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Gone with the wind: A learning curve analysis of China's wind power industry

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Key words: Learning curve; wind power; China; Clean Development Mechanism; climate change

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Abbreviations

- CDM: Clean development mechanism
- CER: Certified emission reduction
- GHG: Greenhouse gas
- GW: Gigawatt
- kW: Kilowatt
- kWh: Kilowatt-hour
- MW: Megawatt
- MWh: Megawatt-hour
- O&M: Operation and maintenance
- PDD: Project design document
- R&D: Research and development
- SOE: State-owned enterprise
- UNFCCC: United Nations Framework Convention on Climate Change

1 Introduction

Since Arrow (1962) conceptualized the notion of learning by doing, numerous empirical studies have shown that productivity of workers and firms often rises with accumulation of experience (e.g., Barrios and Strobl, 2004). The analysis linking experience accumulation and productivity gains (learning curve analysis) has recently been extended to low-carbon technology fields, primarily to assess learning in renewable energy technology fields in industrialized countries. For example, a number of studies examined learning in wind power technology for Europe (e.g., Söderholm and Sundqvist, 2007) and the United States (Nemet, 2012). However, the learning curve literature has so far paid much less attention to low-carbon technologies in developing countries.

The emergence of China's wind power industry is one of the most impressive cases of technological catch-up. China's wind power market expanded exponentially over the last decade and now represents more than a quarter of global wind power installations (GWEC, 2014). The rapid increase in wind turbine installations was accompanied by the emergence of a successful local industry, which currently dominates China's wind power market (Lewis, 2013). However, despite the growth in wind power installation and manufacturing capacity, China has struggled to improve its wind power generation performance (Huenteler et al., 2018). This is largely due to grid connection delays and a widespread problem of wind power curtailment. Curtailment is when grid operators choose to "spill" wind generation, meaning it is not captured by the grid, but essentially wasted. Such curtailment is usually done in order to preserve grid stability, but may be done for a variety of other factors, both technical and political. Whatever the motivation, curtailment results in foregone revenue to wind generators, and has a large impact on the financial performance of wind farms. The curtailment problem started in 2009, and remains a major problem (Lewis, 2016a). China experienced record levels of curtailment in 2016 accounting for 17% of the annual wind power generation (Reuters, 2017).

Previous learning curve analyses on the Chinese wind power industry were conducted using *predictive* measures of costs and generation performance of wind power. Using the bid prices offered under China's Wind Resource Concession Program between 2003 and 2007, Qiu and Anadon (2012) found that learning through wind turbine installation and manufacturing as well adoption of new wind power technologies led to bid price reductions of 4.1% - 4.3% per doubling of installed capacity and new technology adoption. Tang and Popp (2016) analyzed *ex ante* estimations of costs and capacity factors[1] of China's wind farms registered under the Clean Development Mechanism (CDM) between 2002 and 2009 and found that wind turbine installation experience, especially the cooperating experience between a developer and its partner foreign turbine manufacturer, led to cost reductions and improvement in the predictive measure of generation performance. Lam et al. (2017) also analyzed China's wind farms registered under the CDM between 2004 and 2012 to find that the learning rate on the *predicted* levelized cost of electricity was between 3.5% and 4.5% per doubling of installed capacity, which was much lower than those experienced in Denmark and Germany during similar stages of industry development.

Given the current mismatch between capacity and generation in the Chinese wind power industry (Yang et al., 2012), questions remain about whether experience drives not only installations but also *actual* wind power generation in China. The main purpose of this study

[1] A capacity factor measures the amount of power generation as a share of how much could be generated if the wind turbines operated at full capacity.

is to provide a quantitative analysis of how the experience and knowledge of wind farm developers and turbine manufacturers contributed to both capacity-related productivity (turbine size and unit turbine costs) and *actual* power generation of wind farms in China during the rapid market expansion phase between 2005 and 2012. This is an important period for the learning curve analysis because the industry accumulated a significant amount of experience in this phase, while wind power curtailment became a serious problem. This study uses an original dataset of 312 Chinese wind farms that were registered and issued carbon credits under the CDM. The wind farms in this dataset represent 16.5 gigawatts (GW) of installed wind turbine capacity or 21% of China's total grid-connected turbine capacity in 2012. A key strength of the dataset is that it contains the actual amount of electricity generated from the CDM wind farms. Therefore, this study can analyze the relationship between capacity- and generation-based output measures and the experience and knowledge levels of developers and manufacturers, while controlling for capital stock, wind resources, wind support policies, and other factors that may influence the productivity measures. The capacity and generation data were third-party verified as part of the CDM approval process. The analysis demonstrates that the experience and knowledge accumulation during the rapid market expansion phase did not lead to productivity gains in the output measures. This indicates that even the unprecedented market growth did not result in technological learning.

This study begins with explaining the context of technological learning in the Chinese wind power industry (section 2). Section 3 introduces the empirical strategy for data analysis, the results of which are summarized in section 4. The contributions, policy implications and limitations of this study are discussed in section 5, followed by conclusions in section 6.

2 Technological learning in the Chinese wind power industry

2.1 Expansion of China's wind power market

The Chinese government initiated wind power technology development efforts during the sixth Five-Year Plan period of 1981 to 1985 (Shi, 1986). Until the mid-1990s, the efforts were mostly confined to small domestic wind turbines and a few imported models from Denmark. The Chinese wind power market began expanding in 1994, when the Ministry of Electric Power issued the Provisions for Grid-Connected Wind Farm Management (MOEP, 1994). The provisions required grid operators to remunerate wind power with wind farm costs plus a reasonable profit. A series of support policies followed, including preferential loan schemes (e.g., the "Double Increase Program" in 1995, and additional loans for wind farm development in 1996), which led to the government successively increasing national wind power installation targets (e.g., the 10th Five-Year Plan in 2001) as well as industrial policy support schemes for wind turbine science, technology and local manufacturing (e.g., National High Tech Research and Development—R&D—Programs, or 863 Programs, in 1996 and 2001). As a result, the industry experienced its first wave of rapid expansion from 1994 to 2002, with annual growth rates exceeding 100% over several years, and annual installations mostly in the double-digit megawatt (MW) range (see Figure 1).

The second wave of expansion started in the mid-2000s with a triad of significant policies targeting the wind power sector. First, the Chinese government started the Wind Resource Concession Program in 2003 (NDRC, 2003). This program was a key driver of the wind market expansion between 2003 and 2007, totaling 3,350 MW of new wind turbine installations through five rounds of competitive bidding (Lewis, 2013). Wind farms were selected on the lowest price per kilowatt-hour (kWh) basis, resulting in some limited price discovery in what had long been a market highly distorted by subsidies (Qiu and Anadon, 2012). The concession program was also instrumental in fostering domestic manufacturing capacity as it mandated government-selected wind farms to domestically procure a minimum share of the equipment (Lewis, 2013). Second, the first Renewable Energy Law, which entered into force in 2006, set a legal framework for mandatory grid connection and full purchase of renewable energy projects, and authorized the establishment of feed-in tariffs (NPC, 2005). Third, China gained access to the CDM following its ratification of the Kyoto Protocol and its establishment of domestic CDM regulations in 2005 (NCCC, 2005). Under the CDM, GHG mitigation projects implemented in non-Annex I countries (e.g., China) can claim carbon credits (CERs: Certified Emission Reductions) for the amount of GHG emission reductions they achieved. The CERs can be sold on the market, which provides the projects with additional financial support. As much as 64 GW or 80% of China's total installed turbine capacity had obtained CDM registration by 2012 (Chan and Huenteler, 2015).

The three policies were complemented by another round of successively increasing targets in the 2007 Medium- and Long-Term Plan for Renewable Energy Development in China (NDRC, 2007), the establishment of a unified nationwide wind power tariff system guaranteeing fixed returns on investment (NDRC, 2009), and the 2006 update of the 863 Program for supporting the further development of MW-size wind turbines (MOST, 2006). These policies, along with additional support measures, drove massive expansion in the Chinese wind power market from 2004 onwards, with annual growth rates again exceeding 100% over several consecutive years. The capacity increase propelled China into the top spot in the global wind turbine installation and manufacturing rankings. As of 2015, China was home to 34% of total global installed wind turbine capacity (GWEC, 2016).

[Insert Figure 1 here]

2.2 Catch-up by the Chinese wind power industry

The growth of the Chinese wind power market was accompanied by the rise of domestic industry that gradually caught up in technological capabilities with early-mover countries such as Europe and the United States (Ru et al., 2012). One measure of technological sophistication in the wind turbine industry is the wind turbine size, measured in electric capacity (MW). Figure 2 shows the catch-up of Chinese turbine manufacturers as indicated by a selection of installed turbine prototypes indicating benchmarks of technological sophistication among leaders in the industry.

[Insert Figure 2 here]

The catch-up process is also reflected in the gradually increasing market shares of domestic turbine manufacturers (see Figure 3), and their cumulative market shares (see Table 1). In the developers' market, Chinese companies are even more prominent. Dominating the mix are China's "big-five" power companies, state-owned enterprises (SOEs) which have invested about 80% of the cumulative installed turbine capacity at the end of 2011 (Spratt et al., 2014). While private companies, including wholly foreign owned ones, are now increasingly engaged in China's wind power development, their market shares still remain minimal. In China, SOEs generally have better access to finance due to their "long and deep relations" with the state-owned commercial banks (Spratt et al., 2014, p. 19). In addition, numerous foreign companies have reported facing difficulty in obtaining government approval for wind farm development (Lewis, 2013). This again means that the virtual non-existence of foreign developers is not necessarily a sign of superior domestic capabilities. The market shares do not directly reflect technological capabilities because Chinese manufacturers benefited from a variety of preferential treatment by both the government and state-owned developers (Lewis, 2013).

[Insert Figure 3 here]

[Insert Table 1 here]

2.3 Productivity of wind farms in China

This study analyzes the following three output measures to assess learning effects on the productivity of wind farms in China: (1) turbine size, (2) unit turbine costs, and (3) *actual* power generation. The first and second indicators are capacity-related productivity measures, while the third is generation performance. In the sample of 312 CDM wind farms in China, the average turbine size increased by 48% and the average unit turbine cost decreased by 8% between 2005 and 2011. However, the monthly average power generation per installed wind turbine (megawatt-hours or MWh/turbine) declined in 2007 then increased somewhat, but deteriorated again between 2011 and 2012 (see Figure 4). The generation performance decline in 2007 corresponds to the start of the massive expansion of China's wind power market and the influx of many new Chinese turbine manufacturers into the market, while the deterioration of generation performance starting in 2011 may be due to the wind power curtailment. The commonly used evidence of catch-up by China's wind power industry (an increase in installed turbine capacity or turbine size) does not consider the productivity of wind power technologies when they are put into use. Therefore, questions remain about how the significant experience accumulated in the Chinese wind power industry contributed to productivity gains, especially in terms of *actual* generation performance.

[Insert Figure 4 here]

The most conventional learning curve model relates productivity gains to learning by doing. That is, knowledge accumulation through repetition of similar tasks increases workers' productivity (Bahk and Gort, 1993). There are two types of experience that are important to a wind farm developer's learning by doing: (1) installation experience and (2) operation and maintenance (O&M) experience (Nemet, 2012). First, a developer needs to make decisions on technology and site selection at the time of wind farm installation. Key to the technology selection are the overall cost, efficiency and reliability of wind turbines. It is also crucial to select a windy site because the amount of wind energy available increases with the cube of wind speed. Second, wind farms need to be operated to maximize the power output and minimize the O&M costs. To this end, it is essential to optimize turbine control and grid integration, minimize the share of time wind turbines are out of service for maintenance, and to schedule the maintenance during non-windy periods of the year.

Learning also takes place at the manufacturer's side. The accumulation of experience by a manufacturer may contribute to turbine quality improvements in two distinct ways. First, a manufacturer may increase its productivity through repetition of manufacturing work, i.e., learning by doing. Thus, the turbine quality may be influenced by the cumulative manufacturing experience of the manufacturer at the time of wind farm installation. Second, a manufacturer may engage in activities aimed at new knowledge creation such as R&D. The accumulation of new knowledge may result in innovations and greater productivity, or learning by searching (Kouvaritakis et al., 2000). The stock of knowledge accumulated by the time of wind farm installation will then determine the quality of the turbine installed in the wind farm. Furthermore, technological learning is facilitated by the interaction between a developer and its partner manufacturer, i.e., a user and producer of innovation (Lundvall, 1988). This is because successful innovation requires attention to users' needs (Laursen, 2011). Moreover, a stable user-producer relationship reduces transaction costs, leading to an accelerated pace of innovation and learning (Fagerberg, 1995). The wind farm installation involves close interaction between a developer and its partner manufacturer supplying technologies. Their joint experience in installation may thus have distinct contributions to productivity growth (Tang and Popp, 2016).

Common across all of the different learning mechanisms is that the stock of knowledge is assumed to depreciate over time due to employee turnover, layoffs, and forgetting things over time. Hence, if the nature of experience is comparable, knowledge gained from recent experience is more valuable than that associated with earlier experience (Benkard, 2000).

Note that there are several possible explanations for China's stagnating power generation performance other than the inexperience of the firms operating in China, including delayed interconnection, integration challenges, and first-mover resource advantages. China faces significant disparities between energy resources and load centers, which requires an extensive transmission infrastructure. Despite the government's establishment of large scale "wind power bases" in order to allow for transmission planning to occur far in advance (Wen, 2012), wind farms have frequently faced delays in being connected to the grid. Installed wind power capacity that is not generating electricity due to delayed grid connection may therefore result in a decrease in generation performance (Yang et al., 2012).

Along with transmission, the other major technical challenge plaguing wind power development in China is integration. Some of China's best wind resources are concentrated in northern China, which is also one of the most coal-rich parts of the country. The major technical challenge related to integrating large amounts of wind power, particularly in Eastern Inner Mongolia, is balancing a grid based on wind and coal. With few gas power or hydropower plants, coal power plants are ramped up and down to keep the grid stable (e.g., for cycling, load-following, peaking generation, and ancillary services), significantly reducing their overall efficiency (Kahrl et al., 2011). Running coal plants that provide combined heat and power trumps wind farms; particularly in the wintertime when the heat is needed. As a result, China's wind power installations have faced a widespread problem of wind power curtailment (Lewis, 2016a).

Another reason for the stagnating generation performance could be related to first-movers having occupied the best wind resource sites, while the followers need to use sites with lower wind speed. Any analysis of generation performance must therefore attempt to control for all of these potential confounding factors. The next section explains the empirical strategy for a learning curve analysis of the Chinese wind power industry.

3 Data and methods

3.1 Estimation methodology

The estimation begins by adopting a modified Cobb-Douglas production function that was applied in Nemet (2012) for a learning curve analysis of California's wind power industry using power generation data:

$$Y_{it} = f(K_{it}, W_{it}, P_{it}, X_{it}, Q_i) \quad (1)$$

where Y_{it} refers to the output level of wind farm i at time t. As discussed in section 2.3, this study uses (1) actual power generation as a generation-based output indicator, as well as (2) turbine size and (3) unit turbine costs as capacity-related output measures. The output is determined by the capital stock, K_{it}, wind resources, W_{it}, policies affecting wind farms, P_{it}, stock of knowledge derived from cumulative experience, X_{it}, and equipment quality, Q_i. Labor input is dropped from the model because such data are not publicly available for the Chinese wind power industry. This is unlikely to be a significant omission given that labor costs of wind farms typically account for only about 10% of the total costs (Kirkegaard et al., 2009, p. 38; Neumann et al., 2002, p. 13). Note also that the skill levels of labor are captured by the experience variable, X_{it} (Nemet, 2012).

The model takes into account various types of learning by developers and manufacturers. At the developer's side, installation and O&M experience contributes to productivity enhancement. While the wind farm installation is a one-time decision, O&M requires periodical decisions during the lifetime of the wind farm. Thus, X_{it} is split into a developer's cumulative installation experience at the time of installation, I_i, and its cumulative O&M experience at time t, O_{it}. The output of wind farms is also influenced by a manufacturer's cumulative experience in turbine manufacturing, M_i, and its stock of knowledge accumulated through R&D activities by the time of installation, R_i. Furthermore, the cumulative installation experience shared by a developer and its partner manufacturer by the time of installation, J_i, may influence the output level in a way that is distinct from the learning through unshared installation experience. In order to avoid double counting of experience, the amount of joint installation experience, J_i, is subtracted from a developer's installation experience, I_i, and from a turbine maker's manufacturing experience, M_i.

The equipment quality, Q_i, is measured by capital vintage as newer capital vintages embody greater technological progress (Barrios and Strobl, 2004). This essentially captures industry-wide technological progress that is common to all wind farms. As China's wind power industry has actively engaged in international technology transfer (Lewis, 2013), the industry has likely benefited from the technological progress both within and outside China. The model thus adds a variable measuring the technological progress in the global wind power industry.

In the case of China, it may be important to distinguish SOEs with private ones. SOEs tend to have better resources and political connections, which may influence the performance of wind farms (Tang and Popp, 2016). Thus, dummies for state-owned manufacturers, $S_{MAKE,i}$, and state-owned developers, $S_{DEV,i}$, are added to the model.

It is important to control for power market characteristics as they influence a utility's power dispatch decisions and developers' investment decisions. For example, a growing demand for electricity requires a large amount of power supply in general. Furthermore, a reliable integration of wind power requires back-up power sources with load-following capabilities. In

China, gas-fired power capacity is negligible[2] and hydropower plants are mostly located in the south, distant from the large wind power bases in the northern area. This makes coal-fired power to serve as a back-up source for wind power integration (Yang et al., 2012). As discussed above, a utility may decide to curtail wind power generation. The model thus includes the annual electricity demand in the province where a wind farm i is located, E_{it}, the installed capacity of steam turbines for power generation in the province (mostly, coal-fired power generation), $G_{STEAM,it}$, the installed capacity of hydropower turbines in the province, $G_{HYDRO,it}$, and, as a proxy measure of curtailment, the share of wind power in the total power generation capacity in the province, C_{it}.[3] Note that curtailment is more likely in provinces with a high penetration rate (Li et al., 2014). In contrast, a moderate level of wind power penetration may encourage market competition and drive productivity improvements. These suggest an inverted U-shaped relationship between the output levels and wind power penetration rates. Therefore, a squared term of C_{it} is also added to the model. Based on the above, the final model is specified as follows. Log-transformation is applied to all the ratio variables because they have right-skewed distributions. For variables with zero-value observations (e.g., the experience and knowledge stock variables), a very small number (0.0001) is added to the original observations because the log-transformation would otherwise yield negative infinity. The variable definitions are summarized in Table 2.

$$Y_{it} = f(K_{it}, W_{it}, P_{it}, I_i, O_{it}, M_i, R_i, J_i, Q_i,$$
$$S_{MAKE,i}, S_{DEV,i}, E_{it}, G_{STEAM,it}, G_{HYDRO,it}, C_{it}, C_{it}^2) \qquad (2)$$

[2] Gas-fired power capacity accounted for only 2.7% of China's total power generation capacity in 2009 (Yang et al., 2012).

[3] Data on province-level curtailment rates are available, but not used in the analysis because of an endogeneity problem (e.g., the amount of wind power generation determines curtailment rates).

[Insert Table 2 here]

3.2 Data and variables

The compiled dataset includes the characteristics and power generation of 312 CDM wind farms that were installed in China between 2005 and 2011 and generated wind power between 2006 and 2012. The sample includes CDM wind farms that submitted monitoring reports to the United Nations Framework Convention on Climate Change (UNFCCC), a UN body overseeing the CDM, by the end of 2012. This is because the analysis uses actual power generation as one of the output indicators, which can be determined only after the wind farms have been operational. The sample covers 21% of China's total grid-connected turbine capacity in 2012, which essentially excludes CDM wind farms that have not submitted monitoring reports to the UNFCCC and non-CDM wind farms.

The dataset is hand-coded from 258 project design documents (PDDs) and 962 monitoring reports, all of which are publicly available on the UNFCCC website (UNFCCC, 2016). While the information on wind farm characteristics can be obtained from the PDDs, the actual power generation data are only available in monitoring reports. Some wind farms use two or three wind turbine models, in which case the wind farms are split into multiple batches so that each batch represents one turbine model. This explains why the dataset contains 312 CDM wind farms (including split batches) based on the data collected from 258 PDDs. In this process, power generation and capital investment data are apportioned pro rata to each batch's installed turbine capacity. The panel data are unbalanced because the wind farms started operation at different times, with an increasing number of wind farms starting in the latter part of the analysis period. The data quality is considered high because the data are independently verified during the CDM project assessment processes (Tang and Popp, 2016).

The CDM dataset is complemented by a proprietary dataset obtained from Huaxia Wind (2013), which covers all Chinese wind farms including non-CDM ones between 1989 and 2012. Although this full-sector dataset does not contain power generation data, it includes information on the name, location, turbine model, installed capacity, commissioning date and developer of all wind farms in China. Therefore, it enables the construction of variables measuring experience in installation and operation as well as turbine manufacturing in the entire Chinese wind power industry. Moreover, the full-sector dataset enables the use of the Heckman selection model to address the potential selection bias due to the moderate coverage of the CDM sample (Heckman, 1979). For implementing the Heckman selection model, it was necessary to merge the CDM and full-sector datasets. Because they do not share a common wind farm identifier, the wind farms in the CDM dataset had to be manually matched with those in the full-sector dataset. Following the procedures in Chan and Huenteler (2015), each CDM wind farm was checked for its name, location, turbine model, installed capacity and developer, and matched with a wind farm in the full-sector dataset. In terms of installed capacity, 97% of the CDM sample was successfully matched with the full-sector dataset. When integrating the CDM and full-sector datasets, the unmatched CDM wind farms caused duplicates because they were not deleted in the full-sector dataset. However, the error was considered small enough to justify the use of the integrated dataset for addressing the selection issue. The following sections explain each of the variables used in the analysis.

3.2.1 Output variables

The actual power generation of a wind farm, $Y_{GEN,it}$, is measured by the monthly power generation data are averaged over a quarter (in MWh/month). The monthly power generation data are obtained from the monitoring reports of the CDM wind farms. The amount of wind power generation fluctuates within a year due to the strong seasonality in wind speed. In addition, most wind farms in the sample started operation in the middle of the year, making it necessary to adjust the power generation data for the start of wind farm operation. The monthly power generation data—as opposed to yearly data—are necessary to take these issues into account. A drawback of the monthly data is that they inflate the sample size without adding much variation in data values. To strike a balance, the monthly power generation is averaged over a quarter.

The turbine size of a wind farm, $Y_{SIZE,i}$, is the rated capacity of the wind turbine model used in the wind farm (in kW). The unit turbine costs of a wind farm, $Y_{CAPEX,i}$, are measured by the amount of capital investment per MW of installed turbine capacity (in million 2005 RMB/MW). The turbine size and cost data are obtained from PDDs.

3.2.2 Experience and knowledge stocks

The variables of interest are those measuring experience and knowledge stocks. A developer's cumulative experience in wind farm installation, I_i, is measured by the cumulative capacity of wind turbines installed in China by the developer, minus the cumulative capacity of wind turbines jointly installed by the developer and its partner manufacturer, prior to the installation of a given wind farm (in GW). As power generation data are not available for non-CDM wind farms, a developer's operating experience, O_{it}, is measured by the product of the cumulative installed turbine capacity and the number of days passed since the wind farm installation (in

TW-days). A manufacturer's cumulative experience in turbine manufacturing, M_i, is measured by the cumulative installed capacity of wind turbines supplied in China by the manufacturer, minus the cumulative capacity of wind turbines jointly installed by the manufacturer and its partner developer, prior to the installation (in GW). The joint cumulative experience in installation, J_i, is measured by the cumulative capacity of wind turbines jointly installed by a developer and its manufacturer prior to the wind farm installation (in GW).

A manufacturer's knowledge stock, R_i, is measured by the cumulative number of patents the manufacturer filed in wind power technology fields prior to the wind farm installation. The patent data are obtained from Derwent Innovations Index (Thomson Reuters, 2014). The patent applications are weighted by their family size[4] to take into account the value of the patented inventions (Popp et al., 2011). The patent data include all patent applications filed by Chinese manufacturers. For international manufacturers operating in China, the data only include patents that were filed in China because only these can be expected to be the result of R&D activities for China. This restriction is applied because the analysis concerns learning by searching in the Chinese wind power market. There are limitations to the use of patents as a measure of knowledge stock; e.g., not all inventions are patented or patentable (Archibugi and Pianta, 1996). Despite their limitations, patents are used widely as a measure of innovation activities because they provide a wealth of information on the invention and the applicants, and can be disaggregated to specific technology fields (e.g., Popp et al., 2011).

[4] The patent family size refers to the number of countries in which protection of the invention has been sought. As patenting is a costly and time-consuming process, the geographical coverage of a patent application is assumed to be associated with the value of the invention (OECD 2009, pp.139–140).

Experience and knowledge depreciate over time. This depreciation effect is modeled using the perpetual inventory method (Peri, 2005). For illustration, the calculation of O_{it} is shown below. The same procedure applies to I_i, M_i, R_i and J_i, except that the discounted knowledge stock for these variables is fixed over the wind farm lifetime as they concern one-time decisions at the installation.

$$O_{it} = (1 - \delta)O_{it-1} + e_{it-1} \quad (3)$$

where O_{it} is the depreciated stock of previously acquired operating experience in quarter t, e_{it-1} the amount of new operating experience gained in quarter $t-1$, and δ the rate of knowledge depreciation per quarter. The default knowledge depreciation rate is 2.6% per quarter or 10% per year, which is a value commonly used in the literature (e.g., Dechezlepretre et al., 2011).

3.2.3 Wind resource

The wind resource available at the wind farm site is an important determinant of wind power generation. However, only about a quarter of the CDM sample reports wind resource assessment in the PDDs. Alternatively, wind speed data are extracted from the publicly available 3TIER Global Wind Dataset (IRENA, 2014). This dataset contains the annual average wind speed at 80 meters above ground, simulated using over 10 years of hourly data (in m/s). The wind speed data are available on a 2-arc-minute (ca. 5 km) resolution grid, which is a sufficiently accurate measure of site-specific wind speed. The geographical coordinates of wind farms are obtained from the PDDs, and used to match each wind farm with the closest grid in the 3TIER dataset.

Wind turbines typically have cutout speeds, above which they shut down in order to avoid damages to the equipment. Therefore, the direct use of wind speed is likely to result in overestimation of the wind resource available for power generation. One way to address this issue is by converting the annual average wind speed into full load hours, i.e., the number of hours which a wind turbine would spend at full load if it always operated at that level. European Environment Agency (2009) offers a suitable methodology, which estimates full load hours based on power-velocity curves of wind turbine models and a Weibull distribution for taking into account the variation in wind speed over a year (for the application of this methodology, see also Prässler and Schaechtele, 2012).[5] This approach assumes a 1.5 MW wind turbine model for evaluating Europe's onshore wind energy potential. In comparison, the average size of wind turbines in this study's database is 1.3 MW. The small difference in the turbine size causes slight overestimation of full load hours, but this small bias is considered acceptable. The full load hours are multiplied by the wind farm capacity to derive a measure of wind resource available at the wind farm site, i.e., the expected amount of monthly power generation of a wind farm given the annual average wind speed (in MWh/month), $W_{SITE,i}$.

A limitation of the 3TIER data is that they only provide annual average wind speeds. This makes it necessary to control for seasonal variation in wind speed. He and Kammen (2014) provide the monthly average wind capacity factors for each province in China, which are simulated using the hourly wind speed data obtained from 3TIER. In this study, these monthly capacity factors are averaged over a quarter to derive the expected amount of monthly power generation in a given province for each quarter (in MWh/month), $W_{PRV,it}$. In the absence of site-specific wind speed data measured over time, the combined use of $W_{SITE,i}$ and $W_{PRV,it}$ is the best available measure of the wind resource.

[5] The estimation formula for onshore wind farms is as follows. Full load hours (hours per year) = Annual average wind speed at hub height (in meters per second) x 626.51 – 1,901.

3.2.4 Policy variables

The model adds variables for policies particularly important for wind farms in China between 2005 and 2012: power purchase tariff, local content requirements, and the CDM. Note that the list excludes policies that existed but did not substantially change over the observation period because they cannot have caused any *change* in the output levels during the period.

Power tariffs, $P_{TARIFF,i}$, are obtained from the actual bidding prices for the 2005-2008 period. In 2009, the Chinese government divided China's provinces into one of four onshore wind resource categories and set different feed-in tariffs for each category (Hu et al., 2013). Tariff levels are usually fixed for the entire lifetime of a wind farm or reduced after a certain operation period (e.g., 30,000 full load hours). In the former case, the lifetime tariff levels are used. In the latter case, the tariff levels for the first operation period are used because the first operation period is sufficiently long to cover the entire period of investigation.[6] The tariff information is obtained from the PDDs and converted into real values (in 2005 RMB/kWh).

Local content requirements, $P_{LCR,i}$, are expressed as the minimum share of wind farm equipment that needs to be procured within China (in %). The local content requirement rate was first 40% in 1996, then increased to 50% in 2003 and to 70% in 2004, and finally abandoned in 2009 (Gosens and Lu, 2013). The local content requirement rate at the time of wind farm installation is used in the analysis. While there were numerous other types of protectionist measures used in China during the time period examined, the local content requirements were most certainly the largest barrier to entry for foreign firms into the Chinese wind market since it required a significant localization of overseas supply chains (Lewis, 2013)

[6] Onshore wind farms typically operate about 2,000 to 2,500 full load hours per year (Krohn et al., 2009, p. 65).

As a result, the local content requirement rate is used as a proxy for other protectionist measures that were in place including tariff and non-tariff barriers.

The impact of the CDM is measured by the annual average secondary CER prices, $P_{CER,t}$, (in 2005 USD/tCO_2e). Secondary CERs are carbon credits that have been issued by the UNFCCC and can be traded at exchanges. The secondary CER price information is obtained from the World Bank's publications (Capoor and Ambrosi, 2009, 2007; Kossoy and Guigon, 2012).

3.2.5 Other control variables

Capital stock, K_{it}, is measured by the depreciated capital investment of a wind farm (in million 2005 RMB). The capital investment data are obtained from the PDDs. As a default, it is assumed that the capital fully depreciates at a constant rate over a turbine lifetime of 20 years (Krohn et al., 2009). The industry-wide technological progress, Q_i, is measured by the global average turbine size in the quarter before the wind farm installation (in kW). Dummies for state-owned turbine manufacturers, $S_{MAKE,i}$, and state-owned developers, $S_{DEV,i}$, are constructed by confirming the company ownership on the company websites. Data on the annual electricity demand (in TWh/year), E_{it}, the installed capacity of steam turbines for power generation (in MW), $G_{STEAM,it}$, the installed capacity of hydropower turbines (in MW), $G_{HYDRO,it}$, and the share of wind power in the total power generation capacity (in %), C_{it}, in each province are collected from China Electric Power Yearbook 2006-2013 (e.g., China Electric Power Yearbook 2013). Table 3 provides descriptive statistics for the dataset (see Table A.1 for a correlation matrix).

[Insert Table 3 here]

4 Results

The analysis begins with model (1), which is a panel data analysis regressing power generation on variables measuring the capital stock, wind resource, policy, power market characteristics, industry-wide technological progress and firm ownership. Model (2) adds experience and knowledge stock variables to model (1). In order to address the selection issue, the Heckman's two-step estimation procedure was used for the model estimation. In the first step, a selection equation was estimated with the full-sector dataset using all the regressors listed above except for the capital stock, wind resources, and power purchase tariffs (data were not available for these excluded variables). In the second stage, an outcome equation was estimated with the CDM sample, regressing power generation on all the aforementioned variables.[7] The outcome equation was estimated with a random effect model as the use of wind-farm-fixed effects would have dropped most of the variables of interest, i.e., time-invariant experience and knowledge stock variables, I_i, M_i, R_i and J_i. As the residuals of the models were found unequal across wind farms, standard errors were clustered on wind farms to address heteroskedasticity. Furthermore, year- and province-fixed effects were added to control for any unobserved time-varying factors affecting all wind farms (e.g., changes in national and international policies not explicitly measured) and time-invariant heterogeneity across provinces (e.g., distance from load centers, grid infrastructure).

Models (3) – (6) are cross-sectional analyses using the turbine size and unit turbine costs as dependent variables. Only the observations in the first quarter of wind farm operation were

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[7] For models (1) and (2), the estimated correlation between the errors in the selection and outcome equations was not significantly different from zero at the 0.05 significance level, and the hypothesis that the two equations were independent could not be rejected. This indicated that the selection bias was not a serious concern.

used because the turbine size and unit turbine costs do not vary over time. The estimation of these models also followed the Heckman's two-step procedure.[8] While the selection equation was estimated with the same procedure as explained above, the following adjustments were made to the outcome equation estimation due to the difference in the dataset structure: the ordinary least squares estimator was used with robust standard errors clustered on wind farms; the quarterly average wind resource ($W_{PRV,it}$) and operating experience (O_{it}) were dropped as they were highly correlated with the site-specific wind resource ($W_{SITE,i}$) and a developer's installation experience (I_i), respectively[9]; year-fixed effects were dropped because they caused perfect multicollinearity with the secondary CER price ($P_{CER,t}$) and industry-wide technological progress (Q_i); the capital stock variable (K_{it}) was dropped in models (5) – (6) because the capital expenditure was used to calculate unit turbine costs.

The estimation results are summarized in Table 4. The results of models (1) and (2) show that generation performance ($Y_{GEN,it}$) improves with greater capital stock (K_{it}) and wind resource ($W_{SITE,i}$ and $W_{PRV,it}$). The addition of the experience and knowledge stock variables (I_i, O_{it}, M_i, R_i and J_i) slightly improves the overall model fit. However, none of the coefficient estimates of these variables is statistically significant. The other variables do not appear to influence the generation performance. This demonstrates that the wind power generation performance between 2006 and 2012 was mainly driven by the capital and wind resource inputs, but not by the experience and knowledge levels of wind farm developers and turbine manufacturers.

[8] For models (3) and (4), there was evidence of selection bias at the 0.05 significance level, while this was not the case for models (5) and (6).

[9] The pairwise correlation between $W_{PRV,it}$ and $W_{SITE,i}$ was 0.844, and that between O_{it} and I_i 0.949.

Models (3) – (4) use the turbine size ($Y_{SIZE,i}$) as an output measure. As expected, greater capital stock (K_{it}) and higher secondary CER prices ($P_{CER,t}$) are associated with larger turbine size. Somewhat surprisingly, there is strong evidence that smaller turbines tend to be installed at better wind resource sites ($W_{SITE,i}$). This is most likely because better wind resource sites have been taken by first-movers with early-generation wind turbines. There is also moderate evidence that state-owned manufacturers ($S_{MAKE,i}$) on average supplied smaller turbines. The inclusion of the experience and knowledge variables improves the overall model fit. However, the results show either statistically insignificant (I_i, M_i and J_i) or even negative (R_i) learning effect on the turbine size.

Models (5) – (6) are cross-sectional analyses on unit turbine costs ($Y_{CAPEX,i}$). The results show that unit turbine cost reductions are expected in provinces with higher shares of wind power in their total power generation capacity (C_{it}), perhaps due to stronger market competition. Local content requirements also contributed to unit turbine cost reductions through localization of wind turbine supply chains. The positive correlation between unit turbine costs and power purchase tariffs ($P_{TARIFF,i}$) demonstrates that feed-in tariffs, a cost-recovery pricing policy, encouraged investments in wind farms with smaller profit margins. While the experience and knowledge stock variables slightly improve the overall model fit, the results again show either statistically insignificant (M_i and R_i) or negative (I_i and J_i) learning on unit turbine costs.

A robustness test is performed applying alternative knowledge depreciation rates of 0% and 5.4% per quarter, which are equivalent to 0% and 20% per year (±100% of the default rate as in Hascic and Johnstone 2011). As shown in Table A.2, the estimation results are very similar to the main results applying the default knowledge depreciation rate. The only material change is that, in models (9) and (10) analyzing the turbine size, a developer's installation experience alone (I_i) became statistically significant at the 0.10 significance level when applying the higher knowledge depreciation rate of 5.4% per quarter. Besides this marginal support for learning by doing on the turbine size, the results are not sensitive to the choice of a knowledge depreciation rate because most of the experience and knowledge stock variables did not matter much for the three output measures.

Another robustness test is conducted on the capital depreciation rate for the models analyzing generation performance. This robustness test is not applicable to the models on the turbine size and unit turbine costs as they are cross-sectional analyses using only the first-quarter observations. This sensitivity analysis is important because the more the capital is assumed to depreciate over the turbine lifetime, the more the productivity will be positively attributed to the experience and knowledge stocks. Although the default turbine lifetime of 20 years is a common assumption used in the financial analysis of wind farms, some studies have also used a turbine lifetime of 15 years (Hughes, 2012) and 25 years (Staffell and Green, 2014). Table A.3 summarizes the estimation results assuming full capital depreciation over 15 and 25 years. The results are still very similar to the main results. In particular, the results assuming a shorter turbine lifetime strengthen the finding of limited learning on generation performance.

5 Discussion

5.1 The findings and contributions to the literature

This study found limited evidence of learning on *actual* wind power generation, turbine size and unit turbine costs during the rapid expansion phase of China's wind power industry between 2005 and 2012. A developer's installation experience, a turbine maker's manufacturing experience and knowledge stock, and joint installation experience of a developer and its partner manufacturer did not lead to improvements in the three output measures.

China has been successful in expanding wind power capacity, but wind power generation has not increased as much due to various reasons including inadequate grid infrastructure (Lu et al., 2016), a lack of financial incentives for transmission and back-up generation providers to integrate wind power (Yang et al., 2012), and inferior wind turbine quality (Lu et al., 2016). “[L]arge scale” and “high speed” were the main focus during the rapid expansion phase of China’s wind power development, and the industry began to pay greater attention to quality control only around 2011 as challenges became more apparent (Li et al., 2012, p. 54). Furthermore, the increasing number of domestic turbine manufacturers led to intense or even “unreasonable” price competition (Li et al., 2014, p. 23). Consequently, many foreign manufacturers pulled out of the Chinese market as their more expensive products lost demand. This brought wind power technology prices down to such low levels that manufacturers could not invest sufficiently in technology improvement and quality assurance (Li et al., 2012). It is hence reasonable that differences in generation performance and turbine size are explained by differences in capital invested per wind farm rather than the experience and knowledge stock of developers and manufacturers. Given the intense price competition, it is also reasonable that the reductions in unit turbine costs were strongly correlated with market competition measured by the share of wind power in the provincial generation capacity, but not with the experience and knowledge stock variables.

These findings are important empirical contributions to the learning curve literature on China’s wind power industry, which has otherwise generally supported significant technological learning in the industry (Qiu and Anadon, 2012; Tang and Popp, 2016).

A key difference between this study and the others is that this study used *actual* power generation as one of the indicators of technological learning. Common indicators used in the literature are turbine costs or prices, and *predicted* generation performance. In the learning curve literature on low-carbon technologies in the developing world, and in the smaller subset focusing on China's wind power sector, this study is the first to use *actual* power generation as an output measure. This distinction is important because technologies often perform differently from the design specifications when they are put into use (e.g., Lam et al., 2016).

5.2 Limitations and future work

China's wind power industry between 2005 and 2012 is a case of technological learning in a rapidly growing, capital-intensive renewable energy industry with largely localized supply chains. The capital-intensive nature of the wind power industry may partly explain the limited evidence of learning by doing because learning in such industries mainly results from the fine-tuning of production techniques than from workers becoming more efficient at tasks they repeatedly perform (Benkard, 2000). Furthermore, international knowledge spillovers may play a more prominent role in industries with more global supply chains. Future research should thus consider comparing capital-intensive industries with labor-intensive ones, and industries with local and global supply chains.

6 Conclusions and policy implications

This study examined how accumulation of experience and knowledge by wind farm developers and turbine manufacturers contributed to productivity gains in China's wind power industry during its rapid expansion phase between 2005 and 2012. The learning mechanisms examined in this study were learning by doing through a developer's installation experience, a turbine maker's manufacturing experience, and joint installation experience of a developer and its partner manufacturer, as well as learning by searching through a turbine manufacturer's R&D activities. The analysis of 312 CDM wind farms in China found that none of these learning mechanisms resulted in improvements in *actual* power generation, turbine size and unit turbine costs. The improvements in generation performance and turbine size instead were explained by differences in capital invested per wind farm, suggesting that larger and more expensive wind farms performed better. It is also found that reductions in unit turbine cost were achieved by intense price competition, pursued at the expense of technology improvement and quality assurance, rather than being driven by learning.

Most experts agree that while local content requirements were instrumental in supporting the initial development of China's turbine manufacturing industry (Kuntze and Moerenhout, 2013), they did little to transfer foreign technology to China, or to foster knowledge transfer between foreign and Chinese wind power firms (Lewis, 2013). It is then not surprising that this study found the policy did little to improve generation performance and only slightly contributed to the turbine size increase. It was also found that China's state-owned manufacturers supplied smaller turbines than other manufacturers including foreign ones. This points to a deficiency in Chinese turbine manufacturers being able to supply quality products, at least between 2005 and 2012.

The finding that better wind resource sites were occupied by smaller turbines points to the opportunity for improving generation performance through repowering, i.e., replacing old wind turbines with modern, more productive ones. Repowering of wind farms is common in Europe and the US, but only recently started in emerging wind power markets including China (IEA, 2013).

The lack of learning through experience and knowledge accumulation during the rapid expansion phase of China's wind power industry suggests a trade-off between the pace of the build-up of domestic industry and productivity gains. As a result, as countries pursue low-carbon development paths, they should be cognizant that while scale-up can happen quickly, fostering the technological capability of local industry can take a long time. It is hence crucial to complement deployment policies with carefully designed innovation policies for developing and refining local technological capability.

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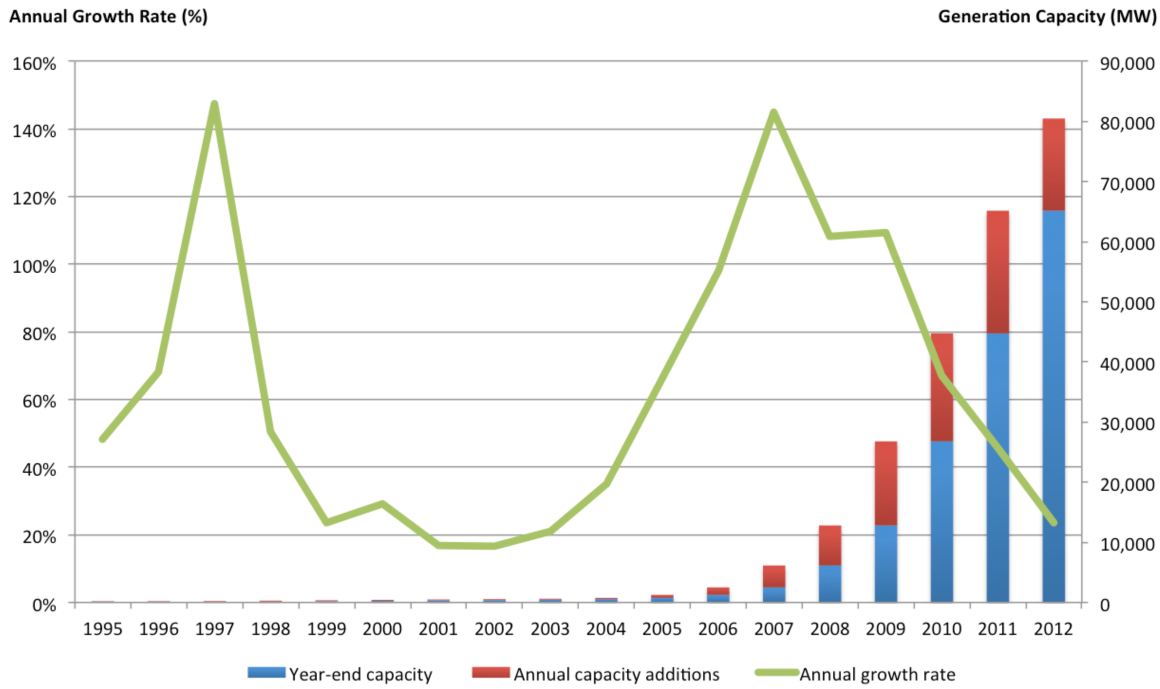


Figure 1 Expansion of the Chinese wind power market, 1995-2012

Source: Huaxia Wind (2013)

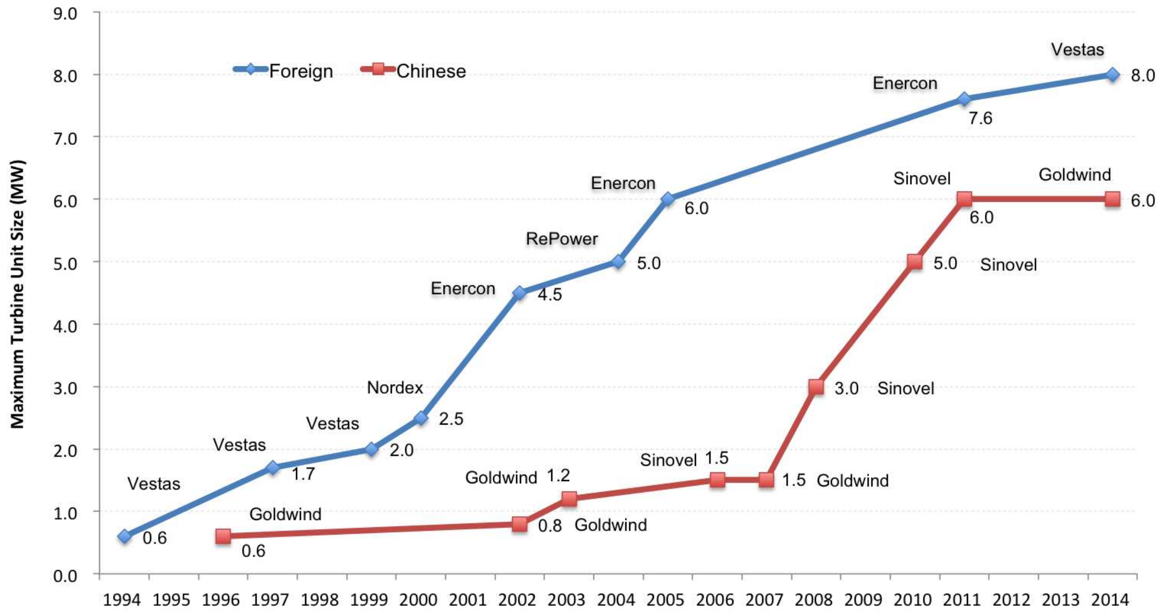


Figure 2 Size of wind turbines developed by international and Chinese manufacturers, 1994-2014

Source: Lewis (2016b)

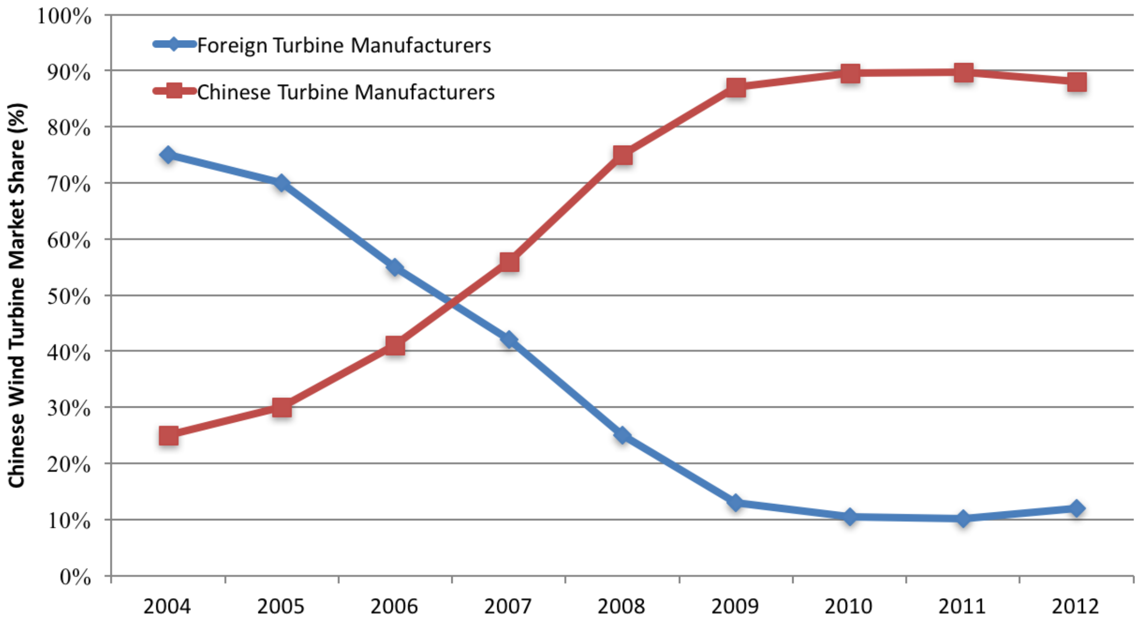
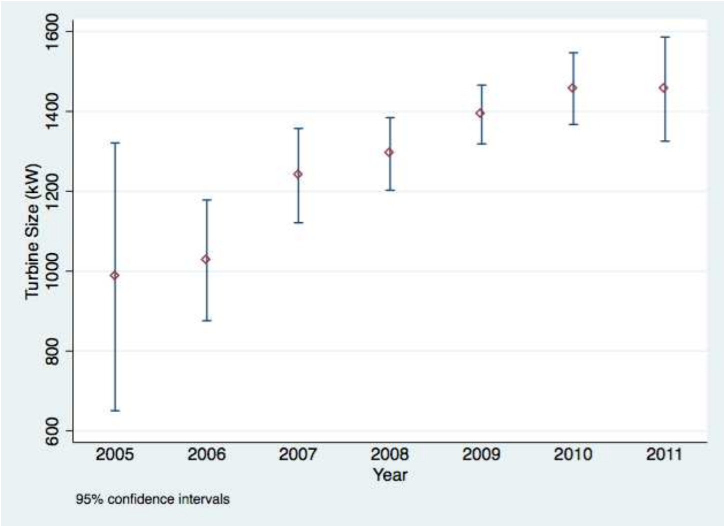


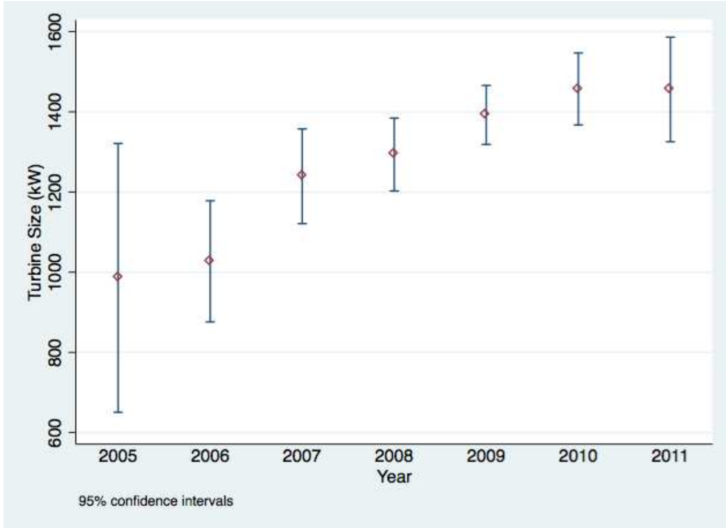
Figure 3 Market share breakdown of China's annual wind turbine installations, 2004-2012

Source: Lewis (2014, p.26)

(a)



(b)



(c)

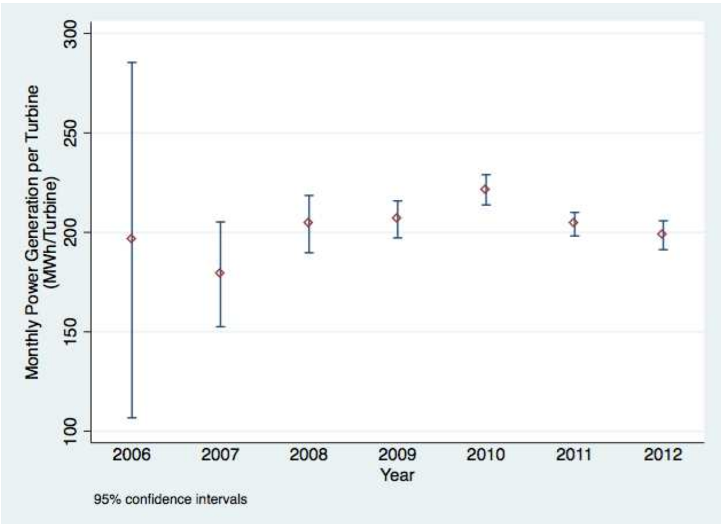


Figure 4 (a) The average turbine size, (b) unit turbine costs, and (c) monthly power generation per turbine of the CDM wind farms in the sample

Note: The means and 95% confidence intervals are shown. The year of installation is shown for the turbine size and cost figures, while the year of operation is used for the generation figure.

Table 1 Cumulative market shares of turbine manufacturers and wind farm developers in the Chinese wind power market, 1994-2012

	Turbine manufacturers		Wind farm developers	
1	Goldwind (CHN)	21.4%	China Guodian Corporation (CHN)	22.5%
2	Sinovel (CHN)	17.1%	Datang Group (CHN)	11.9%
3	United Power (CHN)	11.1%	Huaneng (CHN)	11.8%
4	Dongfang Turbine (CHN)	11.0%	Huadian (CHN)	6.8%
5	Vestas (DNK)	5.4%	China Guangdong Nuclear Wind Power Corporation (CHN)	5.5%
6	Gamesa (ESP)	4.6%	Guohua (CHN)	5.5%
7	Shanghai Electric Group (CHN)	3.8%	China Power Investment (CHN)	3.8%
8	Mingyang (CHN)	3.0%	China Resources (CHN)	3.4%
9	XEMC Wind Power (CHN))	2.9%	Jingneng (CHN)	2.5%
10	GE Wind (USA)	2.7%	China Suntien Green Energy (CHN)	2.1%
	Others	16.9%	*Others*	24.2%

Source: Huaxia Wind (2013)

Table 2 Variable definitions

Symbol	Description
t	Calendar time in quarter
i	Wind farm identifier
Y_{it}	Output level of wind farm i in quarter t
K_{it}	Capital stock of wind farm i in quarter t
W_{it}	Wind resource available for wind farm i in quarter t
P_{it}	Value of policy variables for wind farm i in quarter t
I_i	Cumulative installation experience of the developer of wind farm i at the time of installation (excluding joint installation experience with its partner manufacturer)
O_{it}	Cumulative operating experience of the developer of wind farm i in quarter t
M_i	Cumulative manufacturing experience of the manufacturer supplying turbines to wind farm i at the time of installation (excluding joint installation experience with its partner developer)
R_i	Knowledge stock of the manufacturer supplying turbines to wind farm i at the time of installation
J_i	Cumulative joint installation experience of the developer and its partner manufacturer of wind farm i at the time of installation
Q_i	Global average wind turbine size in the quarter before the time of installation of wind farm i
$S_{MAKE,i}$	State-owned manufacturer dummy for wind farm i
$S_{DEV,i}$	State-owned developer dummy for wind farm i
E_{it}	Annual electricity demand in the province where wind farm i is located in quarter t
$G_{STEAM,it}$	Cumulative installed capacity of steam turbines for power generation in the province where wind farm i is located in quarter t
$G_{HYDRO,it}$	Cumulative installed capacity of hydropower generation in the province where wind farm i is located in quarter t
C_{it}	Share of wind power in the total power generation capacity in the province where wind farm i is located in quarter t

Table 3 Descriptive statistics for the dataset

Variable		Unit	Obs	Mean	Std. dev.	Min	Max
$Y_{GEN,it}$	Monthly average power generation of wind farm *i* in quarter *t*	MWh/month	3,372	7,914	6,342	76	78,060
$Y_{SIZE,i}$	Wind turbine size of wind farm *i*	kW	3,372	1,268	385	600	3,000
$Y_{CAPEX,i}$	Capital investment per megawatt of wind farm *i*	Million 2005 RMB/MW	3,372	8.0	1.1	5.5	13.1
K_{it}	Capital stock of wind farm *i* in quarter *t*	Million 2005 RMB	3,372	342	258	5	3,154
$W_{SITE,i}$	Expected monthly power generation given the annual average wind speed at wind farm site *i*	MWh/month	3,372	10,452	8,030	155	81,800
$W_{PRV,it}$	Expected monthly power generation in quarter *t* given the quarterly average wind speed in the province where wind farm *i* is located	MWh/month	3,372	6,696	6,019	60	63,218
$P_{TARIFF,i}$	Power purchase tariff applicable to wind farm *i*	2005 RMB/kWh	3,372	0.47	0.08	0.18	0.75
$P_{LCR,i}$	Local content requirement applicable to wind farm *i*	%	3,372	59.1	25.0	0.0	70.0
$P_{CER,t}$	Annual average secondary CER price in quarter *t*	2005 USD/tCO_2e	3,372	11.8	5.7	2.6	22.7
I_i	Cumulative installation experience of the developer of wind farm *i* at the time of wind farm installation	GW	3,372	0.3	0.6	0.0	4.8
O_{it}	Cumulative operating experience of the developer of wind farm *i* in quarter *t*	TW-days	3,372	1.2	1.3	0.0	6.3
M_i	Cumulative manufacturing experience of the manufacturer of wind farm *i* at the time of wind farm installation	GW	3,372	1.1	1.6	0.0	9.9
R_i	Knowledge stock of the manufacturer of wind farm *i* at the time of wind farm installation	No. of patent applications	3,372	240	464	0	2,527
J_i	Cumulative joint installation experience of the developer and its partner manufacturer of wind farm *i* at the time of wind farm installation	MW	3,372	0.1	0.2	0.0	1.6
Q_i	Global average wind turbine size in the quarter before the installation of wind farm *i*	kW	3,372	1,478	104	1,209	1,655
$S_{MAKE,i}$	State-owned manufacturer dummy for wind farm *i*	-	3,372	0.61	0.49	0	1
$S_{DEV,i}$	State-owned developer dummy for wind farm *i*	-	3,372	0.98	0.15	0	1
E_{it}	Annual electricity demand in the province where wind farm *i* is located in quarter *t*	TWh/year	3,372	183	108	13	462
$G_{STEAM,it}$	Cumulative installed capacity of steam turbines for power generation in the province where wind farm *i* is located in quarter *t*	MW	3,372	38,252	19,606	2,970	69,820
$G_{HYDRO,it}$	Cumulative installed capacity of hydropower generation in the province where wind farm *i* is located in quarter *t*	MW	3,372	2,799	3,957	136	33,060
C_{it}	Share of wind power in the total power generation capacity in the province where wind farm *i* is located in quarter *t*	%	3,372	13.2	7.8	0.1	23.8

Note: Missing observations are listwise deleted. A knowledge depreciation rate of 2.6% per quarter (10% per annum) is assumed. The capital stock of wind farms is assumed to fully depreciate over 20 years. The descriptive statistics are shown in a panel setup (wind farm by quarter). For the cross-sectional analysis, only the observations in the first quarter are used.

Table 4 Model estimation results

	Dependent variable	(1) ln (Generation)	(2) ln (Generation)	(3) ln (Turbine size)	(4) ln (Turbine size)	(5) ln (CAPEX per MW)	(6) ln (CAPEX per MW)
Capital stock							
K_{it}	ln (Capital stock)	0.258 ***	0.257 ***	0.201 ***	0.195 ***		
		(0.082)	(0.081)	(0.076)	(0.071)		
Wind resource							
$W_{SITE,i}$	ln (Expected generation given the annual average wind speed at the wind farm site)	0.177 **	0.176 **	-0.165 **	-0.152 **	0.004	0.005
		(0.074)	(0.073)	(0.070)	(0.065)	(0.011)	(0.009)
$W_{PRV,it}$	ln (Expected generation given the quarterly average wind speed in the province)	0.561 ***	0.561 ***				
		(0.045)	(0.045)				
Policy							
$P_{TARIFF,i}$	ln (Power purchase tariff)	-0.146	-0.150	0.003	-0.013	0.212 ***	0.212 ***
		(0.154)	(0.153)	(0.173)	(0.155)	(0.044)	(0.048)
$P_{LCR,i}$	ln (Local content requirements)	-0.0005	-0.0005	0.004	0.009 *	-0.007 ***	-0.004 *
		(0.003)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
$P_{CER,t}$	ln (Secondary CER price)	0.028	0.028	0.237 *	0.276 **	-0.193	-0.156
		(0.038)	(0.040)	(0.128)	(0.120)	(0.142)	(0.136)
Learning by developer							
I_i	ln (Installation experience alone)		0.004		0.010		0.012 **
			(0.008)		(0.006)		(0.006)
O_{it}	ln (Operating experience)		0.0001				
			(0.0266)				
Learning by manufacturer							
M_i	ln (Manufacturing experience alone)		-0.0002		0.015		-0.016
			(0.0086)		(0.010)		(0.010)
R_i	ln (Knowledge stock)		0.002		-0.012 ***		0.001
			(0.004)		(0.004)		(0.003)
Joint learning by developer and manufacturer							
J_i	ln (Joint installation experience)		-0.003		-0.002		0.009 ***
			(0.005)		(0.005)		(0.003)

Table 4 (continued) Model estimation results

	Dependent variable	(1) ln (Generation)	(2) ln (Generation)	(3) ln (Turbine size)	(4) ln (Turbine size)	(5) ln (CAPEX per MW)	(6) ln (CAPEX per MW)
Power market characteristics							
C_{it}	ln (Share of wind power in the total power generation capacity in the province)	0.197	0.197	-0.014	-0.002	-0.073 ***	-0.073 ***
		(0.128)	(0.126)	(0.079)	(0.073)	(0.027)	(0.026)
C_{it}^2	ln^2 (Share of wind power in the total power generation capacity in the province)	-0.039	-0.039	0.013	0.015	-0.004	-0.004
		(0.030)	(0.030)	(0.013)	(0.012)	(0.004)	(0.004)
E_{it}	ln (Electricity demand in the province)	0.067	0.061	-0.282	0.027	0.158	0.249
		(0.475)	(0.472)	(0.377)	(0.367)	(0.255)	(0.253)
$G_{STEAM,it}$	ln (Installed capacity of steam turbines for power generation in the province)	0.072	0.074	-0.036	-0.096	-0.027	-0.061
		(0.318)	(0.317)	(0.241)	(0.255)	(0.104)	(0.106)
$G_{HYDRO,it}$	ln (Installed capacity of hydropower turbines in the province)	-0.123	-0.122	0.004	0.030	0.014	0.020
		(0.184)	(0.183)	(0.069)	(0.077)	(0.042)	(0.045)
Industry-wide technological progress							
Q_i	ln (Global average wind turbine size)	0.078	-0.011	1.809 *	1.237	0.671	0.390
		(0.441)	(0.514)	(1.038)	(1.098)	(0.740)	(0.865)
Firm ownership							
$S_{MAKE,i}$	State-owned manufacturer	-0.035	-0.013	-0.007	-0.118 **	-0.021	-0.008
		(0.042)	(0.059)	(0.045)	(0.058)	(0.025)	(0.037)
$S_{DEV,i}$	State-owned developer	-0.106	-0.131	-0.009	-0.063	0.069	0.007
		(0.116)	(0.130)	(0.109)	(0.117)	(0.168)	(0.167)
	Constant	0.641	1.307	-5.901	-2.816	-2.582	-0.674
		(3.946)	(4.483)	(6.945)	(7.130)	(4.431)	(5.254)
Log psuedolikelihood		-1,098.2	-1,072.5	-620.5	-585.8	-366.3	-343.9
Quarterly knowledge depreciation rate		2.6%	2.6%	2.6%	2.6%	2.6%	2.6%
Capital depreciation period		20 years	20 years	N/A	N/A	N/A	N/A
Province-fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects		Yes	Yes	No	No	No	No
Random effects		Yes	Yes	No	No	No	No
Analysis period		2006-2012	2006-2012	2005-2011	2005-2011	2005-2011	2005-2011
No. of wind farms		312	312	312	312	312	312
No. of observations		3,372	3,372	312	312	312	312

Note: * p<0.10, ** p<0.05, and *** p<0.01 (two-tailed). Robust standard errors clustered on wind farms are reported in parentheses. All the models are estimated with the Heckman's two-step procedure (selection model results are not reported).

Appendices

Table A.1 Correlation matrix for the regressors used in the analysis

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)	K_{it}	1.00																	
(2)	$W_{SITE,i}$	0.83	1.00																
(3)	$W_{PRV,it}$	0.79	0.81	1.00															
(4)	$P_{TARIFF,i}$	-0.23	-0.35	-0.30	1.00														
(5)	$P_{LCR,i}$	-0.14	-0.06	-0.09	0.20	1.00													
(6)	$P_{CER,t}$	-0.02	-0.04	-0.09	0.13	0.22	1.00												
(7)	I_i	0.15	0.08	0.09	-0.18	-0.46	-0.23	1.00											
(8)	O_{it}	0.09	0.09	0.08	-0.05	-0.10	-0.55	0.57	1.00										
(9)	M_i	0.16	0.11	0.14	-0.29	-0.53	-0.23	0.23	0.03	1.00									
(10)	R_i	-0.04	0.00	-0.04	0.12	0.02	0.03	-0.07	-0.01	-0.14	1.00								
(11)	J_i	0.16	0.10	0.12	-0.19	-0.47	-0.19	0.43	0.31	0.47	-0.10	1.00							
(12)	Q_i	0.16	0.08	0.14	-0.44	-0.49	-0.36	0.49	0.17	0.56	-0.08	0.45	1.00						
(13)	$S_{MAKE,i}$	0.12	0.13	0.15	-0.32	-0.09	-0.12	0.14	0.07	0.36	-0.62	0.26	0.36	1.00					
(14)	$S_{DEV,i}$	0.06	0.08	0.05	0.06	0.12	0.03	0.09	0.13	-0.04	0.07	0.06	-0.13	-0.03	1.00				
(15)	E_{it}	0.08	0.08	0.15	0.02	-0.09	-0.23	0.08	0.12	0.04	0.18	0.05	0.21	0.04	0.01	1.00			
(16)	$G_{STEAM,it}$	0.10	0.18	0.22	-0.21	-0.10	-0.20	0.16	0.21	0.05	0.11	0.14	0.23	0.08	-0.03	0.71	1.00		
(17)	$G_{HYDRO,it}$	-0.01	-0.01	-0.04	0.10	-0.06	-0.07	0.10	0.07	0.02	0.08	-0.06	0.04	-0.05	0.03	0.11	-0.21	1.00	
(18)	C_{it}	0.07	0.20	0.18	-0.48	-0.17	-0.35	0.16	0.27	0.26	-0.14	0.24	0.25	0.17	-0.04	-0.21	0.25	-0.40	1.00

Note: Missing observations are listwise deleted. A knowledge depreciation rate of 2.6% per quarter (10% per annum) is assumed. The capital stock of wind farms is assumed to fully depreciate over 20 years.

Table A.2 Robustness test on the knowledge depreciation rate

		(7)	(8)	(9)	(10)	(11)	(12)
Dependent variable		**ln (Generation)**	**ln (Generation)**	**ln (Turbine size)**	**ln (Turbine size)**	**ln (CAPEX per MW)**	**ln (CAPEX per MW)**
Capital stock							
K_{it}	ln (Capital stock)	0.257 ***	0.258 ***	0.193 ***	0.196 ***		
		(0.081)	(0.081)	(0.071)	(0.071)		
Wind resource							
$W_{SITE,i}$	ln (Expected generation given the annual average wind speed at the wind farm site)	0.177 **	0.176 **	-0.151 **	-0.154 **	0.005	0.005
		(0.073)	(0.073)	(0.065)	(0.065)	(0.009)	(0.009)
$W_{PRV,it}$	ln (Expected generation given the quarterly average wind speed in the province)	0.561 ***	0.561 ***				
		(0.045)	(0.045)				
Policy							
$P_{TARIFF,i}$	ln (Power purchase tariff)	-0.149	-0.150	-0.012	-0.013	0.213 ***	0.211 ***
		(0.153)	(0.153)	(0.154)	(0.155)	(0.048)	(0.048)
$P_{LCR,i}$	ln (Local content requirements)	-0.001	-0.001	0.009 *	0.009 *	-0.004 *	-0.004 *
		(0.003)	(0.003)	(0.005)	(0.005)	(0.002)	(0.002)
$P_{CER,t}$	ln (Secondary CER price)	0.028	0.028	0.277 **	0.274 **	-0.154	-0.158
		(0.040)	(0.039)	(0.120)	(0.121)	(0.135)	(0.138)
Learning by developer							
I_i	ln (Installation experience alone)	0.004	0.004	0.009	0.010 *	0.013 **	0.011 **
		(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.005)
O_{it}	ln (Operating experience)	0.001	-0.001				
		(0.027)	(0.026)				
Learning by manufacturer							
M_i	ln (Manufacturing experience alone)	-0.0001	-0.0002	0.014	0.016	-0.015	-0.016
		(0.0085)	(0.0086)	(0.010)	(0.010)	(0.010)	(0.011)
R_i	ln (Knowledge stock)	0.002	0.002	-0.012 ***	-0.012 ***	0.001	0.001
		(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Joint learning by developer and manufacturer							
J_i	ln (Joint installation experience)	-0.003	-0.003	-0.002	-0.002	0.009 ***	0.009 ***
		(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)

Table A.2 (continued) Robustness test on the knowledge depreciation rate

Dependent variable		(7) ln (Generation)	(8) ln (Generation)	(9) ln (Turbine size)	(10) ln (Turbine size)	(11) ln (CAPEX per MW)	(12) ln (CAPEX per MW)
Power market characteristics							
C_{it}	ln (Share of wind power in the total power generation capacity in the province)	0.197	0.197	-0.003	-0.001	-0.074 ***	-0.072 ***
		(0.126)	(0.126)	(0.073)	(0.073)	(0.026)	(0.026)
C_{it}^2	ln^2 (Share of wind power in the total power generation capacity in the province)	-0.039	-0.039	0.015	0.015	-0.004	-0.004
		(0.030)	(0.030)	(0.012)	(0.012)	(0.004)	(0.004)
E_{it}	ln (Electricity demand in the province)	0.062	0.060	0.024	0.029	0.249	0.247
		(0.472)	(0.472)	(0.366)	(0.367)	(0.253)	(0.250)
$G_{STEAM,it}$	ln (Installed capacity of steam turbines for power generation in the province)	0.074	0.074	-0.099	-0.092	-0.062	-0.060
		(0.317)	(0.317)	(0.255)	(0.254)	(0.107)	(0.106)
$G_{HYDRO,it}$	ln (Installed capacity of hydropower turbines in the province)	-0.122	-0.122	0.031	0.028	0.020	0.020
		(0.183)	(0.183)	(0.076)	(0.077)	(0.044)	(0.045)
Industry-wide technological progress							
Q_i	ln (Global average wind turbine size)	-0.007	-0.016	1.290	1.178	0.400	0.389
		(0.511)	(0.516)	(1.091)	(1.107)	(0.863)	(0.860)
Firm ownership							
$S_{MAKE,i}$	State-owned manufacturer	-0.013	-0.014	-0.117 **	-0.120 **	-0.008	-0.007
		(0.060)	(0.059)	(0.058)	(0.058)	(0.037)	(0.037)
$S_{DEV,i}$	State-owned developer	-0.133	-0.129	-0.060	-0.068	0.000	0.015
		(0.130)	(0.130)	(0.118)	(0.117)	(0.169)	(0.166)
	Constant	1.271	1.346	-3.197	-2.381	-0.737	-0.665
		(4.469)	(4.494)	(7.078)	(7.190)	(5.236)	(5.232)
Log psuedolikelihood		-1,071.0	-1,075.3	-584.7	-587.5	-342.9	-345.2
Quarterly knowledge depreciation rate		0.0%	5.4%	0.0%	5.4%	0.0%	5.4%
Capital depreciation period		20 years	20 years	N/A	N/A	N/A	N/A
Province-fixed effects		Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects		Yes	Yes	No	No	No	No
Random effects		Yes	Yes	No	No	No	No
Analysis period		2006-2012	2006-2012	2005-2011	2005-2011	2005-2011	2005-2011
No. of wind farms		312	312	312	312	312	312
No. of observations		3,372	3,372	312	312	312	312

Note: * p<0.10, ** p<0.05, and *** p<0.01 (two-tailed). Robust standard errors clustered on wind farms are reported in parentheses. All the models are estimated with the Heckman's two-step procedure (selection model results are not reported).

Table A.3 Robustness test on the capital depreciation rate

		(13)		(14)	
Dependent variable		**ln (Generation)**		**ln (Generation)**	
Capital stock					
K_{it}	ln (Capital stock)	0.250	***	0.260	***
		(0.081)		(0.081)	
Wind resource					
$W_{SITE,i}$	ln (Expected generation given the annual average wind speed at the wind farm site)	0.183	**	0.174	**
		(0.073)		(0.073)	
$W_{PRV,it}$	ln (Expected generation given the quarterly average wind speed in the province)	0.561	***	0.561	***
		(0.045)		(0.045)	
Policy					
$P_{TARIFF,i}$	ln (Power purchase tariff)	-0.145		-0.151	
		(0.153)		(0.153)	
$P_{LCR,i}$	ln (Local content requirements)	-0.0004		-0.001	
		(0.0034)		(0.003)	
$P_{CER,t}$	ln (Secondary CER price)	0.025		0.030	
		(0.040)		(0.040)	
Learning by developer					
I_i	ln (Installation experience alone)	0.003		0.004	
		(0.008)		(0.008)	
O_{it}	ln (Operating experience)	0.001		-0.001	
		(0.027)		(0.027)	
Learning by manufacturer					
M_i	ln (Manufacturing experience alone)	-0.0003		-0.0001	
		(0.0086)		(0.0086)	
R_i	ln (Knowledge stock)	0.002		0.002	
		(0.004)		(0.004)	
Joint learning by developer and manufacturer					
J_i	ln (Joint installation experience)	-0.003		-0.003	
		(0.005)		(0.005)	
Power market characteristics					
C_{it}	ln (Share of wind power in the total power generation capacity in the province)	0.197		0.197	
		(0.127)		(0.126)	
C_{it}^2	$\ln^2$ (Share of wind power in the total power generation capacity in the province)	-0.039		-0.039	
		(0.030)		(0.030)	
E_{it}	ln (Electricity demand in the province)	0.059		0.061	
		(0.473)		(0.472)	
$G_{STEAM,it}$	ln (Installed capacity of steam turbines for power generation in the province)	0.080		0.072	
		(0.318)		(0.317)	
$G_{HYDRO,it}$	ln (Installed capacity of hydropower turbines in the province)	-0.124		-0.121	
		(0.183)		(0.183)	

Table A.3 (continued) Robustness test on the capital depreciation rate

Dependent variable		(13) ln (Generation)	(14) ln (Generation)
Industry-wide technological progress			
Q_i	ln (Global average wind turbine size)	-0.101	0.040
		(0.521)	(0.511)
Firm ownership			
$S_{MAKE,i}$	State-owned manufacturer	-0.013	-0.014
		(0.059)	(0.059)
$S_{DEV,i}$	State-owned developer	-0.131	-0.131
		(0.130)	(0.130)
	Constant	1.956	0.931
		(4.534)	(4.463)
Log psuedolikelihood		-1,073.5	-1,072.2
Quarterly knowledge depreciation rate		2.6%	2.6%
Capital depreciation period		15 years	25 years
Province-fixed effects		Yes	Yes
Year-fixed effects		Yes	Yes
Random effects		Yes	Yes
Analysis period		2006-2012	2006-2012
No. of wind farms		312	312
No. of observations		3,372	3,372

Note: * p<0.10, ** p<0.05, and *** p<0.01 (two-tailed). Robust standard errors clustered on wind farms are reported in parentheses. Both models are estimated with the Heckman's two-step procedure (selection model results are not reported).