The Learning Process and Technological Change in Wind Power: Evidence from China's CDM Wind Projects

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Abstract: This research examines the determinants influencing technological change in wind power from a learning perspective. The Clean Development Mechanism (CDM) is a project-based carbon trade mechanism under the Kyoto Protocol that has provided financial support for a large share of Chinese wind projects since 2002. Using pooled cross-sectional data of 510 registered CDM wind projects in China that started from 2002 to 2009, this research estimates the effects of different channels of learning—learning through R&D in wind turbine manufacturing, learning from previous experience of installation, and learning through the network interaction between project developer and turbine manufacturer—on technological change, measured as reductions in projected costs across CDM wind projects. In addition, we also test the effects of different learning channels on two subsystems of learning – the costs of wind farm installation and capacity factor respectively. The empirical results show that manufacturer's R&D, previous installation experience and interactions between wind turbine manufacturer and wind project developer all have significant and positive effects on technological change. While the existing literature has suggested that wind power firms can learn from the experience of other wind farm developers, this research indicates that wind power firms mainly learn from their own experience and the knowledge spillovers mostly occur within certain partnerships between wind project developer and foreign turbine manufacturers in China's wind power industry.

Keywords: Climate change, technology transfer, collaboration, learning curves, patents

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1. Introduction

As the world's largest energy consumer and CO_2 emitter, China's energy consumption and carbon emission issues have become a focus of most global climate change and energy security talks. Because China has abundant wind resources with great development potential, increasing the share of wind in China's energy mix is a promising solution (Wang, 2010). China's wind industry has developed rapidly during the past ten years. The annual growth rate of wind installed capacity exceeds 100% from 2003 to 2009 and China became the worlds' largest wind power country in terms of cumulative installed capacity in 2010 (GWEC, 2011). As a result of this massive wind capacity expansion, China has also developed a domestic wind power equipment supply chain and manufacturing technology has been advanced. The three largest domestic wind turbine manufacturers were ranked among the top ten wind turbine manufacturers in the world by 2010 (Wang et al., 2012). This immense progress is driven by a variety of policy instruments that the Chinese government has implemented to incentivize investment in wind energy, including domestic policies and international support.

Perhaps the most notable international support program for the development of renewable energy in China is the Clean Development Mechanism (CDM). The CDM is an international carbon trade mechanism under the Kyoto Protocol that supports projects reducing carbon emissions in developing countries. Through these projects, CDM facilitates the adoption of climate-friendly technologies in developing countries. A secondary goal of the CDM is to help developing countries achieve sustainable development. The transfer of new technologies to recipient countries can help with the goal of achieving sustainable development, particularly if the technologies transferred lead to knowledge spillovers that reduce the future costs of emissions reductions within the country (Popp, 2011). In this paper, we use data on CDM wind projects in China to assess the impact of technology transfer and learning on renewable energy costs in the country. We ask whether expected project costs fall after other similar projects in the country. Moreover, we consider whether costs fall throughout the country or just locally. More localized effects would be more suggestive of spillovers. At the opposite extreme, project costs falling throughout the country (and perhaps across the world as well) would suggest other types of technological changes at work, such as the development of more efficient turbines by leading global manufacturers. In addition, we also test the effects of different learning channels on technological change.

Our study contributes to both the technological learning literature and the literature on China's wind energy policies. While understanding the impact of technological change in developing countries is important, data for such studies is hard to come by. As such, most studies of learning-by-doing and learning-by-searching for renewable energy focus on developed countries (Ibenholt, 2002; Junginger et al., 2005; Taylor et al., 2006; Junginger et al., 2008; Nemet, 2012). In this paper, we use CDM project design documents (PDD) to collect data on the expected costs of proposed projects. This contrasts with the work of Qiu and Anadon (2012), the only empirical research explaining the cost reduction of wind power in China. Qiu and Anadon use data from the bidding process of China's national wind concession program. While the CDM data are expected costs, rather than actual costs, the expected costs are audited and verified through the CDM registration process. In contrast, participants bidding in the national wind concession program may have incentives to understate the true costs of wind production to win the auction. Thus, our data offers both a valuable check on the data used by Qiu and Anadon as well as providing for a much larger sample. We discuss the advantages and disadvantages of each data source in greater detail in section 2 and section 4.

In addition to providing one of the first studies of learning in the Chinese wind industry, our paper also adds to the learning literature by incorporating collaboration theories to explain the learning process and provides evidence for learning-by-interacting effect. Previous studies on the relationship between policy instruments and the technological progress in China's wind industry are mainly qualitative and descriptive research with a focus on domestic policies. However, most of them do not analyze the link between policy tools and the technological change. The detailed data in CDM project design documents allows us to study the relationship among various actors in the development of China's wind industry, including project developers and turbine manufacturers. We show that these collaborations are important sources of the learning that takes place in the Chinese wind industry.

Our research has policy implications for international climate policy makers and the Chinese government. Studying one of the world's largest wind power producers in which most of the wind projects are supported by CDM, our research sheds light on how international collaboration, such as CDM, can lead to technological progress in wind power. We provide evidence of spillovers that will be of use to both policy advocates and researchers modeling the effect of climate policies. Moreover, by focusing on the roles of various actors in the wind industry, our research increases the understanding of the learning process in China's wind industry and helps the Chinese government better target policies to facilitate different channels of learning, especially learning through the collaboration between wind farm developers and wind turbine manufacturers.

We proceed with a review of previous work on policy tools and technological change in China's wind power, including a discussion of the important roles of CDM in the development of China's wind industry, and the standardized CDM project process. Section 3 provides the theoretical framework for learning process in wind projects and presents our hypotheses. Section 4 discusses the data and empirical models that we use to test the effects of different channels of learning. Section 5 and section 6 analyze the empirical results and summarizes our main conclusions respectively.

2. The CDM and the Development of China's Wind Industry

2.1 Policy instruments and technological change in China's wind industry

Due to the market failures in renewable energy technology innovation and deployment, policy tools are often used to induce the technological change. Currently, wind power is less cost-competitive than electricity generated from coal because the negative externalities of fossil fuel power are not included in the energy price. In addition, the knowledge spillover effects lead to under-investment in wind technology innovation and deployment in private sector.

To address these market failures and reduce the technology and market risks perceived by wind power investors, the Chinese government has implemented a bundle of domestic policies to facilitate wind power deployment and to promote domestic wind technology advancement, such as the national wind concession program, mandating that a share of electricity be generated from renewable energy, tax relief for wind farms, a power surcharge for renewables, and R&D subsidies. In addition, the Chinese government has also actively engaged in international collaboration, fostering international technology transfer through import tax relief and the CDM (Zhang et al., 2009). As shown in Table 1, these policy instruments can be further classified as supply-side policies that subsidize the wind technology R&D activities and demand-side policies that subsidize the demand for wind technologies.

Table 1: Matrix for China's wind technology policy tools

	Domestic	International
Supply Side	- National basic research program (973 Program, 1997) - National high-tech R&D program (863 Program, 1986) - National key technology R&D program (TKPs, 1982)	
Demand Side	- National wind concession program (2003-2008) - Power surcharge for wind power (2006) - The wind power share target in the Medium and Long-Term Development Plan for Renewable Energy in China (2007) - Relief of VAT and import tax for wind turbines (2008) - NDRC Notice on policy to improve grid-connected power pricing for wind power generation (2009)	The Clean Development Mechanisms (CDM)

Previous studies on the relationship between policy instruments and the technological achievement in China's wind industry are mainly qualitative and descriptive research. They systematically reviewed policies that support wind industry, and then described the technological change in terms of the upgrading of wind turbine size, increased innovation and patenting activities of domestic turbine manufacturers, and cost reduction in turbine manufacturing and electricity generation (Zhang et al., 2009; Wang, 2010; Ru et al., 2011; Huang et al., 2012; Huang et al., 2012; Wang et al., 2012;). Although some scholars studied the mechanisms that how the policy support induced the technological progress in wind turbine manufacturing industry (Ru et al, 2011), most descriptive and qualitative research did not analyze the link between policy instruments and the technological change.

Empirical research explaining technological change in China's wind power is rare. Using wind projects from China's national concession programs[1] from 2003 to 2007, Qiu and Anadon (2012) applied the learning curve model to examine the factors influencing the price of wind power measured by the bidding price of each bidder participating in the public bidding process of the national concession programs. They found that the joint-learning from technology adoption and wind projects installation experience, localization of wind turbine manufacturing, and wind farm economies of scale significantly affect the price of wind power. However, the sample in this study only contained 15 wind projects, which accounts for less than 50% of the total installed capacity nationwide during the observing period. In addition to its small and less representative sample, the bidding price used as the dependent variable may underestimate the cost of wind power production. Larger players, such as big state-owned developers that are not driven by a profit-maximization objective, can commit to below cost prices in order to win the contract first (Yang et al, 2010; Wang, 2010). The winning price has been criticized as being much lower than the reasonable price (Li et al., 2008).

In this paper, we use data from CDM wind projects in China to explain technological change in China's wind power. These data provide a more representative sample and less distorted production cost of wind power, as described in more detail below. Moreover, our empirical analysis on CDM wind projects sheds light on how international collaboration, such as international carbon trade, leads to technological progress in wind power, which is often neglected in previous qualitative and descriptive research.

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[1]Prior to 2009, any wind project in China with capacities over 50 MW would go through a national concession bidding process managed by the central government to select its developer. Potential developers were invited to join this public bidding process. The bidder who offered the "best price" under the terms provided by the bidding method would win the right to build the wind farm and sell the electricity at its bidding price to the grid. From 2003 to 2008, five rounds of national concession bidding programs produced 18 wind projects (Zhang et al., 2009; Wang et al., 2012; Qiu et al., 2012).

2.2 **CDM as a Demand-Side Policy for Wind Technology**

The CDM is a project-based carbon trade mechanism under the Kyoto Protocol that allows developed countries with carbon emission constraints to purchase emission credits by financing projects that reduce carbon emissions in developing countries. In addition to carbon emission reduction, CDM also encourages developed countries to transfer climate-friendly technologies to developing countries and stimulates sustainable development in developing countries through technological change.

CDM has played a very important role in the development of China's wind industry. The Chinese government has actively use of CDM to provide financial support for over 80 % of its wind projects since China ratified the Kyoto Protocol in 2002. In the early 2000s, wind projects had very low returns in China. To incentivize investment in wind farms and make wind projects more financially feasible in China's power market, the Chinese government encouraged and even acted as a broker to engage wind farm developers in CDM project application.

As a demand-side policy that subsidizes the users of wind technology, CDM has, to a great extent, facilitated the adoption of wind technology in China since 2002. As shown in Figure 1, the annual incremental installed capacity from wind projects registered as CDM projects contributes to a large share of the annual incremental installed capacity in China.[2] From 2003 to 2009, the total installed capacity from CDM wind projects account for 74.7% of the total installed capacity in China. In addition to wind power deployment, CDM has also turned out to be a good practice for wind project operation and management because it facilitates China's

[2] The annual total installed capacity data comes from the statistics in yearbooks of Chinese Wind Energy Association and the annual report on China Wind Power. The annual CDM installed capacity data is collected by the authors from CDM Pipeline and CDM project design documents. Due to the CDM registration process, the incremental installed capacity from CDM projects in 2009 is incomplete. Thus, the CDM share shown for 2009 may be lower than the actual share.

wind industry to learn advanced wind technologies and scientific monitoring mechanisms. From Figure 2, we can see that the average size of the wind turbines used in CDM projects has increased from 0.90 MW in 2002 to 1.45 MW in 2009.

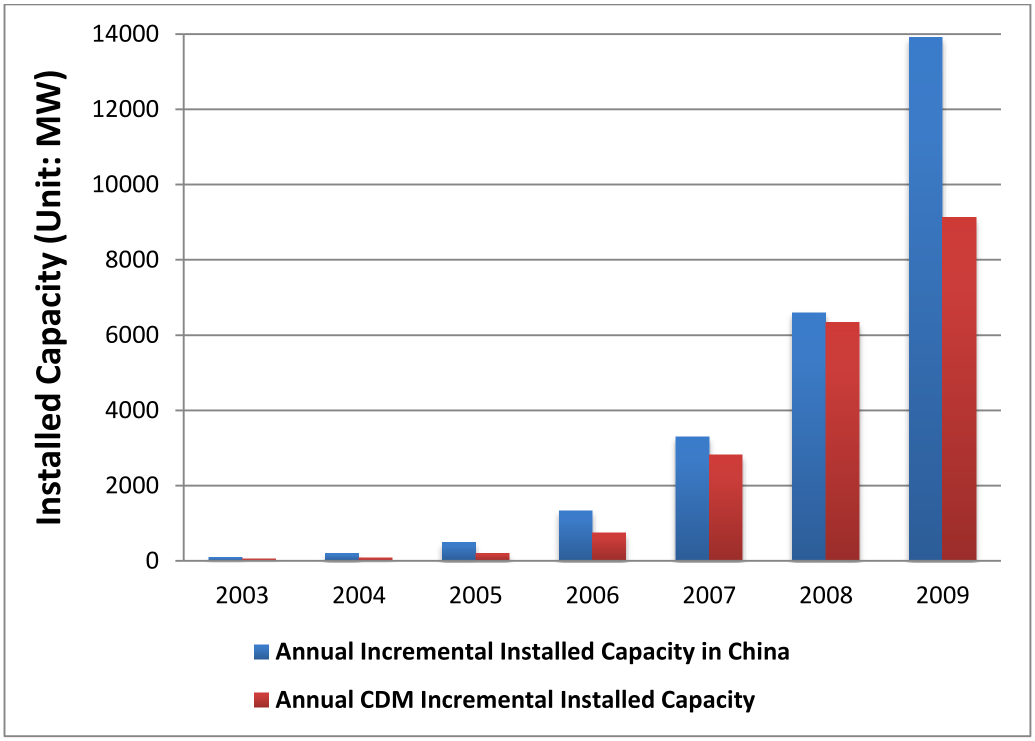


Figure 1: Share of Annual Incremental CDM Wind Installed Capacity in China's Wind Power

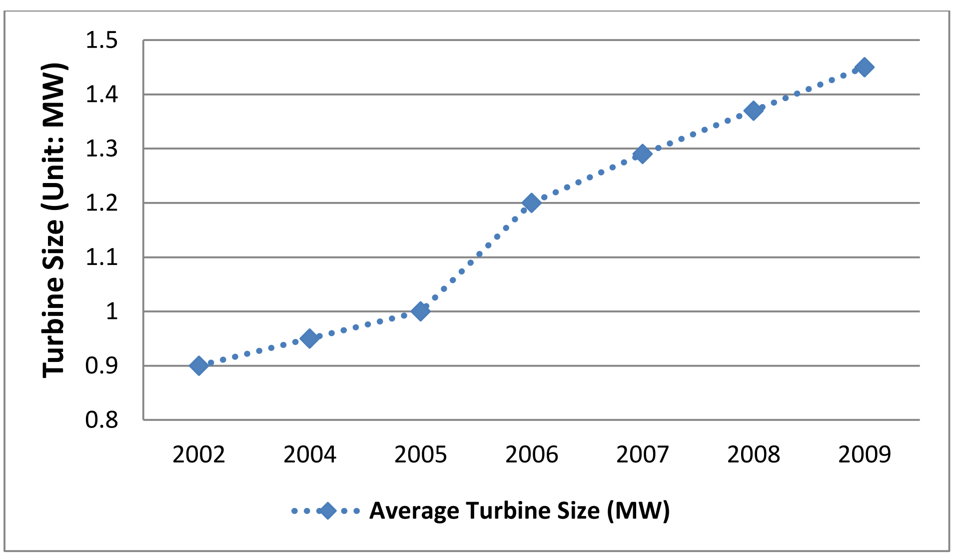


Figure 2: Average Size of Wind Turbines in CDM Projects by Year

2.3 The standardized CDM project process and the validity of project documents

All the CDM wind projects are registered and managed in a highly standardized and transparent process according to the CDM legal framework under the Kyoto Protocol. The key criteria for CDM project approval is whether a project demonstrates its "additionality", which means that the proposed wind project could not be developed without the revenue from CDM carbon trading due to high financial risk or technical barriers. If a project cannot demonstrate the additionality by using the method provided by CDM rules, its application will be rejected. Once a wind project has been approved by the CDM executive board (EB) for CDM registration, it can get emission credits, which are called certified emission reductions (CERs), based on its annual electricity generation. The project developer can sell these CERs to emission credit buyers from developed countries and use this revenue to subsidize its investment. On average, the economic incentive from CDM revenue is about 0.1 RMB/kWh, which approximately equals to 16.7-20% of the electricity price of wind power (Li, 2010; Zhang et al, 2009).

A typical CDM wind project cycle has six steps as shown in Figure 3. As a first step, a wind project developer should follow the CDM documentation requirements to prepare and submit a standardized project design document and supporting materials including a financial analysis if it considers to apply for CDM in its project design and construction phase. The project design document and supporting materials must be validated by a 3rd party auditing agency (i.e. the designated operational entity, or DOE) accredited by the EB according to check whether the proposed project meets the CDM requirements before it can register as a CDM project. During its operational phase, the carbon emission reduction from the project activity is then monitored and verified by another 3rd party agency according to the methods specified in the validated project design document and the EB will issues CERs to the project developer based on the verification.

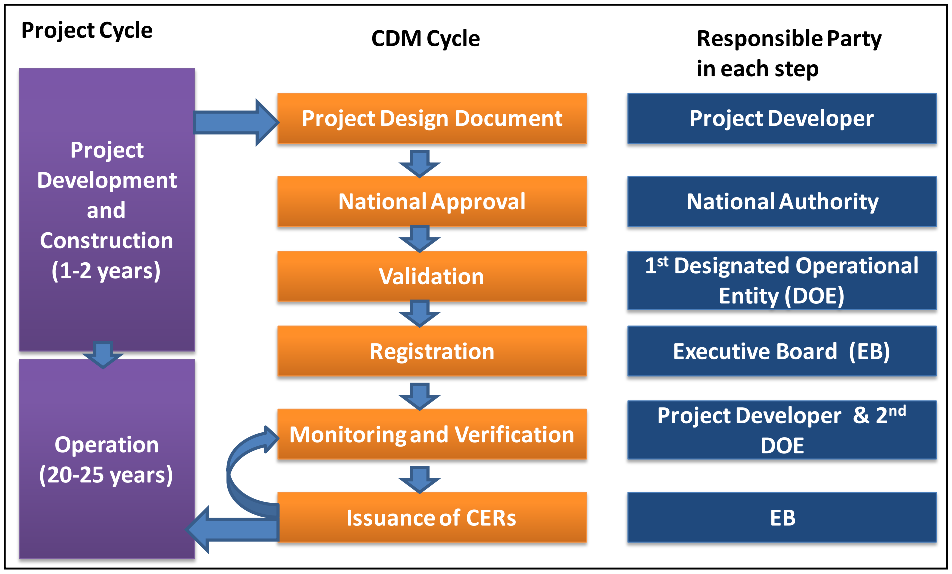


Figure 3: A Standard CDM Project Cycle

These independent and transparent auditing and monitoring procedures ensure the validity of the CDM project documents. For all the projects that come into the registration step, their project design documents and supporting financial analysis are available on the CDM official website for public comments before registration. In addition, the validation and monitoring reports are also available on the CDM website to provide a record of the whole process.

3. Theoretical Framework and Hypotheses

The CDM has subsidized the majority of China's wind projects and has facilitated the technological change of China's wind industry during the past ten years. We use CDM wind projects in China to analyze the learning process in China's wind industry and to examine the effects of different channels of learning on technological change. We measure technological change as the reduction of electricity production cost across different wind projects. The learning process in our study refers to how knowledge related to wind power is acquired and diffused among different participants in the wind projects, including project developers and wind turbine manufacturers. In China, power generation and power transmission are separated. Wind project developers are power companies in charge of power generation, which are either state-owned enterprises (SOE) or private Chinese power companies. Another important participant in wind projects is the wind turbine manufacturer, which produces, supplies wind turbines, and works closely with project developers. Both domestic and foreign manufacturers participate in CDM wind projects in China.

Following the technological learning and collaboration theories, we identify the following channels of learning that could lead to the reduction of electricity production cost.

3.1 Learning by Doing (LBD)

In the literature on innovation and technological learning, the traditional learning curve model explains technological change, measured by productivity increase, as a function of learning from the accumulation of experience in production (Arrow, 1962). In energy technology research, the experience curve has been widely used to model the cost reduction of renewable technologies, such as solar photovoltaics, wind turbine manufacturing, and wind power production (Junginger et al., 2005; Nemet, 2006 & 2012; Qiu et al., 2012; Patridge, 2013).

In wind power, the unit cost of electricity production could be reduced through the accumulation of experience in wind turbine manufacturing and installation, and/or through the accumulation of experience in wind project development and operation. As the wind turbine manufacturer' experience in turbine production and installation increases over time, the cost of manufacturing a wind turbine and installing a wind turbine will decrease. When the wind project developer accumulates more experience in project development and operation, it will know more about how to pick a best site, select a suitable wind turbine and operate the wind farm efficiently, which will also result in the cost reduction of wind power. Thus, the first two hypotheses we test are:

H_1: The more project developing and operating experience that the CDM project developer has, the lower unit cost that the observed CDM project will have.

H_2: The more production and installation experience that the wind turbine manufacturer has accumulated, the lower unit cost that the CDM project using its wind turbines will have.

3.2 Knowledge Spillover Effects

Within the learning-by-doing literature, a subset identifies knowledge spillover effects, which finds that firms can learn from a competitor firm's experience, but the spillovers have smaller effects than internal experience (Thornton and Thompson, 2001). Especially for new technology that has been commercialized, commercial use is hard to hide from rival firms. In this sense, wind power companies can also learn how to develop and operate a wind farm from external experience, such as the experience from other developer's wind projects (Nemet, 2012; Qiu et al., 2012).

For CDM projects, the transparent project registration and monitoring process allows adequate information sharing on project design and operation among project developers, which may particularly facilitate the knowledge spillovers across CDM projects. Therefore, we also test:

H_3: The existing wind project operation experience from other firms in the industry also leads to lower production cost of the current CDM project.

3.3 Learning by Searching (LBS)

The cost reduction of wind power could also be a result of wind technology innovation through research, development and demonstration (RD&D), which is often called "learning-by-searching" (LBS) in the technological learning literature. RD&D will bring new materials or introduce new production processes into the production, which could result in the increase of productivity or cost reduction (Junginger et al, 2005; Kahouli-Brahmi, 2008; Qiu et al, 2012). In wind industry, such technological improvements through RD&D include larger turbines, lighter materials, more efficient turbine design and improved control systems, which could either reduce the cost of a wind turbine or increase the efficiency of converting wind energy to electricity. Built on the one-factor learning curve model which only considers the LBD effect in wind industry, several studies uses two-factor learning model to disentangle the impacts of R&D and cumulative experience on technological change in wind power (Soderholm & Klassen, 2007; Soderholm & Sundqvist, 2007; Qiu and Anadon, 2012). While the empirical studies on that cover a long period of time (10-20 years) in European wind power sector suggest that R&D is the dominant factor, Qiu and Anadon's research, which looks at China's wind industry between 2003 and 2007, does not successfully separate the effect of LBS and LBD due to the multicollinearity between their LBD and LBS variables. In contrast, we use a firm-specific stock of knowledge, described in section 4, to identify and test the learning-by-searching effect:

H_4: The greater the knowledge stock that a wind turbine manufacturer has accumulated through its R&D, the lower the unit production cost of the CDM project using its turbines will be.

3.4 Learning by Interacting (LBI)

The literature on technological learning has discussed another channel of learning – learning by interacting (LBI). Improving the network interactions between research institute, manufacturers and end-users allows for better diffusion of knowledge (Grubler, 1998; Junginger et al, 2005). Especially, a collaborative and long-term partnership will increase the likelihood of tacit knowledge transfer, for it will increase the trust between the two parties and reduce information asymmetry (Schneider, 2008).

Similarly, the collaboration literature also points out that interagency collaboration facilitates resource and knowledge sharing among network partners. In the inter-firm networks, firms can have some degrees of access to the specialized knowledge of their partners while exploiting and enhancing the existing knowledge and capacities within themselves (Cohen and Levinthal 1990; Inkpen and Beamish 1997). The trust that network partners have between each other is found to be instrumental in reducing transaction costs, improving investments and stability in relations, and stimulating learning, knowledge sharing, and innovation (Koppenjan and Klijin, 2004). Previous cooperative ties between the network partners are positively associated with the development of inter-firm trust (Inkpen & Currall 2004).

In a wind project, the project developer works with its turbine supplier in many stages, such as turbine installation, operation and maintenance. Another important channel of technological learning in CDM wind projects is the joint learning between project developer and wind turbine manufacturer on installation and operation through their collaboration in one or multiple wind projects. According to CDM project design documents, frequent communication and training activities regarding operating and maintaining between turbine suppliers and project developers contributes to the dissemination of wind power generation technology. Therefore, our last hypothesis is:

H_5: The more cooperation that the developer has with the same manufacturer prior to the current CDM project, the lower production cost of this project will be.

4. Data and Descriptive Statistics

To examine the effects of different channels of learning among CDM wind project participants on reductions in electricity production costs across wind projects, we use pooled cross-sectional data of 510 registered CDM wind projects in China that started construction from 2002 to 2009. These projects were developed by 92 developers and used wind turbines from 33 turbine manufacturers. Therefore, each project developer and each turbine manufacture have participated in one or more than one CDM wind project in China. A developer may have cooperated with the same wind turbine manufacturer in several projects.

We have combined several datasets for this study. The CDM project data, including information on project costs, project size, turbine size, annual electricity production, project developer, and turbine manufacturers, are collected from the validated CDM project design documents and its attached financial analysis spreadsheet for each project, which are publicly available on CDM official website.[3] Data on installed wind capacity by manufacturer and province comes from the yearbooks and annual reports of Chinese Wind Energy Association. The patent data for knowledge stock calculation are obtained from the Delphion database.

[3] http://cdm.unfccc.int/Projects/projsearch.html

4.1 Key Variables

4.11 Dependent variables

We have several dependent variables to examine different aspects of technological change. To measure the overall technological change in wind power, we use unit electricity production cost of the wind farm as our primary dependent variable, which allows us to compare with the previous literature on technological learning in wind power. To further find out how different learning channels affect the electricity production cost, we decompose the overall learning effects into two subsystems of learning, which are wind farm construction and installation, and the operation of the wind farm. We examine these two subsystems by looking at capital cost per kWh and the capacity factor of the wind farm correspondingly.

1) **Electricity production cost**

The primary dependent variable is the projected unit cost of electricity production of project *i* that starts construction in year *t* (***Unit_cost***$_{it}$), which can also be called levelized cost. We calculate the unit electricity production cost by dividing the project life cost by its life electricity production estimated in the project financial analysis, which captures the projected average cost of generating one unit (kWh) of electricity by the project. The unit cost is calculated as follows:

$$(\boldsymbol{Unit\_cost})_{it} = \sum_{j=1}^{n} \frac{\boldsymbol{Capital_j} + \boldsymbol{O}\&M_j}{(\boldsymbol{1}+\boldsymbol{r})^j} \Big/ \sum_{j=1}^{n} \frac{\boldsymbol{Electricity_j}}{(\boldsymbol{1}+\boldsymbol{r})^j}$$

where ***Captital***$_j$ is the static construction investment in the ***j***th year in project life, ***O&M***$_j$ is the annual operation and maintenance expenditures in year ***j***, and ***Electricity***$_j$ represents the annual electricity generated by the wind farm in year ***j***. Both project costs and electricity production are discounted at a discount rate ***r*** = 8%, which is the benchmark internal rate of return on total investment used in CDM project financial analysis according to the State Power Corporation's "Interim Rules on Economic Assessment of Electrical Engineering Retrofit Projects". The year that project ***i*** starts construction, represented by ***t***, corresponds to the first year in its project life (i.e. j=1). To make the unit costs comparable among projects that started construction in different years, we calculate the real unit cost, capital cost and O&M cost using 2005 prices.

We collect our cost data from individual validated CDM project design documents and a financial analysis spreadsheet that is included for each project, which is publicly available on CDM official website. While these are expected costs, using the CDM data provides several advantages. To prove additionality, proposed projects must not be financially viable without the ability to generate and sell emissions credits. Thus, project developers have no incentive to understate costs, which would overestimate technological progress. At the same time, since we only use projects that have been validated and registered, the proposed project costs have been evaluated by independent auditors. Projected costs that are unreasonably high would lead to rejection of a proposed project. For capital costs, the validating agencies usually crosscheck estimated capital costs with the actual costs specified in construction and equipment purchase contracts. According to the CDM validation guidelines and the validation reports we have examined, the estimated capital costs are very close to the real capital investment. Moreover, many project design documents used actual capital costs in their financial analyses. For O&M costs, the auditing agencies compared the estimated costs with public statistics and other similar CDM wind projects. Based on the comparison, they must determine that the projected O&M cost data used in CDM project design document are reasonable before validating the project.

Thus, we believe that our cost measurement is more reasonable and credible than the national concession bidding prices used by Qiu and Anadon, 2012. As discussed in 2.1, the bidding prices in the national concession program could be much lower than the actual price, which is often a strategy used by the developer to win the project first without considering the long-term project profitability (Li et al., 2008; Yang et al, 2009; Wang, 2010). Absent the availability of actual cost data for Chinese wind farms, we believe that our data provide the most accurate representation of electricity production costs for wind projects in China.

2) Unit capital cost

Wind farm capital investment costs have a major influence on the costs of electricity production (Junginger et al., 2005), which include costs of wind turbines foundations, land, grid connection, civil works, and turbine installation etc. We calculate the estimated unit capital cost in a similar way:

$$(\boldsymbol{Unit\_capital})_{it} = \sum_{j=1}^{n} \frac{\boldsymbol{Capital_j}}{(\mathbf{1}+\boldsymbol{r})^{j}} / \sum_{j=1}^{n} \frac{\boldsymbol{Electricity_j}}{(\mathbf{1}+\boldsymbol{r})^{j}}$$

3) Capacity factor

We use projected capacity factor to measure the operational performance of a wind farm. The capacity factor is the ratio of the actual electricity produced by a wind farm in a given period, to its potential output if it was operated at full nameplate capacity for the entire period. We calculate the capacity factor of CDM wind project $\boldsymbol{i}$ using the following formula:

$$(\boldsymbol{CF})_i = \frac{\boldsymbol{Annual\ Electiricity}}{\mathbf{24}\boldsymbol{hrs/day} * \mathbf{365}\ \boldsymbol{days} * \boldsymbol{Proejct\ Size}}$$

Although the annual electricity production data we collect from validated CDM project design documents are estimated generation, the electricity generation is monitored after the project starts its operation. According to the monitoring reports that we have examined, the estimated annual electricity production is very close to the actual electricity generation.

The capacity factor of a wind farm is mostly determined by the availability of wind on the site. In addition, the transmission line capacity, electricity demand, and routine maintenance also affect capacity factor. Given the wind quality in a particular region, we expect the project developing experience will help a developer pick a better site, select suitable wind turbines and make the best use of the wind resource at the site, which will all lead to the increase of capacity factor. In addition, the quality of wind turbines and the interactions between the developer and its turbine manufacturing partners may also help to improve the performance.

4.12 Manufacturer's knowledge stock

To test the effect of learning by searching on electricity production cost, we use manufacturer's knowledge stock(LBS_{mft}), which we measure using the cumulative patent applications related to wind power that the manufacturer supplying wind turbine in project *i* has until year *t*-1. We lag the use manufacturer's knowledge stock to account for the time needed to convert an innovation to mass manufacturing. Since knowledge related to wind power may depreciate over time, we use a 15% depreciation rate to calculate the knowledge stock in our empirical model. [4] The knowledge stock variable is calculated as follow:

$$LBS_{mft}=LBS_{t-1}*(1-\rho) + NP_{t-1} \qquad \textbf{(1)}$$

where LBS_{t-1} represents the knowledge stock that the manufacturer already has in year t-1, ρ is the depreciation rate, and NP_{t-1} represents the number of new patents that the manufacturer applied for in year *t*-1.

[4] We also test the effects of knowledge stock calculated with a 10% depreciation rate. The results are not sensitive to the choice of discount rates.

We date patent applications by the priority date, which is the earliest application date anywhere in the world, because this corresponds most closely to when the innovative activity actually took place and avoids complications resulting from different processing times for different patents. We identify relevant patents using the International Patent Classification (IPC), which is a classification system developed by the World Intellectual Property Organization and used by patent offices around the world to identify the technology represented in each patent. IPC classification F03D represents wind energy patents. These patents include innovations pertaining to wind turbine manufacturing, installation, testing and monitoring, and better ways to maintain the wind turbine during operation. We use the data collected for each manufacturer by year to calculate the cumulative knowledge stock using equation (1). If a CDM project use wind turbines from two manufacturers, we calculate the weighted average knowledge stock using the shares of their installed capacity in this project as weights.

4.13 Experience at different levels and spillovers

We test the effects of wind project developing and operating experience for different participants and at the different levels. At the micro level, we have a project developer's experience, the turbine manufacturer's experience, and the cooperating experience between the developer and its partner turbine manufacturer. At the aggregate level, we test the effects of provincial level wind project developing experience and the experience from the whole industry. A project developer's experience (LBD_{dev}) is measured by its cumulative installed capacities in CDM projects through year t-1. A manufacturer's experience (LBD_{mft}) is measured by its cumulative installed capacities through year t-1. Similarly, provincial experience ($Spill_{province}$) and industrial experience ($Spill_{industry}$) are also measured by the cumulative installed capacities within a province and in the whole industry through year t-1 respectively. To test the spillover effects, a developer's own experience is subtracted from the aggregate level experience, so that aggregate experience for each project *i* can be interpreted as the experience of the rest of the industry.

Finally, the collaboration between a project developer and manufacturer *(LBI)* is measured by calculating the cumulative capacity of previous CDM projects using both the same developer and manufacturer. This can be thought of as the shared CDM experience between the developer and the manufacturer. If a CDM project use wind turbines from two manufacturers, we calculate the weighted average cooperating CDM experience using the shares of their installed capacity in this project as weights. Data for installed capacities for project developers in CDM projects are calculated using the project design documents, while the data for each manufacturer's installed capacities and the installed capacities at aggregate levels is collected from China's Wind Energy Association. Although the project developer could have wind projects that are not included in the CDM database, the non-CDM installed capacities will only account for a small share of total experience because CDM supports over 80% of China's wind projects.

4.2 Control Variables

To accurately assess the impact of learning on the cost of wind projects, we must also control for other project features that affect the costs of generating wind power:

- **Wind turbine size (*$Turbine\_size_i$*)**. Larger wind turbines access greater wind resources available at greater heights, allowing them to capture more energy so as to produce more power. Data for the size of wind turbines comes from project design documents. If a CDM project has more than one type of wind turbines, we use average wind turbine size, which is the total project size divided by numbers of wind turbines.

- **Wind project scale (*Project_size*$_i$).** Wind projects with larger installed capacity will have economies of scale. As a result, the unit production cost will be reduced (Berry 2009, Qiu and Anadon, 2012; Partridge, 2013). The project capacity data is also in project design document.

- **Wind resource quality.** If the project site has better wind resource, it should be able to produce electricity at lower cost. The wind resource quality is measured by dummy variables $\boldsymbol{W_{1i}}, \boldsymbol{W_{2i}}, \boldsymbol{W_{3i}}$ $\boldsymbol{W_{4i}}$ **,** representing the four wind resource categories specified by the 2009 Feed-in Tariffs for Wind Power in China (NDRC, 2009). W_{1i} indicates that project *i* is located in the best wind quality region while W_{4i} indicates that the project is located in the region with the least wind resources. According to the location information of the project site, $\boldsymbol{W_{ji}}$ is coded as 1 if the project is located in region *j*. Otherwise, $\boldsymbol{W_{ji}}$ equals zero.

- **Characteristics of manufacturers and developers.** In our sample, foreign turbine manufacturers include General Electric, Vestas, Gamesa, Suzlon, and Nordex. If the wind turbine manufacturer is one of them, $\boldsymbol{Foreign_{mft}}$ equals to 1. Although some of these firms have developed subsidiaries in China, we still treat them as foreign manufacturers because their patents belong to the parent companies. This allows us to test whether projects using foreign manufactured turbines on average have lower production costs than projects using domestic wind turbines.

We also control the ownership of the project developer. We classify project developers into three groups based on their ownerships and market power in electricity generation market, which are state-owned enterprises (SOE) regulated and supervised by central government, SOEs regulated and supervised by local government, and private enterprises (Li et al., 2012). We use three dummy variables $\boldsymbol{SOE_{dev}}$, $\boldsymbol{LSOE_{dev}}$, and $\boldsymbol{Private_{dev}}$ to represent the three categories of developers respectively.

In China, the SOE developers regulated and supervised by central government dominate power generation market so that they have more bargaining power when developing a wind project. By the end of 2011, the top nine central SOE developers have contributed 73.8% of the cumulative installed capacity in China (Li et al., 2012). From 2006 to 2010, 90% of wind projects in China are developed by SOE developers. Private developers only account for less than 10% of cumulative installed capacity in China (Li et al., 2010 & 2012). Therefore, we expect that central SOE developers have the lowest production costs on average among the three categories.

Table 2 summarizes the description of explanatory variables for different channels of learning and control variables.

Table 2: Key Variables in the Empirical Model

Variable	Description
$\boldsymbol{LBS_{mft}}$	**Manufacturer's knowledge stock**: Cumulative patents related to wind power that the manufacturer has in year *t*-1.
$\boldsymbol{LBD_{mft}}$	**Experience from manufacturer:** Manufacturer's cumulative installed capacities in year *t*-1. (GW)
$\boldsymbol{LBD_{dev}}$	**Experience from project developer in CDM projects:** Project developer's cumulative installed capacities in CDM projects in year *t*-1. (GW)
$\boldsymbol{Spill_{prov}}$	**Experience from wind projects in a province**: Cumulative installed capacities in province *r* in year *t*-1. (GW)
$\boldsymbol{Spill_{industry}}$	**Experience from the whole industry**: Cumulative installed capacities of the whole industry in year *t*-1. (GW)
$\boldsymbol{LBI}$	**Collaborative experience between project developer and manufacturer**:

	Cumulative capacities installed by this developer and the same manufacturer in previous CDM projects in year *t*-1. (GW)
<u>Control Variables</u>	
$\boldsymbol{Turbine\_size_i}$	The average size of wind turbines of project.
$\boldsymbol{Project\_size_i}$	The installed capacity of project *i*.
$\boldsymbol{W_{1i,} W_{2i,} W_{3i}\ W_{4i}}$	Wind resources in the site of project *i*.
$\boldsymbol{Foreign_{mft}}$	Binary variable, whether the manufacturer in project *i* is a foreign firm.
$\boldsymbol{SOE_{dev}}$	Binary variable, whether the project developer in project *i* is a state-owned enterprise regulated and supervised by the central government.
$\boldsymbol{LSOE_{dev}}$	Binary variable, whether the project developer in project *i* is a state-owned enterprise regulated and supervised by the local government.
$\boldsymbol{Private_{dev}}$	Binary variable, whether the project developer in project *i* is a private firm.
$\boldsymbol{Province}$	Province dummies, control for regional time-invariant heterogeneity.
$\boldsymbol{Year}$	Start year dummies, control for policies, input prices, and other omitted variables changing over time.

4.3 Descriptive Statistics

Table 3 reports the summary statistics for major variables used in our empirical models.

Table 3 Summary Statistics

Variable	Mean	Std.dev.	Max	Min	N
Unit cost (RMB/kWh)	0.523	0.076	1.007	0.335	492
Unit capital cost (RMB/kWh)	0.425	0.066	0.780	0.256	492
Unit O&M cost (RMB/kWh)	0.098	0.028	0.227	0.011	492
Capacity factor	0.253	0.028	0.367	0.144	510
Manufacturer's knowledge stock (Decay rate = 0.15)	18.40	36.9	228.8	0	504
Manufacturer's cumulative installed capacity (GW)	0.685	0.777	2.621	0	504
Developer's cumulative installed capacity in CDM projects (GW)	0.722	0.965	3.338	0	510
Cooperating installed capacity in CDM projects (GW)	0.123	0.214	0.938	0	510

Province level cumulative installed capacity (GW)	0.791	1.029	3.679	0	510
Industrial level cumulative installed capacity (GW)	3.518	2.420	6.602	0.056	510
Average turbine size (MW)	1.34	0.38	3	0.6	510
CDM project size (GW)	0.059	0.048	0.4005	0.00935	510
Foreign manufacturer	0.176	0.382	1	0	510
Central SOE developer	0.70	0.46	1	0	510
Local SOE developer	0.11	0.32	1	0	510
Private developer	0.19	0.39	1	0	510
Wind category 1	0.2	0.400	1	0	510
Wind category 2	0.288	0.453	1	0	510
Wind category 3	0.125	0.332	1	0	510
Wind category 4	0.387	0.487	1	0	510

Figure 4 shows the trend of the average unit cost of CDM projects started from 2004 to 2009.[5] We also decompose the unit cost into the unit capital cost and unit O&M cost in order to observe the change of each part over time. All costs are calculated using 2005 prices. From the following figure, we can see that the unit production cost and its two components generally have downward trends from 2005 to 2009, which is consistent with the rapid technological progress in China's wind power during this period. The unit project cost falls by 12.1 % and the unit capital cost falls by 10.8 %. Unit O&M cost drops most sharply, which decreases 17.4 % from 2005 to 2009.[6]

[5] Although the earliest CDM wind projects in China started from 2002, we cannot calculate their unit costs due to the missing data in their project design documents.
[6] While the average project cost is lower in 2004, we only have one observation that has cost data among the 4 projects that started in 2004 in our sample. Thus, these data may not be representative of all the projects in 2004.

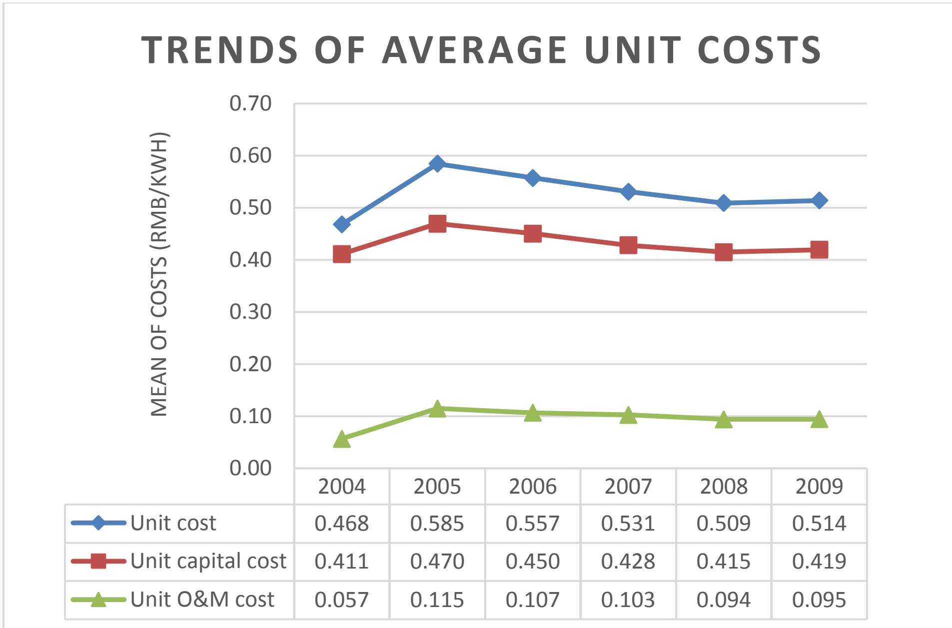
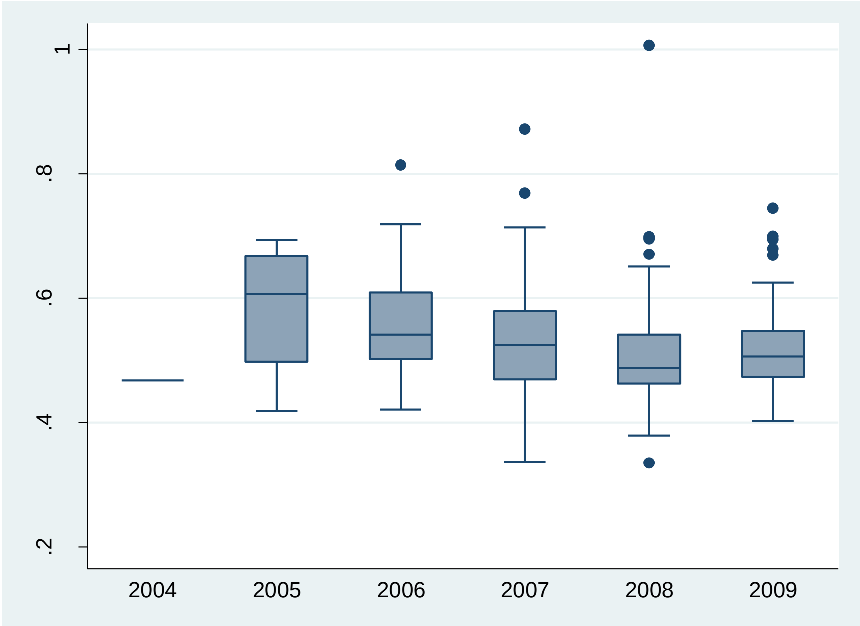


Figure 4: The Trends of Project Unit Costs from 2004 to 2009

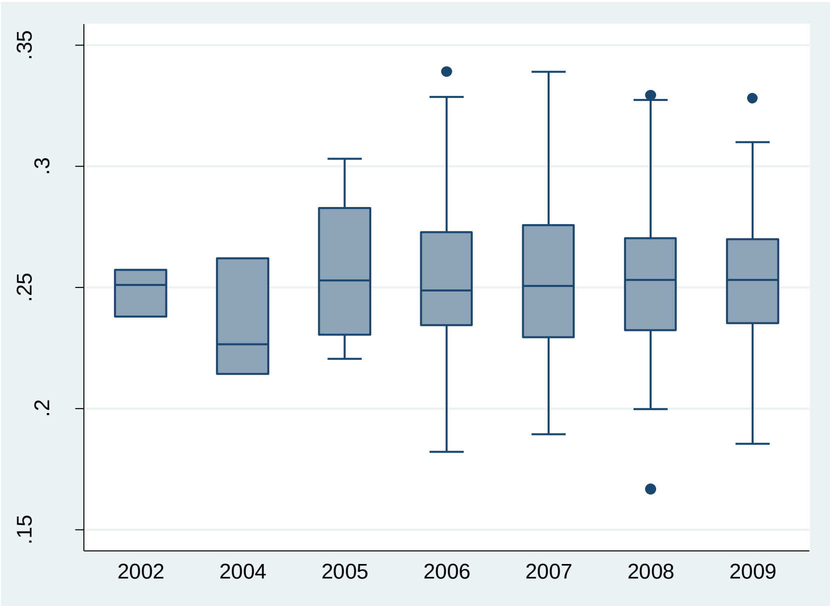
Figure 5 shows the variation of the unit costs of CDM wind projects that started in each year. The line within the box for each year represents the median unit cost for projects starting in that year, which is consistent with the trend of average unit cost in Figure 2. Except for several outliers, the variation of unit costs among projects started in the same year also becomes narrower from 2007 to 2009. This descriptive result indicates that the technological change occurs in the whole wind industry over time.

While we observe that the average project unit cost and its components have downward trends from 2005 to 2009, project capacity factors, as shown in Figure 6, do not show a clear trend during this period. Since the capacity factor is mainly determined by the wind resource available, one possibility is that projects started earlier could pick the sites with better wind resources and limited choices were left for the latter projects.



Notes: The horizontal line in the middle of each box represents the median, while the box represents the range between the first and third quantiles. The upper and lower horizontal lines represent the most extreme values which within Q3+1.5(Q3-Q1) and Q1-1.5*(Q3-Q1). Dots represent outlier observations.

Figure 5: Variation of Unit Production Costs in Each Year



Notes: The horizontal line in the middle of each box represents the median, while the box represents the range between the first and third quantiles. The upper and lower horizontal lines represent the most extreme values which within Q3+1.5(Q3-Q1) and Q1-1.5*(Q3-Q1). Dots represent outlier observations.

Figure 6: Variation of Capacity Factors in Each Year

5. Empirical Model and Results

To explain what has led to the project cost reduction over time, we test the effects of different learning channels gradually in three steps using OLS regressions. In all three steps, we examine the effect of learning-by-searching from the manufacturer. The differences among the three steps are that we explore the impact of wind project developing and operating experience from the macro level to more micro level.

First, we test the effects of aggregate level experience, which include the province level experience and the experience from the whole industry. In the second step, we separate both the developer's and the manufacturer's project experience from the aggregate level experience in order to examine the effects of learning from developer or manufacturer's internal experience and the knowledge spillover effects. In the last step, we further separate the shared CDM project experience between the developer and the manufacturer from their cumulative individual experience so that we can test the effects of learning-by-interacting.

In addition to testing the learning effects on overall electricity production, we further examine the two subsystems of learning – wind farm installation and operation – by using unit capital cost and capacity factor as dependent variables correspondingly. This allows us to see where the cost reduction occurs and how different learning channels influence the subsystems of electricity production.

5.1 Aggregate level experience

1) **Effects on unit production cost**

As the first step, we test the effects of provincial and industrial level experience using equation (2), which includes the manufacturer's knowledge stock, provincial installation experience, and industry-wide installation experience. We subtract the provincial experience from the industrial level experience in order to separate the spillovers from province where project ***i*** is located and spillover from the experience in other provinces.[7]

$$ln(Unit\_cost_{it}) = \beta_0 + \beta_1 LBS_{mft} + \beta_2 Spill_{province} + \beta_3\,(Spill_{industry} - Spill_{province}) + \beta_4 Turbine_{size_i} + \beta_5\, Project_{size_i} + \beta_6 W_{1i} + \beta_7 W_{2i} + \beta_8 W_{3i} + \beta_9 Foreign\_mft_i + \beta_{10} DOE\_dev_i + \beta_{11} LDOE\_dev_i + Province\_Dummies + Year\_Dummies + u_i \quad \textbf{(2)}$$

To control the effects of other factors that influence electricity production cost, we also include project size, wind turbine size, wind quality in the project site, and characteristics of the manufacturer and developer in our empirical model. We use province dummies to control for the regional time-invariant heterogeneity across provinces, such as the topographical and meteorological features, transmission infrastructure, and investment environment. We further add year fixed effects to control for other omitted variables that change over time for all the projects starting in the same year, such as national policies, input prices, global changes in technology, and other unobserved factors.

Table 4 reports the estimates of learning-by-searching effects, and the effects of aggregate level wind project developing and operating experience on unit production costs. We estimate three models adding different fixed effects. The learning-by-searching effect, captured by manufacturer's knowledge stock, is significant across all three models. However, the magnitude of LBS effect is very small. In the short run, one more patent from the manufacturer will roughly bring down the unit production cost by 0.04%. For learning-by-doing effect, the aggregate level project developing experience variables have significant negative effects on unit production costs only in model (1) and (2), which omit year fixed effects. When we add year

[7] While most learning models use a log-log format, so as to interpret the coefficients as learning rates, we do not use logs for our explanatory variables as we have many zeros when decomposing experience in the later models.

Table 4: Effects of Aggregate Level Experience on Unit Production Cost

Dependent Variables	(1) ln(unit_cost)	(2) ln(unit_cost)	(3) ln(unit_cost)
Knowledge stock	-0.00036**	-0.00043***	-0.00037**
of manufacturer	(0.00016)	(0.00016)	(0.00015)
Province level experience	-0.01289***	-0.00060	0.00457
(GW)	(0.00459)	(0.00553)	(0.00723)
Industrial level experience	-0.00198	-0.00767***	
(GW)	(0.00289)	(0.00296)	
Turbine size (MW)	0.00493	0.00296	0.01149
	(0.01768)	(0.01499)	(0.01503)
Project size (GW)	-0.56645***	-0.36233***	-0.32164***
	(0.16180)	(0.12352)	(0.12414)
Wind category 1	-0.17891***	-0.12902***	-0.13557***
	(0.01620)	(0.02883)	(0.02839)
Wind category 2	-0.11512***	-0.09189***	-0.09914***
	(0.01391)	(0.02714)	(0.02696)
Wind category 3	-0.07442***	-0.00964	-0.00948
	(0.01733)	(0.02484)	(0.02184)
Foreign manufacturer	0.04398**	0.05392***	0.03793**
	(0.01846)	(0.01705)	(0.01609)
Central SOE developer	-0.05103***	-0.04428***	-0.04186***
	(0.01150)	(0.01022)	(0.01008)
Local SOE developer	0.02538	0.02357	0.02352
	(0.02418)	(0.02010)	(0.01862)
Province fixed effects	No	Yes	Yes
Year fixed effects	No	No	Yes
Constant	-0.52935***	-0.14135*	-0.12832
	(0.02422)	(0.08181)	(0.09902)
Observations	486	486	486
R-squared	0.396	0.604	0.668

Note: Robust standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Industrial level experience omitted in model (3) with year fixed effects because the sum of provincial experience and industrial experience equals to the total industry-wide capacity in a given year, which is correlated with the year dummies.

fixed effects in model (3), the aggregate province level experience becomes insignificant. We do not include industrial level experience when adding year fixed effects to the model, as the sum of provincial experience and industrial experience equals to the total industry-wide capacity in a given year, which is correlated with the year fixed effects.

While the evidence of learning from macro level project experience is not clear, the results for other control variables are as expected. Both project size and wind resource quality significantly influence the project unit cost and the effects are consistent with existing literature. Projects with larger size benefit from economies of scale, leading to a reduction of electricity production cost. Projects located in regions with lower wind resource quality have higher unit electricity generation cost than projects in regions with better wind quality.

Characteristics of manufacturer and developer also significantly affect electricity production cost. On average, the unit costs of projects using wind turbines supplied by foreign manufacturers are expected to be 4% to 5% higher than projects using wind turbines from domestic manufacturers. Since foreign manufacturers usually have higher knowledge stock than domestic manufacturers, this results suggests that turbines from foreign manufacturers have higher price/kWh than domestic wind turbines when we have controlled for manufacturer's knowledge stock. The unit production costs of projects developed by central SOE developers are estimated to be approximately 4% to 5% lower than private developers' projects.

2) Effects on unit capital cost and capacity and capacity factor

Based on equation (2), we use capital cost per kWh and the project capacity factor as dependent variables to test the learning effects in wind farm installation and operation. Table 5 compares the results from previous model (3) and the results from models testing these two subsystems of learning. All the models include both province fixed effects and year fixed effects.

Table 5 Effects of Aggregate Level Experience on Unit Capital Cost and Capacity Factor

	(1)	(2)	(3)
Dependent Variables	ln(unit cost)	ln(unit capital cost)	ln(capacity factor)
Knowledge stock	-0.00037**	-0.00042**	0.00032***
of manufacturer	(0.00015)	(0.00021)	(0.00012)
Province level experience	0.00457	-0.00296	-0.00875
(GW)	(0.00723)	(0.00888)	(0.00595)
Turbine size	0.01149	0.03683**	0.05319***
(MW)	(0.01503)	(0.01858)	(0.01097)
Project size	-0.32164***	-0.33291**	0.13045*
(GW)	(0.12414)	(0.13833)	(0.07282)
Wind category 1	-0.13557***	-0.20836***	0.13308***
	(0.02839)	(0.02820)	(0.03098)
Wind category 2	-0.09914***	-0.17539***	0.10357***
	(0.02696)	(0.02607)	(0.03064)
Wind category 3	-0.00948	-0.02110	-0.00796
	(0.02184)	(0.02033)	(0.01626)
Foreign manufacturer	0.03793**	0.04489**	0.00644
	(0.01609)	(0.01961)	(0.01397)
Central SOE developer	-0.04186***	-0.08436***	0.01837**
	(0.01008)	(0.02092)	(0.00859)
Local SOE developer	0.02352	-0.04343*	-0.01271
	(0.01862)	(0.02403)	(0.01521)
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Constant	-0.12832	-0.41078***	-1.62062***
	(0.09902)	(0.09795)	(0.07880)
Observations	486	486	502
R-squared	0.668	0.579	0.603

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Industrial level experience omitted in all models because the sum of provincial experience and industrial experience equals to the total industry-wide capacity in a given year, which is correlated with the year dummies.

The results are highly consistent across three models. The LBS effects are significant for wind farm construction and installation, operation, and the overall electricity production process. Increases in a manufacturer's knowledge stock both reduce the unit production cost and unit capital cost while increasing the capacity factor. However, LBD on the aggregate level, captured by the province level wind project development experience is not significant in any of our models. Comparing the three models, we notice that projects using wind turbines from foreign manufacturers or domestic manufacturers do not have significant differences on their capacity factors, but do have higher costs in column (1) and (2), further indicating that wind turbines from foreign manufacturers are sold at higher prices than domestic wind turbines when controlling for the knowledge stock embodied in foreign turbines.

5.2 Effect of developer's internal experience and spillover effects

1) **Effects on unit production cost**

In the second step, we consider each project developer and manufacturer's individual experience. To do so, we must also subtract the developer's experience $\boldsymbol{LBD_{dev}}$ and the manufacturer's experience $\boldsymbol{LBD_{mft}}$ from the aggregate level experience $\boldsymbol{Spill_{industry}}$ in equation (2). As a result, the knowledge spillover from other projects in the industry is calculated as $\boldsymbol{(Spill_{industry} - LBD_{dev} - LBD_{mft} + LBI)}$[10], where $\boldsymbol{LBI}$ represents the previous cooperating experience on joint projects between a developer and a manufacturer that we will discuss in 5.3. The empirical model specification is:

$$\begin{aligned} ln(Unit\_cost_{it}) = {} & \beta_0 + \beta_1 LBS_{mft} + \beta_2 LBD_{mft} + \beta_3 LBD_{dev} + \beta_4\,(Spill_{industry} \\ & - LBD_{mft} - LBD_{dev} + LBI) + \beta_5 Turbine_{size_i} \\ & + \beta_6\, Project_{size_i} + \beta_7 W_{1i} + \beta_8 W_{2i} + \beta_9 W_{3i} + \beta_{10} Foreign_{mft_i} + \beta_{11} DOE_{dev_i} + \beta_{12} LDOE_{dev_i} \\ & + Provinc\_Dummies + Year\_Dummies + u_i \end{aligned} \qquad \mathbf{(3)}$$

Table 6 shows the regression results of equation (3). Once again we estimate three model specifications with different fixed effects. The LBS effect is significant across all the models and

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[10] Because $\boldsymbol{LBI}$ is the overlap between $\boldsymbol{LBD_{mft}}$ and $\boldsymbol{LBD_{dev}}$, we add it back to avoid double subtraction from the industrial experience.

the magnitude is similar to what we have found in 5.1. While we observe no meaningful learning-by-doing effects from aggregate level experience, we now find learning to be important as we separate the developer's CDM project experience and manufacturer's experience from the aggregate level experience. In particular, a developer's previous experience from CDM projects

Table 6 Learning-by-doing Effect and Spillover Effect

Dependent Variables	(1) ln(unit_cost)	(2) ln(unit_cost)	(3) ln(unit_cost)
knowledge stock of manufacturer	-0.00024*	-0.00035**	-0.00029**
	(0.00014)	(0.00014)	(0.00013)
Manufacturer' experience (GW)	-0.00223	-0.00488	-0.01816
	(0.00601)	(0.00489)	(0.02285)
Developer's experience in CDM projects (GW)	-0.03101***	-0.02718***	-0.03938*
	(0.00501)	(0.00456)	(0.02017)
Spillover from the industry (GW)	0.00161	-0.00001	-0.01605
	(0.00298)	(0.00248)	(0.02444)
Turbine size (MW)	0.00341	0.00202	0.01068
	(0.01754)	(0.01464)	(0.01481)
Project size (GW)	-0.57580***	-0.38520***	-0.34063***
	(0.15441)	(0.12270)	(0.12296)
Wind category 1	-0.19221***	-0.13382***	-0.14092***
	(0.01299)	(0.02839)	(0.02805)
Wind category 2	-0.11907***	-0.08570***	-0.09387***
	(0.01219)	(0.02710)	(0.02688)
Wind category 3	-0.07856***	-0.01146	-0.01251
	(0.01674)	(0.02254)	(0.01974)
Foreign manufacturer	0.03483*	0.04602***	0.03097*
	(0.01821)	(0.01692)	(0.01607)
Central SOE developer	-0.02104*	-0.01728	-0.01624
	(0.01271)	(0.01135)	(0.01126)
Local SOE developer	0.03484	0.03335*	0.03259*
	(0.02453)	(0.02009)	(0.01885)
Province fixed effects	No	Yes	Yes
Year fixed effects	No	No	Yes
Constant	-0.52014***	-0.38794***	-0.45777***
	(0.02343)	(0.09862)	(0.10299)
Observations	486	486	486
R-squared	0.453	0.674	0.684

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

significantly reduces the project unit cost across all three models, although it is only significant at the 10 percent level when including year fixed effects. The magnitude of the coefficient on developer's experience in model (3) shows that the unit cost of wind power in CDM projects nearly falls by 4% for each additional 1 GW of previous installed capacity in CDM projects by the developer. On average, the size of a CDM wind project is approximately 60 MW, which means that 1 GW installation will take place through 16 to 17 CDM projects. Thus, a typical CDM project by the same developer will lead to around 0.23% to 0.25% decrease in future unit costs. For most central SOE developers and some local SOE developers, they have around 10 new CDM projects in 2009. It will only take one to two years for these developers to increase 1 GW installation. In contrast, while the knowledge embodied in a manufacturer's turbine reduces costs, the manufacturer's previous project experience does not have a significant effect on unit production costs.

2) Effects on unit capital cost and capacity and capacity factor

Again, we test the two subsystems of learning – the wind farm installation and operation using the same set of explanatory variables, and compare the results with the overall learning for electricity production. As shown in Table 7, different learning channels have consistent impacts on unit production cost, unit capital cost and capacity factor.

Wind projects benefit from manufacturers' R&D. A manufacturer's knowledge stock of manufacturers both drives down the unit production cost and unit capital cost while raising the capacity factor. However, the LBS effect is very small. The LBD effects from the developer's internal experience are also significant across all models. The impact on unit capital cost is slightly higher than its impact on unit cost. The unit capital cost will fall by 4.64% and the capacity factor will increase by 1.1% if the developer increases additional 1 GW installed capacity in CDM projects. Similar to the results in 5.1, we see that the foreign manufacturer dummy affect both costs variables while it has no significant effect on capacity factor.

Table 7 Learning-by-doing and Spillover Effects on Unit Capital Cost and Capacity Factor

	(1)	(2)	(3)
Dependent Variables	ln(unit cost)	ln (unit capital cost)	ln(capacity factor)
Knowledge stock of manufacturer	-0.00029**	-0.00031*	0.00028**
	(0.00013)	(0.00018)	(0.00012)
Manufacturer' experience (GW)	-0.01816	-0.02013	0.00529
	(0.02285)	(0.02752)	(0.00471)
Developer's experience in CDM projects (GW)	-0.03938*	-0.04638*	0.01094**
	(0.02017)	(0.02475)	(0.00446)
Spillover from the industry (GW)	-0.01605	-0.01245	0.00107
	(0.02444)	(0.02942)	(0.00345)
Turbine size (MW)	0.01068	0.03342*	0.05349***
	(0.01481)	(0.01817)	(0.01085)
Project size (GW)	-0.34063***	-0.34582***	0.14495*
	(0.12296)	(0.13293)	(0.07389)
Wind category 1	-0.14092***	-0.21581***	0.13587***
	(0.02805)	(0.02739)	(0.02877)
Wind category 2	-0.09387***	-0.16919***	0.10083***
	(0.02688)	(0.02500)	(0.02837)
Wind category 3	-0.01251	-0.02476	-0.00556
	(0.01974)	(0.01851)	(0.01512)
Foreign manufacturer	0.03097*	0.03535*	0.01231
	(0.01607)	(0.01951)	(0.01405)
Central SOE developer	-0.01624	-0.00684	0.00791
	(0.01126)	(0.01453)	(0.00974)
Local SOE developer	0.03259*	0.05485**	-0.01550
	(0.01885)	(0.02443)	(0.01528)
Province fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Constant	-0.45777***	-0.64313***	-1.62209***
	(0.10299)	(0.10847)	(0.07938)
Observations	486	486	502
R-squared	0.684	0.607	0.606

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

Compared with the results in 5.1, the results in Table 7 indicate that project developers learn from their own experience in wind farm construction and operation. While we find some evidence of industry-level spillovers in section 5.1, the importance of these spillovers disappears when we separate learning effects into experience of the turbine manufacturer and experience of the project developer. In contrast, previous studies that find evidence of wind power firms learning from the industrial experience (Nemet, 2012; Qiu and Anadon, 2012) do not separately control for the experience of different actors in the industry.

5.3 Effects of collaborating experience and other channels of learning

1) Effects on unit production cost

Finally, we further separate CDM experience by considering the role of collaboration in CDM wind projects. Here, we consider experience on joint projects between a developer and a manufacturer separately from both the developer and manufacturer's experience on other projects. We do this by subtracting the shared cumulative installed capacities in CDM projects between the developer and the manufacturer from their own cumulative installed capacities. In this way, we are able to examine the effect of learning-by-doing and learning-by-interacting. The empirical model is:

$$\begin{aligned} ln(UC_{it}) = \beta_0 + \beta_1 LBS_{mft} + \beta_2(LBD_{mft} - LBI) + \beta_3\ (LBD_{dev}\ - LBI) + \beta_4\ (Spill_{industry} \\ - LBD_{mft} - LBD_{dev}\ + LBI) + \beta_5 LBI + \beta_6 Turbine\_size_i \\ + \beta_7\ Project\_size_i + \beta_8 W_{1i}\ + \beta_9 W_{2i} + \beta_{10} W_{3i} + \beta_{11} Foreign_{mft_i}\ + \beta_{12} DOE_{dev_i} + \beta_{13} LDOE_{dev_i} \\ + Provinc\_Dummies + Year\_Dummies + u_i \end{aligned} \quad \textbf{(4)}$$

In equation (4), $(LBD_{mft} - LBI)$ and $(LBD_{dev} - LBI)$ are the prior experience that the manufacturer and the project developer have respectively[12], and $(Spill_{industry} - LBD_{dev} - LBD_{mft}+LBI)$ represents the knowledge spillovers from the whole industry as we did in 5.2. We estimate the coefficients on these five variables in order to test the five hypotheses in section 3.

Table 8 reports the estimates of different learning effects. Model (1) only has province fixed effects and Model (2) adds year fixed effects. Model (3) further includes an interaction term between foreign manufacturer dummy and the previous cooperating experience between the developer and manufacturer in order to tests whether the collaboration with a foreign manufacturer makes a different on production costs.

Across all three specifications, we see that the LBS effects are significant and the magnitudes are similar to the results in Table 6. For LBD effects, a manufacturer's experience alone still has no significant impact on unit costs. A developer's experience alone matters, but the impact is smaller than its experience including shared experience with the manufacturer as shown in Table 6.

What reduces project costs the most is the repeating collaboration experience between a developer and the same manufacturer, which suggests the learning-by-interacting effect. A 1 GW increase of collaborative installed capacity results in approximately a 4% decrease of the unit electricity production cost. As we have discussed in 5.2, this magnitude indicates that one more CDM wind project that the developer and the manufacturer work together will drive the unit cost to decline around 0.25%. In column (3), the significance of the interaction term with foreign manufacturers indicates that collaborations between developers and foreign manufacturers

[12] Here, we subtract the cooperation experience that the project developer and the manufacturer have together in previous CDM projects to avoid double counting. At the same time, it separates the effect of learning-by-interacting and the effects of participant's independent experience.

generate the greatest cost savings. An additional 1 GW installed capacity by a developer

Table 8: Effects of Collaborating Experience and Other Channels of Learning

Dependent Variables	(1) ln(unit_cost)	(2) ln(unit_cost)	(3) ln(unit_cost)
Knowledge stock of manufacturer	-0.00035**	-0.00029**	-0.00025*
	(0.00014)	(0.00013)	(0.00013)
Manufacturer's experience alone (GW)	-0.00309	-0.00211	-0.00216
	(0.00515)	(0.00572)	(0.00571)
Developer's experience in CDM projects alone (GW)	-0.02418***	-0.02333***	-0.02230***
	(0.00611)	(0.00658)	(0.00655)
Cooperating experience in CDM (GW)	-0.04976**	-0.04149**	-0.03971**
	(0.02037)	(0.01874)	(0.01876)
Spillover from the industry (GW)	-0.00027		
	(0.00252)		
Turbine size (MW)	0.00160	0.01068	0.00929
	(0.01464)	(0.01481)	(0.01493)
Project size (GW)	-0.38001***	-0.34063***	-0.33709***
	(0.12138)	(0.12296)	(0.12246)
Wind category 1	-0.13526***	-0.14092***	-0.14541***
	(0.02881)	(0.02805)	(0.02850)
Wind category 2	-0.08587***	-0.09387***	-0.09348***
	(0.02759)	(0.02688)	(0.02706)
Wind category 3	-0.01283	-0.01251	-0.01419
	(0.02243)	(0.01974)	(0.01983)
Foreign manufacturer	0.04596***	0.03097*	0.03969**
	(0.01692)	(0.01607)	(0.01751)
Central SOE developer	-0.01655	-0.01624	-0.01554
	(0.01142)	(0.01126)	(0.01128)
Local SOE developer	0.03405*	0.03259*	0.03183*
	(0.02011)	(0.01885)	(0.01890)
Foreign manufacturer* cooperating experience			-0.13107**
			(0.06000)
Province fixed effects	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes
Constant	-0.18107**	-0.13652	-0.13711
	(0.08414)	(0.09879)	(0.09880)
Observations	486	486	486
R-squared	0.660	0.685	0.687

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Knowledge spillover from the industry is omitted in both model (2) and (3) with year fixed effects because the sum of all the four experience variables equals to the total industry-wide installed capacity in a given year, which is correlated with the year dummies.

with its foreign manufacturer partner drives down the unit production cost by approximately 15.7%,[15] which is nearly three times greater than the effect of cooperating experience between a developer and a domestic manufacturer. Given that the average CDM project size is approximately 60 MW, one more CDM wind project that a developer builds together with the same foreign manufacturer will reduce the unit cost by almost 1%. The difference between cooperating experience with foreign manufacturers and domestic manufacturers on unit cost reduction suggests that tacit knowledge transfer between foreign manufacturers and project developers is important to maximize the benefits from the transfer of foreign technologies.

2) Effects on unit capital cost and capacity factor

We further test whether the repeated collaboration experience influences unit capital cost and capacity factor. Table 9 compares models with different dependent variables. All models include both province fixed effects and year fixed effects.

As shown in model (1) and model (3), the learning by interacting effects, captured by repeated collaboration experience, have the biggest impacts on both production cost reduction and capital cost reduction. The magnitude of the effect for capital cost reduction is slightly larger than the effect on production reduction. However, the cooperating experience does not have significant effect on capacity factor in model (5). When we further test whether cooperating with foreign manufacturer makes a difference by adding the interaction terms in model (2) and model (4), the cooperating experience with foreign manufacturer partner leads to greater reduction for electricity production costs while it makes no difference on capital costs.

[15] The percentage change is exp (-0.0397 – 0.131) – 1 = -15.7%.

Table 9 Effects of Collaborating Experience on Unit Capital Cost and Capacity Factor

Dependent Variables	(1) unit cost	(2) unit cost	(3) unit capital cost	(4) unit capital cost	(5) capacity factor
Knowledge stock of manufacturer	-0.00029**	-0.00025*	-0.00031*	-0.00027	0.00030**
	(0.00013)	(0.00013)	(0.00018)	(0.00017)	(0.00012)
Manufacturer's experience alone (GW)	-0.00211	-0.00216	-0.00768	-0.00772	0.00512
	(0.00572)	(0.00571)	(0.00704)	(0.00703)	(0.00556)
Developer's experience in CDM projects alone (GW)	-0.02333***	-0.02230***	-0.03393***	-0.03304***	0.01126**
	(0.00658)	(0.00655)	(0.00800)	(0.00798)	(0.00573)
Cooperating experience in CDM (GW)	-0.04149**	-0.03971**	-0.05406**	-0.05252**	0.00505
	(0.01874)	(0.01876)	(0.02299)	(0.02314)	(0.01987)
Turbine size (MW)	0.01068	0.00929	0.03342*	0.03221*	0.05332***
	(0.01481)	(0.01493)	(0.01817)	(0.01825)	(0.01093)
Project size (GW)	-0.34063***	-0.33709***	-0.34582***	-0.34276**	0.14699**
	(0.12296)	(0.12246)	(0.13293)	(0.13291)	(0.07374)
Wind category 1	-0.14092***	-0.14541***	-0.21581***	-0.21969***	0.13427***
	(0.02805)	(0.02850)	(0.02739)	(0.02766)	(0.03026)
Wind category 2	-0.09387***	-0.09348***	-0.16919***	-0.16885***	0.10052***
	(0.02688)	(0.02706)	(0.02500)	(0.02479)	(0.02982)
Wind category 3	-0.01251	-0.01419	-0.02476	-0.02621	-0.00811
	(0.01974)	(0.01983)	(0.01851)	(0.01852)	(0.01573)
Foreign manufacturer	0.03097*	0.03969**	0.03535*	0.04288**	0.00991
	(0.01607)	(0.01751)	(0.01951)	(0.02138)	(0.01422)
Central SOE developer	-0.01624	-0.01554	-0.00684	-0.00624	0.00899
	(0.01126)	(0.01128)	(0.01453)	(0.01453)	(0.01001)
Local SOE developer	0.03259*	0.03183*	0.05485**	0.05419**	-0.01548
	(0.01885)	(0.01890)	(0.02443)	(0.02451)	(0.01544)
Foreign manufacturer* cooperating experience		-0.13107**		-0.11329	
		(0.06000)		(0.08382)	
Province fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Constant	-0.13652	-0.13711	-0.45304***	-0.45354***	-1.62272***
	(0.09879)	(0.09880)	(0.09859)	(0.09857)	(0.07932)
Observations	486	486	486	486	502
R-squared	0.685	0.687	0.607	0.608	0.606

Note: Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. Knowledge spillover from the industry is omitted in all the models because the sum of all the four experience variables equals to the total industry-wide installed capacity in a given year, which is correlated with the year dummies.

The results above indicate that the repeated partnership between developer and the same manufacturer mostly drive down the capital cost in the construction and installation stage while it does not show significant impact on operational performance in terms of capacity factor.

Instead, the developer's own experience is sufficient to provide guidance on siting turbines to improve the electricity generated from each new site. Since the unit capital costs on average account for approximately 80% of the unit electricity production cost of a wind project, we also observe that the cooperating experience matters most for the production cost reduction on the whole. When we further differentiate between the cooperating experience with foreign manufacturer and domestic manufacturer, the results suggest that the repeated partnership with a foreign manufacturer facilitates knowledge diffusion between partners beyond the construction and installation stage, which improves the overall performance of the wind farm.

6. Conclusions

Using CDM wind projects started between 2002 to 2009 in China, this paper examines the effects of different channels of learning – learning through R&D in wind turbine manufacturing, learning from firm's previous experience of installation, learning from the experience of other firms, and learning through collaboration between wind turbine manufacturer and project developer—on technological change in China's wind industry in terms of electricity production cost. In addition to the electricity generation cost, we further test the learning effects in two subsystems of electricity production: wind farm installation costs and capacity factor.

Our empirical analysis successfully separates learning-by-searching effect from the joint learning effect of LBS and LBD used in previous research on China's wind power industry. Wind projects benefit from the knowledge stock of their turbine manufacturers in both wind farm installation and operation, which result in lower electricity production costs. However, the learning-by-searching effect is much smaller than what has been found for European wind power over a long period of time (Soderholm & Klassen, 2007; Soderholm & Sundqvist, 2007). This is reasonable because our observation period is too short for patents to be fully commercialized and to have large impact on cost reduction. Another reason could be that turbines with advanced technology also have higher prices while the electricity production is limited by the technological capacity of the wind farm or the transmission system. Finally, since our data includes only patents taken out in China, it may be that these innovations are not as significant as those made by global manufacturers and patented in developed countries. On the whole, the apparent learning-by-searching effect suggests that supply-side policies are still needed to encourage further innovation in turbine manufacturing. At the same time, government should also use demand-side policy tools to facilitate the commercialization and diffusion of these novel wind technologies.

The empirical results also provide evidence of learning-by-doing effect for wind project developers in China. While finding LBD effects is consistent with previous research, our paper is the first to separately identify the experience of manufacturers and project developers. Developers are more likely to benefit from their past internal experience in both wind farm installation and operation, which significantly drive down the overall electricity production costs. Unlike previous research, when we separate the experience of developers and manufacturers, knowledge spillover effects from the industry as a whole are less important.

Taking one step further, we find that what really matters for reducing electricity production costs is not just the experience of a particular project developer or turbine manufacturer, but the joint project experience between the developer and the same manufacturer through their repeated interaction. The repeated partnership between developers and turbine manufacturers leads to lower electricity production costs, particularly for capital costs. Our results provide justification for the trend of integrating turbine manufacturing with wind project developing in China's wind industry. Both domestic manufacturers such as Goldwind and foreign manufacturers such as Gamesa have begun to either form subsidiaries to develop wind projects or partner with certain existing developers in order to get more involved in project developing (Li, 2012). This finding also suggests that the wind energy association or local government could set up platforms or forums to connect developers and manufacturers in advance, particularly the small developers that newly enter the market.

One goal of the Clean Development Mechanism is to enable technology transfer to countries hosting CDM projects. Our results also provide evidence that, by encouraging cooperation between local project developers and turbine manufacturers, the CDM is successful in this goal. However, more research is necessary to establish the mechanisms through which these partnerships cause costs to fall. While it may be the case that the reduction of capital costs is a result of joint learning between the developers and manufacturers on wind farm installation, we cannot rule out that the cost savings are simply the result of economically reciprocal wind turbine purchase contracts between partners based on their repeated collaboration. Distinguishing between these explanations requires further qualitative data to rule out the latter explanation or to separate the impacts of these two explanations.

Finally, our strongest evidence for the learning-by-interacting effect occurs when a wind project developer repeatedly collaborates with a foreign manufacturer. In addition to the transfer of physical technology, the transfer of tacit knowledge through the partnership drives down the electricity production cost to a great extent. In the light of this finding, it may not be wise for Chinese government to prevent foreign manufacturers from entering and competing with other domestic manufacturers in the turbine manufacturing market.

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