlation matrix for regressors used in Table 4.

| Variable | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| 1 Capital stock | 1 | | | | | |
| 2 Wind resource | −0.022 | 1 | | | | |
| 3 lexpepprj | 0.604 | −0.009 | 1 | | | |
| 4 lexpepfrmx | −0.029 | −0.028 | 0.234 | 1 | | |
| 5 lexpepstax | −0.233 | −0.129 | 0.200 | 0.213 | 1 | |
| 6 lexpepwldx | −0.262 | 0.175 | 0.220 | 0.348 | 0.747 | 1 |

Table 7: Indices of collinearity for independent variables used in Table 4.

| | Variance Inflation Factor | Tolerance (1/VIF) | $R^2$ | Eigen value | Condition index |
|---|---|---|---|---|---|
| Capital stock | 2.18 | 0.458 | 0.542 | 2.067 | 1.000 |
| Wind resource | 1.25 | 0.801 | 0.199 | 1.632 | 1.126 |
| lexpepprj | 2.2 | 0.455 | 0.545 | 1.056 | 1.399 |
| lexpepfrmx | 1.21 | 0.825 | 0.175 | 0.815 | 1.593 |
| lexpepstax | 2.78 | 0.360 | 0.640 | 0.251 | 2.868 |
| lexpepwldx | 3.23 | 0.310 | 0.690 | 0.179 | 3.400 |
| Aggregate | 2.14 | | | | 3.400 |

Table 8: Descriptive statistics for variables in regressions shown in Table 5. Experience stocks are at time of installation; $\lambda = 0.42$.

| Variable | n | Mean | Std.dev. | Min. | Max. |
|---|---|---|---|---|---|
| Electric output | 195 | 3.42 | 8.36 | 0.00 | 86.65 |
| Capital stock | 195 | 5.29 | 9.04 | 0.01 | 49.01 |
| Wind resource | 195 | 409.1 | 63.9 | 167.3 | 505.2 |
| Turbine size | 195 | 149.9 | 119.5 | 20.0 | 750.0 |
| Imported turbine | 195 | 0.57 | 0.50 | 0.00 | 1.00 |
| Op.Exp., firm | 195 | 32.9 | 53.3 | 0.0 | 295.8 |
| Op.Exp., state | 195 | 476.4 | 346.1 | 90.5 | 1466.7 |
| Op.Exp., world | 195 | 176.4 | 315.4 | 8.8 | 2429.9 |
| Inst.exp., firm | 195 | 50.4 | 75.5 | 0.0 | 469.8 |
| Inst.exp., state | 195 | 1209.0 | 811.9 | 30.7 | 4261.4 |
| Inst.exp., world | 195 | 221.3 | 167.1 | 45.2 | 1180.8 |

Table 9: Correlation matrix for regressors used in Table 5.

| Variable | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|
| 1 Wind resource | 0.016 | 1 | | | | | | | |
| 2 Turbine size | −0.331 | −0.004 | 1 | | | | | | |
| 3 Imported turbine | −0.110 | −0.020 | 0.340 | 1 | | | | | |
| 4 iexpepfrmx | −0.209 | −0.007 | 0.334 | 0.294 | 1 | | | | |
| 5 iexpepstax | −0.414 | −0.026 | 0.411 | 0.250 | 0.495 | 1 | | | |
| 6 iexpepwldx | −0.474 | −0.040 | 0.585 | 0.223 | 0.460 | 0.810 | 1 | | |
| 7 iexpnifrmx | 0.020 | 0.018 | 0.050 | 0.175 | 0.595 | 0.182 | −0.031 | 1 | |
| 8 iexpnistax | 0.071 | 0.031 | −0.152 | 0.047 | 0.143 | 0.361 | −0.134 | 0.483 | 1 |
| 9 iexpniwldx | −0.365 | −0.027 | 0.467 | 0.162 | 0.384 | 0.829 | 0.830 | 0.124 | 0.257 |

Table 10: Indices of collinearity for independent variables used in Table 5.

| | Variance Inflation Factor | Tolerance (1/VIF) | $R^2$ | Eigen value | Condition index |
|---|---|---|---|---|---|
| Capital stock | 1.32 | 0.755 | 0.245 | 3.763 | 1.000 |
| Wind resource | 1 | 0.996 | 0.004 | 1.761 | 1.462 |
| Turbine size | 1.73 | 0.580 | 0.420 | 1.118 | 1.835 |
| Imported turbine | 1.22 | 0.822 | 0.178 | 0.999 | 1.941 |
| Op.Exp., firm | 2.66 | 0.376 | 0.624 | 0.781 | 2.195 |
| Op.Exp., state | 9.13 | 0.110 | 0.890 | 0.687 | 2.341 |
| Op.Exp., world | 15.26 | 0.066 | 0.934 | 0.492 | 2.766 |
| Inst.exp., firm | 2.5 | 0.401 | 0.599 | 0.232 | 4.025 |
| Inst.exp., state | 4.83 | 0.207 | 0.793 | 0.129 | 5.397 |
| Inst.exp., world | 6.28 | 0.159 | 0.841 | 0.038 | 9.963 |
| Aggregate | 4.59 | | | | 9.963 |

Table 11: Additional coefficient estimates for linear regression with year-of-installation fixed effects. Dependent variable is quarterly electricity production at time of installation. All ratio variables are in logs.

| | (1) base model | (2) wind ×exp | (3) size ×exp | (4) fwd qtr lag all | (5) fwd qtr lag ext |
|---|---|---|---|---|---|
| $K$ capital stock, $W$ wind resource, $Q$, quality, and $P$ policy | | | | | |
| Capital stock | 0.698*** | 0.689*** | 0.693*** | 0.732*** | 0.732*** |
| | (15.67) | (15.59) | (15.14) | (20.18) | (19.74) |
| Wind energy | 0.611** | 0.724** | 0.598** | 0.337 | 0.328 |
| | (2.24) | (2.33) | (2.19) | (1.23) | (1.17) |
| Turbine size | 0.323*** | 0.322*** | 0.298*** | 0.357*** | 0.358*** |
| | (5.82) | (5.85) | (3.75) | (7.07) | (7.00) |
| Imported | 0.245*** | 0.262*** | 0.263*** | 0.304*** | 0.296*** |
| | (3.38) | (3.52) | (3.58) | (4.13) | (4.01) |
| Policy: capital | -0.171 | -0.143 | -0.146 | -0.360** | -0.382** |
| | (-0.74) | (-0.58) | (-0.60) | (-2.12) | (-2.10) |
| $X$, Experience at time of installation | | | | | |
| Inst.exp, firm | 0.156* | 0.403 | 0.111 | 0.0909 | 0.101 |
| | (1.94) | (1.00) | (0.85) | (1.40) | (1.41) |
| [a] Inst.exp$^2$, firm | -0.0304** | -0.0291* | -0.0304* | -0.0197* | -0.0213 |
| | (-1.98) | (-1.88) | (-1.94) | (-1.74) | (-1.60) |
| Inst.exp, external | 0.953* | 0.0799 | 0.101 | 0.405 | 0.646 |
| | (1.70) | (0.06) | (0.08) | (0.17) | (0.28) |
| Inst.exp$^2$, external | -0.0934** | -0.0332 | -0.0352 | -0.0557 | -0.0721 |
| | (-1.99) | (-0.34) | (-0.36) | (-0.32) | (-0.43) |
| Interaction terms | | | | | |
| Wind×exp | | -0.0418 | | | |
| | | (-0.62) | | | |
| Size×exp | | | 0.0103 | | |
| | | | (0.41) | | |
| constant | -7.385*** | -4.868 | -4.056 | -3.779 | -4.618 |
| Depreciation ($\lambda$) | 0.420 | 0.420 | 0.420 | 0.420 | 0.420 |
| adj. $R^2$ | 0.699 | 0.701 | 0.700 | 0.760 | 0.760 |
| observations | 195 | 195 | 195 | 192 | 192 |

[a] *** p<0.01, ** p<0.05, * p<0.1.