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Heterogeneities in energy technological learning: Evidence from the U.S. electricity industry

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While the role of organizational learning in improving firm performance is well documented, there are still questions on what drives technological learning. This is evident in the electricity industry where the growth of renewable energy technologies has been pervasive. Vicarious learning contributes to the adoption of emerging technologies through successful inter-firm knowledge sharing and transfer. However, there is hesitation to adoption that characterizes vicarious learning especially in the context of intra-firm learning. This paper investigates the differences in knowledge acquisition within and across electricity firms in the U.S. The learning curve model is applied to a longitudinal study of 5573 plants belonging to 1542 U.S. electricity firms between 1998 and 2010. This study finds: (i) The capacity growth of the solar photovoltaic technology is positively associated with intra-firm knowledge acquisition; (ii) The effect of financial incentives on the adoption of solar and wind technologies is higher under inter-firm learning; (iii) The higher the stringency of policy mandates, the more varied is the progress on technological change across technologies; (iv) Knowledge sharing between firms are higher for wind technology than for solar technology. These findings combine to show disparities in the learning trends of technologies across and within firms' boundaries.

1. Introduction

Within the past decade, billions of dollars have been invested in clean technologies. This has led to a clean energy revolution in the U.S. electricity sector. Yet, sustaining market competition and maintaining competitive advantage for U.S. electricity firms remain key issues. Knowledge acquisition and technological innovation are becoming effective tools for harnessing competition and designing firms' profit maximization strategies. This article seeks to explore the mechanisms of knowledge acquisition, either between firms or within a firm, on the adoption of energy technologies among U.S. electricity firms. For that purpose, this study inspects the heterogeneity related to knowledge acquisition within and across electricity firms. Furthermore, questions of environmental regulations and firms' desire to innovate and maximize profits are complex and intricate. Thus, to shed more light on the mechanisms underlying firm innovation, this paper borrows Vockell (2001)'s modeling framework from psychology and applies Yelle (1980)'s learning curve model. Combining these models allows us to explain the transfer of learning and how organizations learn from (i) the experience of others, and (ii) their own experience. However, this research differs from the existing literature on the transfer of knowledge in service organizations, such as Darr et al. (1995), by focusing on firms' electricity generating technologies. It carries out a longitudinal study of 5573 plants belonging to 1542 U.S. electricity firms between 1998 and 2010 by generating seven models of the responses in cost per electricity produced.

This paper demonstrates that the acquisition of new knowledge through intra-firm learning by U.S. electricity firms is positively associated with the improvement of a new technology, solar photovoltaic in particular. This paper shows the fruitful relationship between financial incentives for clean technologies and innovation in clean technologies through inter-firm transfer of technology knowledge. The results show that the improvement of knowledge acquisition for wind technologies within electricity firms is stimulated by production tax credits. The analysis further shows that complying with policy instruments often produces diversity in terms of technological progress. The results further demonstrate how inter-firm knowledge acquisition is more prevalent for wind technology than for solar technology, resulting in a higher learning rate for wind technology. Policy mandates and financial incentives have a positive impact on technological innovation. In the

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light of these findings, and given the economical and environmental benefits of emissions reduction, policies designed to cost-effectively grow the adoption of renewable energy are necessary.

The rest of this article is organized as follows. In section 2, the theoretical framework is introduced and the rationale behind each hypothesis is elaborated on. In this section, the article also reviews the theory of organizational learning to further highlight the processes driving how the firm advances along the learning curve. In section 3, the article provides the econometric models with the implications of policy instruments on technological learning or adoption. In this section, the article also describes the research design, industry context, and sources of data. In section 4, the results are presented. Section 5 concludes.

2. Theoretical framework & hypotheses

Uncertainty about the benefits of new technology investment is an essential part of a technology adoption decision. In this section, the article analyzes the mechanisms of inter-firm and intra-firm learning in a technology adoption decision under the condition of regulatory mandates.

2.1. Technological adoption and uncertainty

Baker (2009) develops a model of incremental growth in technology adoption. In this model, the decision maker must decide on the adoption of a technology. Let's consider the following adoption decision characterized by the decision variable t such that

$$\max_{t} E_{\omega}[B(t, \omega)] - c(t) \tag{2.1}$$

where ω is a random variable, E_{ω} is the expectation operator on ω, $B(t, \omega)$ is the benefit of the adoption decision while $c(t)$ is its cost. Without loss of generalization, assuming that this problem is well behaved, the first order condition is given by

$$c'(t) = E_{\omega}\left[\frac{\partial}{dt}B(t, \omega)\right] \tag{2.2}$$

Let t^* be the optimal decision, the solution of (2.2). It implies that adoption occurs if, and only if, the marginal cost of adoption is equal to the expected marginal benefit of adoption, or when the expected marginal benefit exceeds the marginal cost. Under conditions of uncertainty, given the right hand-side of (2.2), the expected marginal benefit is expected to increase for increases in the risk associated with the adoption of the new technology. In the absence of this condition, that is, increases in marginal benefit due to increases in risk, adoption decisions may be infeasible. Thus, it is evident that when the marginal benefit exceeds the marginal cost, the surplus of marginal benefit over marginal cost constitutes a benefit. That is, the decision maker is better off adopting the new technology. However, this outcome is dependent on the change in the probability distribution of the random variable ω. This means that any change that increases (decreases) the expected marginal benefits will cause the optimal decision t^* to increase (decrease). Hence, for all increases in the likelihood of adoption, the expected marginal benefits of the decision will increase. But, this will only happen if the adopted technology displays decreasing returns to scale such that the benefits are convex. Whether or not the adoption of the new technology yields a positive benefit is conditional on other factors. Hence, it can be said that the marginal benefits of the decision on technological adoption are neither strictly convex nor concave.

In a two-period learning model, Epstein (1980) shows that learning yields an improvement over the existing technology and is given by

$$\max_{t_1} E_{\omega}\left[\max_{t_2} B(t_1, t_2, \omega) - c_2(t_2)\right] - c_1(t_1) \tag{2.3}$$

Equation (2.3) is an inter-temporal, but sequential decision making problem. This is because the optimal second period decision t_2^* depends on the optimal first period decision t_1^*. Regrettably, this dependence rather complicates the resolution of the two-period learning model. As a matter of fact, characterizing the marginal benefits is ambiguous given the uncertainty generated by the distribution on ω. The adoption of a new technology is often accompanied by some risks. Some of these risks are associated with uncertainties about benefits, costs, impact of the technology overall and other parts of the business. It is still possible that knowledge transfer within or among firms improves the likelihood of adoption of a new technology. It is also possible that policy mandates increase or decrease the uncertainty related to the adoption of a new technology (Fabrizio, 2012).

2.2. Technological adoption – an example

This illustration illuminates the underlying mechanism on technology adoption decisions. Consider two firms, namely, F_1 and F_2. Both firms are making discrete and simultaneous improvements on an existing technology T_1 to yield a new technology T_2 at cost C. Either of the two firms may adopt the new technology but the firm (F_1) with the breakthrough technology holds the rights to the new technology T_2. Moreover, the adoption of this new technology T_2 yields a benefit B. This adoption is only possible if the payoff of the innovation satisfies $B - C > 0$ (Fabrizio, 2012). Firm F_1 only leases it to another firm or second firm F_2, which assumes the role of a user. Thus, F_2 enjoys benefits B because the payoff of adopting the new technology T_2 satisfies $B > C$. If F_2 does not adopt the new technology, then F_1 still enjoys the benefits B since it still regains the choice of leasing to a new firm. It should be noted here that F_1 does not need to diffuse to create the market for the new technology – the inherent benefits of the technology are sufficient enough to promote adoption. Thus, benefits B may be higher if F_1 is a monopolist. By holding the rights to the new technology, the profitability of the new adoption stays within the innovating firm or the first firm F_1. This is a case of intra-firm learning. On the other hand, by leasing the new technology, the innovating firm diffuses its knowledge among other firms. This is an instance of inter-firm learning. This illustration is consistent with, and succinctly summarizes, the theory of technological innovation and adoption (Ghosh et al., 2007; Teece, 2010).

2.3. Solar technology and intra-firm learning

Intra-firm learning is the process through which firms utilize a new technology once they have adopted it. It enables teams and departments within the firm to transfer knowledge via an ad-hoc transfer mechanism. For example, a new technology may be first incorporated in one division of the firm and subsequently adopted by other business units as the firm learns about the technology (Barden, 2012). On that note, Fuentelsaz et al. (2003) provide evidence on the factors affecting technology diffusion within firms. It is abundantly argued that the firm's capacity to transfer knowledge has a positive impact on its performance. Studies conducted by Baum and Ingram (1998) and Epple et al. (1996) successfully illustrate that knowledge transfer is critical for the firm's long-term survival. A salient characteristic of intra-firm learning is tacit knowledge, which has to do with skills acquisition. As demonstrated by Nelson and Winter (1982), tacit knowledge is an essential part of people and teams within firms. For that matter, tacit knowledge is inherently implicit in that players outside the firm have difficulty in copying or imitating the techniques used inside the firm.

Tacit knowledge is personal and hard to formalize because it is rooted in action, procedures and values (Seidler-de Alwis and Hartmann, 2008). The inability to codify it implies that it is acquired by sharing experiences, by observation and imitation (Balconi, 2002; Kikoski and Kikoski, 2004; Kuan et al., 2015). However, it is essential to note that tacit and explicit knowledge are complementary such that while a firm's competitive advantage is often dependent on its tacit knowledge, but when made explicit, other firms can follow (Nonaka and Toyama, 2015). Thus, in innovation, tacit knowledge initiates the learning process or curve and provides competitive advantage (Kikoski and Kikoski, 2004). Examples of this are predominant in electricity market collusion (Cau and Anderson, 2003; Guerci et al., 2008), improving operational standards (Perjanik, 2016), and learning how-to-learn in the power industry (Carayannis, 1999). Thus, firms that have organized themselves into networks or teams facilitate intra-firm learning such that a new process is diffused with ease of access to internal knowledge. Outside of the electricity sector, we find that firms that were not part of the networks already using Automatic Teller Machines (ATMs) were late to benefit from that technology (Fuentelsaz et al., 2003). It is also noteworthy that Garvin (1993) associates firm learning with the creation, acquisition, and transfer of knowledge inferring that intra-firm learning culminates in the enhancement of the existing technology.

Technological improvement for solar photovoltaics highly depends on the degree to which solar energy is harnessed. Nationwide, there is still a significant room for improvement for commercial PV cells even though the state of California has seen the greatest amount of market penetration for solar PV installations. For example, the cumulative grid-connected PV capacity grew to almost 300,000 kW by 2007 in California alone (Hart and Birson, 2016). More and more firms in California are choosing to invest in solar technology. For example, Ogunrinde et al. (2018) show that solar technology has a total capacity addition of 7668.2 MW through 608 additional generators in the California regional transmission organization network between 2006 and 2015. Hence, investigating how knowledge acquisition affects the adoption of solar technology may open the way for further investments. On that point, Bollinger and Gillingham (2014) have developed a model that seeks to find how internal learning affects the cost of installing new solar technologies. They find evidence of reductions in non-hardware costs for solar PV installations due to learning by contractors within a county.

We hypothesize that technological enhancement from internal firm knowledge accumulation about the technology is more evident for the solar technology than in other technologies. Studies such as Wright (1936) and Zangwill and Kantor (1998) have demonstrated that technological innovation is the foundation of cost reduction and capital efficiency. The introduction of new technologies has created significant economies of scale or efficiency effects as witnessed in the installation of new capacities in solar technology, for example, Bollinger and Gillingham (2014). Furthermore, learning curve analysis have shown a positive relationship between capital efficiency and the development of new technologies (Yelle, 1979; Zangwill and Kantor, 2000). Mansfield (1963) studied the impact of intra-firm learning on the adoption of new technology. The paper finds that as some firms become more accustomed to a new innovation, they are likely to quickly replace their old technology with the new technology while others are slower to make the transition. For electricity firms, a network approach (within their subsidiaries) to their specific experience in their existing technologies is required in order to perceive the intra-firm context of strategic planning. On that note, Karshenas and Stoneman (1995) point that "as the diffusion process develops, the experience of firms with new technologies leads them to update initial estimates of both risk and returns and the level of use of the new technology." Thus, the level of intra-firm learning of an electricity firm is likely to enhance the development of the existing technology. For example, learning to design complete photovoltaic systems is at the core of the development of new PV systems. However, because of competition, knowledge accrued in one domain by one firm may not necessarily translate into knowledge transfer to other firms.

Hypothesis 1. The higher the level of intra-firm knowledge creation, the higher is the technological improvement in solar technology.

Firm-specific learning occurs in a firm within a geographical boundary, defined as the state-level in this analysis. Intra-firm learning is the knowledge that takes place in a multi-unit firm that has operations in different states and is attained by collaboration of groups within the firm aggregated across state boundaries. Hypothesis 1 conveys that such collaborations have benefited solar technology. On the other hand, inter-firm knowledge is primarily achieved when aggregated knowledge across different states is transferred between different firms on a technology, thus contributing to knowledge diffusion. This type of learning, particularly for the renewable technologies, wind and solar, is enhanced by financial incentives such as elimination of sales taxes, investment and production tax credits as explored in Hypothesis 2. This is further explained in the following section.

2.4. Financial incentives: effects on technologies and knowledge spillover

Financial incentives frequently accompany regulatory policies for far reaching clean energy designs. The hurdles hampering efficient operations of renewable energy technologies can often be tackled with financial incentives. These boost access to capital and decrease the load of high initial operation costs. As a result, the creation of new electricity markets and the innovation in more energy-efficient technologies are spurred. Some of the important financial incentives include tax, rebates, grants, performance-based incentives, loan programs, guarantees, and credit enhancements (Cox, 2016). These incentives are part of a regulatory program that ultimately promotes the development of clean technologies. Interestingly, resorting to comparative statics, Shittu et al. (2015) find that investments in clean technologies are shaped by environmental policy choices.

There are several variables that influence the adoption of new technologies by firms operating in the electricity market. These variables mostly represent networks that stimulate learning processes through knowledge synergies. Knowledge synergies refer to scenarios in which the total effects of the interactions between learning processes contribute more to the adoption of the new technology than the individual effects, i.e., the whole is greater than the sum of the parts. This is evident in value creation when firms combine independent knowledge (Lu and Feng, 2010). To achieve this, electricity firms are increasingly recognizing the value of inter-firm collaborative networks (Baker et al., 2013). In particular, inter-firm knowledge spillovers have contributed to the adoption of and innovation in clean technologies. For example, inter-firm knowledge acquisition continues to spur the performance ratio of PV technologies. Validating this point, after surveying several analysis, Baker et al. (2013) observe that investments in solar technologies depend on the degree of learning spillovers across firms investing in solar energy.

In order to introduce renewable energy technologies into the energy system, comparable firms in the electricity market have developed successful collaborative approaches through knowledge-sharing (McDowell, 2015). Within these approaches, productivity is measured by the speed with which the firm can learn, and echoed by technological differences across firms. Insofar as firms deploy efforts to share knowledge, they create platform opportunities that open ways for the different branches within them to share observations and experiences. The resulting platform enables firms to boost their store of knowledge by incorporating knowledge not previously available to them. In turn, they are able to formulate new knowledge via interaction with other organizations. Interestingly, David and Bunn (1988) remark that "the opportunities for entry by firms sponsoring new technical sub-systems, which may be either complementary to or substitutes for those already in the field, should be regarded as fostering the options for innovative action." An illustration is the cost-reducing benefits of wind capacity installations boosted by inter-firm learning transfer. For example, due to new knowledge acquisition in the wind sector, technological innovation has considerably helped drive down unit cost and even effectuated economies of scale in the wind industry (Partridge, 2018). Pointing to successful collaborative approaches across wind firms, Menza and Vachon (2006) observe that the cost of generating wind power and delivering wind energy has steadily decreased over the past decades. For example, Partridge (2018) reports that in the U.S, investment costs per kW for wind energy has fallen to about 27% below the 2009–2010 peak. As a result, investments in wind technologies have increased to the point that from 1990 to 2003, installed wind capacity in the U.S. increased from 1525 MW to 6374 MW (Menza and Vachon, 2006). Thus, inter-firm learning equips firms in clean technologies with the leverage necessary for technological improvement to occur.

Hypothesis 2. The higher the financial incentives for clean technologies, the higher is technological improvement in wind and solar technologies under inter-firm learning.

2.5. Tax credits and learning in wind

Intra-firm learning is achieved by shifting existing knowledge through interaction with different teams within the firm. One of the main metrics of firm learning is learning settings such as seen in groups or teams. Identifying learning settings for knowledge sharing is important for measuring the effect of learning. Within the electricity industry, amendments of environmental regulation often demand that electricity firms adapt their learning mechanisms. Case in point, Nyiwul et al. (2015) find that regulatory scheme tends to improve environmental performance through more stringent optimal standards. This may be due to the fact that regulatory schemes sometimes require firms to produce and share new knowledge. For instance, production tax credits have kept wind energy appealing for investors willing to finance new wind farms (Loomis et al., 2010). This is all the more notable as demand for clean energy sources continues to grow. Referring to the benefits of production tax credits on investments in wind technology, Loomis et al. (2010) also note that the wind industry had grown tremendously since the late 2000s with a plateau of about 10,000 MW of new generating capacity online in 2009. However, the wind industry will not be in this plateau indefinitely because the opportunity to increase the actual potential of wind technology still exists. For example, efforts on advanced storage technologies to ameliorate the intermittency of wind power offers significant expansion opportunity (Jiang et al., 2016; Baker et al., 2018). Thus, to successfully mitigate the unpredictability of wind power, firms are developing more efficient wind turbines integrated with battery storage technologies and these developments are fueled by subsidies and tax credits. These would subsequently contribute to increasing the potential of wind technology. Hence, developing new intra-firm learning mechanisms in wind firms can further the impact of renewable energy.

It is well established that one of the econometric implications of a firm's learning is that unit costs decrease with cumulative production Zangwill and Kantor (1998). A key observation is that technological innovation is both incremental and cumulative and even more so in the electricity industry. The tremendous effect of environmental requirements within the electricity industry is perceived in the development of wind technology. Notably, using an "envelope-based modeling method" applied to data from the California Independent System Operator (CAISO), Jiang et al. (2016) not only quantify the capacity contribution of wind sources but also demonstrate its enhancement of storage. Another endeavor of this paper is to show that production tax credits have successfully fostered intra-firm learning within wind industries with positive results in storage capacities, for instance. As noted by Sharlin (1963), this type of learning has increased the capacity of reliable electricity.

Hypothesis 3. More financial tax credits generate more investment-induced learning within firms for the wind technology.

2.5.1. Regulation and learning

The 1963 Clean Air Acts not only initiated an array of environmental regulations, it also gradually spurred technological innovation. Gauging the impact of the Clean Air Acts on electricity firms' capital and productivity would enlighten policymakers on the relevance of future viable amendments. Elaborating on possible actions by decision makers, Shittu (2014) finds that learning uncertainty allows decision makers to chart a more prudent intermediate path for energy technological growth. Discussing the effects of renewable portfolio standards (RPS) mandates, Weigelt and Shittu (2016) also examine the ramifications of the party-leaning of state legislatures and governorships. Ideally, regulatory mandates should be guided by technological progress in the energy sector as originally intended by the Clean Air Acts (Greenstone, 2002). Progress in electricity generation technologies is a key factor behind productivity and growth in the electricity industry. Intensified competition from merchant electricity generators has stimulated progress in clean technologies through the development of numerous technologies within the electricity industry. For instance, cost competitive wind and solar panels as well as cheap natural gas have significantly lowered the cost of electricity generation. But the question of whether or not technological progress will continue to thrive as policy makers weaken some regulatory mandates is still lingering.

This study contemplates that, in the process of complying with policy instruments, the progress of the electricity sector in terms of knowledge acquisition in the coal, gas, solar, and wind technologies will be heterogeneous. This analysis further implies that the progress induced by technological change within and across electricity firms does not automatically translate into identically declining and increasing economies of scale. After surveying firms in the Turkish electricity industry, Akkemik (2009) finds that scale economies exist throughout the period of analysis to explain declining long-run average costs. Yet, the paper indicates that this effect was reduced largely after 2002 making technological progress to deteriorate from 1984 to 1993 to 1994–2001. Since the electricity industry is always set on adopting new efficient technology and business models, the possibility to simultaneously ascertain profits maximization while meeting regulatory mandates is still attainable.

Regulatory uncertainty added to uncertainty in technological cost makes decisions in technological learning not only necessary but complex. It is quite evident that electricity firms revise their investment decisions as they seek to adapt to regulatory mandates. Renewable portfolio standards, for example, have spurred electricity firms to invest in solar and wind technologies (Morris et al., 2016; Ogunrinde et al., 2018). Given that short term investments in technological learning could decrease future environmental costs, federal and state policies instruments are intended to promote such investments. But, investment in a current technology can potentially increase the future cost of that technology because of the efficiency improvements. Thus, the interaction between policy instruments and investments within and across electricity firms can be conflicting if not designed appropriately. Case in point, looking at more than 1592 electricity firms in the U.S., Weigelt and Shittu (2016) discover that regulatory mandates dampen the effect of competitors' new resource investments on a focal firm's new resource investments. It is likely that this could be due to uncertain economic parameters that policy making cannot exactly capture. But, using an optimal control model, Shittu and Baker (2009) observe that the influence of risk created by regulation on investment decisions under uncertainty depends on model formulation. On the other hand, using a two-stage stochastic programming with recourse (Kamdem and Shittu, 2017; DeLuque and Shittu, 2019), find that carbon abatement policy can successfully be used to mitigate uncertainties in solar and gas technologies. These studies reinforce the importance for firms to harness technological learning through learning by doing, for example, to alleviate the haphazardness created by policy instruments.

Hypothesis 4. The more stringent policy mandates are, the more diverse is the effect of progress on technological change across technologies.

2.6. Relationships among hypotheses

The hypotheses are related by two main premises: (i) financial and tax impacts, and (ii) policy influences. Hypotheses 1 and 2 (H1 and H2) highlight the effect of the strength or relevance of knowledge within and between firms on solar technological improvement. While H1 demonstrates that improvements in solar technology and its adoption are driven by knowledge acquisition within firms, H2 demonstrates that it is financial incentives that strengthen such improvements between firms. Thus, H1 and H2 highlight the different drivers of technological improvement in solar be it within (H1) or between firms (H2). H2 and H3 clearly demonstrate that financial incentives and credits have been largely responsible for knowledge acquisition for wind technology. The difference, however, between H2 and H3 is that financial incentives have been influential to learning in wind technology between firms (H2) while tax credits have supported wind learning within firms (H3). H4 offers an umbrella relationship that focuses on the impact of policy. Specifically, H4 relays the message that policy stringency offers a broad spectrum of firm responses to technological learning and technological change. The range of technical learning in this context is independent of the firm's specific context, i.e., whether or not the learning is intra or inter-firm. However, the heterogeneity of policies will affect firms differently. For instance, policies that are broader and market based may reinforce inter-firm learning at a deeper level than policies that are tapered to individual firms (intra-firm). For example, the RPS policies that are in some states are tailored to investor-owned utilities (IOUs) or those policies specifically apply to the IOUs while the retail choice market mandate applies to all firms in a state. These four hypotheses combine to highlight the heterogeneous nature of learning in the energy industry in the U.S. and projects the asymmetry to learning by technology types.

3. Methods

The three junctures that make up the electricity sector are generation, transmission and distribution. Electricity generation involves the conversion of a fuel supply like coal, gas, or renewable resource like wind or solar into electricity. Transmission involves the power lines that allows the generated electricity to be transferred over long distances at high voltages (to minimize loses) from points of generation to regions of consumption. Distribution entails delivering the transmitted electricity at voltage levels suitable for consumption. This study focuses on the generation and the percentage of renewable resources in a firm's energy generation mix.

The context of this study is based on data from the electricity industry in the U.S. spanning from 1998 through 2010. The enactment of the Public Utilities Regulatory Policies Act or PURPA of 1978 allowed independent power production to sell electricity to utilities (Russo, 2001; Joskow, 1998). These included major electric utilities operated as natural monopolies regulated on a state-by-state basis by public utility commissions. Originally, electricity producers produced, transmitted, and distributed electricity. However, over the last 30 years the electricity generation part of the U.S. energy industry has seen deregulation starting with PURPA in 1978. Then, the Energy Policy Act of 1992 followed, allowing independent power producer ownership by both utilities and non-utilities. Currently, there are over 3000 electricity utilities in the U.S. electricity industry. These utilities encompass independent power producers (IPPs), investor-owned utilities (IOUs), cooperatives, municipal and government utilities. The IPPs originated after the enactment of PURPA. As pointed out by Russo (2001), the PURPA Act effectively created an entrepreneurial opportunity in the private sector to build power plants for the generation of energy sold to utilities. In 2009, the electricity industry supplied 4 million GWh of electricity, of which 70.2% was from fossils such as coal, gas, and oil. Nonetheless, renewable energy sources, other than conventional hydroelectric capacity, accounted for the largest capacity additions in recent years.

During the period of our study, the generation of energy from renewable resources such as solar, biomass and geothermal technologies is more costly in comparison to conventional coal and gas technologies. To spur investments in renewable technologies, a total of 29 U.S. states had enacted energy policies by 2011. These policy instruments can be grouped into two categories, namely financial incentives and policy mandates. Financial incentives are made up of tax incentives, production credits, and rebates. Policy mandates encompass RPS. In this study, the analysis focuses on financial incentives (renewable electricity production tax credits and qualified energy conservation bonds) and mandates (RPS and federal appliance standards). Policy instruments like RPS mandates are less uncertain and more durable while others such as energy bonds are temporary or easily phased out (Hunton and Williams, 2010).

3.1. Data description

This study consists of a longitudinal analysis of data collected from the Platts (2015)'s database. The article centers on data for 5573 electricity plants operating from 1998 through 2010. The dataset comprises regulated utilities and private power companies across 50 U.S. states. The firms in the dataset operate 26 different technologies that include internal combustion engines, steam plants, fossil-fired technologies, photovoltaic systems, wind turbines, and fuel cells. The data include thousands of records on electricity output by firm, technology, and state. The analysis captures the electricity output for each firm in each state and, subsequently, estimates all coefficients within the different regression models.

The data on electricity costs come from four sources. For conventional fossil-based technologies, the technology cost data are extracted from the values used in the calculation of the levelized cost of electricity by the U.S. Energy Information Administration (EIA). Electricity price data by technology type was extracted from the files in the State Energy Data System (SEDS) for coal and gas technologies. The database is detailed to the state level and spans all the years covered in the analysis. Renewable electricity technology cost data were collected from the Environmental Protection Agency (EPA) database on clean energy. The data for wind and solar in the database are based on expert-recommended reports that contain cost information on renewables and collated by the renewable energy team in the Climate Protection Partnerships Division of the EPA. Data on wind in the database come from sources that include the annual report on U.S. wind power installation, cost, and performance trends (Bolinger and Wiser, 2009; Wiser, 2007), a Black and Veatch study on wind energy penetration on costs in the U.S. (Bolinger et al., 2008; Hand, 2008). Solar technology cost data was sourced from a study done by the Lawrence Berkeley National Laboratory (LBNL), "Tracking the Sun: The Installed Cost of Photovoltaics in the U.S. from 1998 to 2007 (2009)" (Wiser et al., 2009); a study titled, "PV Technology, Performance, and Cost, 2007 Update" conducted by the Prometheus Institute and Greentech and reported to the EPA on the $/W cost of solar technology (Maycock and

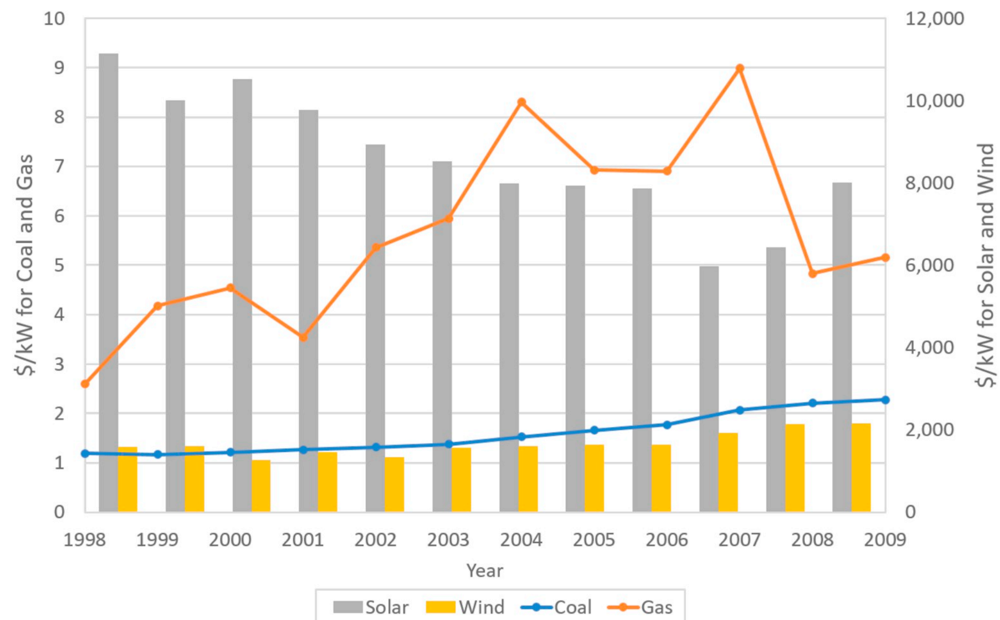

Fig. 1. Historical technology cost.

Bradford, 2007); and the National Renewable Energy Laboratory (NREL) System Advisor Model (Blair et al., 2014). The tracking of the sun data reflects approximately 76% of all grid-connected PV capacity installed in the U.S. from 1998 through 2007 with projections made for the other years. Fig. 1 shows a snapshot of the cost data for the four technologies. Data on financial incentives such as investment credits and production credits are collected from the Database of State Incentives for Renewable Energy (DSIRE). The presentation of all cost data used in the analysis are shown in Table A2 for the sources of the data, Tables A3 and A4 for some descriptive analysis.

3.2. Dependent variables

Technology costs over time are taken as U.S dollars per megawatt-hour. The dependent variable is determined using the logarithm of technology cost over unit electricity produced as applicable for the coal, gas, solar, and wind technology. The article adopts the conventional form of the learning curve described in (Darr et al., 1995). This framework captures cost reduction in electricity production across different technologies and firms. $\zeta(y)$ is the total cost per unit to produce the *y-th* MWh of electricity. It is determined by

$$\zeta(y) = \delta y^{-\beta} \tag{3.1}$$

δ is the total cost of producing the first MWh of electricity. y is the cumulative number of electricity units produced. β is a measure of the rate at which costs are reduced as cumulative output increases. β also stands for the learning elasticity. To effectuate the estimation, equation (3.1) is linearized by taking its logarithmic transform such that

$$\log\zeta(y) = \log\delta - \beta\log y \tag{3.2}$$

In order to assess the testing hypothesis, 6 additional dependent variables are formulated. Table 1 gives a summary of the variables and parameters in the model.

3.3. Independent variables

Data on cumulative electricity output make up the independent variables. The cumulative electricity output is substituted for knowledge acquired through production. Thus, learning, be it firm-specific or intra-firm or inter-firm and by technology portray the independent variables. The latter are lagged by one time period with respect to the response variable.

Table 1
Nomenclature.

$\mathbf{y}$ – cumulative number of units produced
$\boldsymbol{\beta}$ – measure the rate at which costs are reduced
$\boldsymbol{\delta}$ – cost of producing the first MWh of electricity
$\mathbf{k}$ – technology
$\mathbf{i}$ – firm
$\mathbf{s}$ – state
$\mathbf{t}$ – year
$\mathbf{n_{i,t}}$ – number of states
$\mathbf{q_{k,i,s,t}}$ – electricity output
$\boldsymbol{\zeta_{k,i,s,t}}$ – production, installation, & operating costs
$\mathbf{R_{s,t}}$ – percentage of RPS mandates
$\boldsymbol{\Gamma_{s,t}}$ – Republican state controlled legislature
$\mathbf{D_{s,t}}$ – Democratic governorship
$\mathbf{P_{s,t,k}}$ – renewable electricity production tax credits
$\boldsymbol{\Delta_{s,t,k}}$ – qualified energy conservation bonds
$\boldsymbol{\Delta_{s,t,k}}$ – federal appliance standards
$\mathbf{K}$ – number of energy technologies *k* in the dataset
$\mathbf{N}$ – number of firms *i* in the study
$\mathbf{Q_{k,i,s,T}}$ – firm-specific knowledge
$\mathbf{FQ_{k,i,T}}$ – proxy for firm-specific knowledge in all states
$\mathbf{FTQ_{k,T}}$ – proxy for inter-firm learning in a specific technology
$\mathbf{CTQ_{T}}$ – progress of electricity sector in terms of knowledge gained
$\boldsymbol{\theta_{k,i,s,t}}$ – dummy variable for regression residual
$\boldsymbol{\xi_{k,i,s,t}}$ – error of the regression estimate

Specifically, $q_{k,i,s,t}$ represents the electricity output by technology k for a given firm i by state of operation s in year t. Thus, aggregating this output within state-delineated geographical boundaries produces $Q_{k,i,s,T}$ which stands for the *firm-specific* knowledge in a given technology in a given state over time. Thus, in practical terms, firm-specific learning is knowledge accumulated over a given period by each firm in each technology in each specific state that the firm operates in. In other words, this is learning that is inherent to the different subsidiaries of the same firm in a given state. It is evaluated using

$$Q_{k,i,s,T} = \sum_{t=0}^{T} q_{k,i,s,t} \tag{3.3}$$

This firm-specific metric, $Q_{k,i,s,T}$, is the learning elasticity for a firm within a state-level geographic boundary, and when it is aggregated to achieve the cumulative output across all states where that firm has a production plant, the result is the *intra-firm* learning elasticity. Thus, in contrast to firm-specific learning, intra-firm learning is the firm's cumulative knowledge over a period for each technology in across all state-level geographic boundaries in which the firm operates. This firm-specific learning variable is important because it serves as a yardstick for comparison between intra-firm learning and inter-firm learning. Thus, the intra-firm learning is evaluated using

$$FQ_{k,i,T} = \sum_{s=0}^{n_{i,t}} \sum_{t=0}^{T} q_{k,i,s,t} \tag{3.4}$$

Notice the absence of the state index in equation (3.4) that captures intra-firm learning, the cumulative electricity output through year T for all states s in which firm i operates by technology k. For inter-firm knowledge estimation, the cumulative output across all firms is aggregated using $q_{k,i,s,t}$. Thus, $FTQ_{k,T}$ serves as a proxy for inter-firm learning in a specific technology, and it is evaluated using

$$FTQ_{k,T} = \sum_{i=1}^{N} \sum_{s=0}^{n_{i,t}} \sum_{t=0}^{T} q_{k,i,s,t} \tag{3.5}$$

$FTQ_{k,T}$ represents the knowledge that firms, independent of geographic differences, have gained over the years in a specific technology. It also captures the elasticity of knowledge spillover. Also, notice the absence of the state and firm indices in equation (3.5) that captures inter-firm learning. Finally, CTQ_T is a cumulative variable that determines how the electricity sector has progressed in terms of knowledge gained. This determination is done without specific emphasis on the electricity sector in which technology portfolios interface. CTQ_T is evaluated using

$$CTQ_T = \sum_{i=1}^{N} \sum_{s=0}^{n_{i,t}} \sum_{k=0}^{K} \sum_{t=1}^{T} q_{k,i,s,t} \tag{3.6}$$

3.4. Control variables

The control variables are factored by the year and the state. They encompass data on policy instruments, namely policy mandates and financial incentives.

Renewable Portfolio Standards (RPS). A renewable portfolio standard, also known as renewable electricity standard, is one of the largest state-level policies for the promotion of renewable energy. According to NREL (2017), the RPS is “a regulatory mandate to increase production of energy from renewable sources such as wind, solar, biomass and other alternatives to fossil and nuclear electric generation.” Basically, states devise RPS mandates to promote the use of a specific technology through “carve out” provisions. The latter require that a limited percentage of produced electricity originates from non-fossil or nuclear technologies. Several states have already carried through this mandate. However, there are several factors that affect their implementation. For example, each state uses its own criteria to stipulate the technologies found eligible to count towards RPS requirements. Another instance is that state policies diverge when it comes to the sources deemed eligible to satisfy RPS requirements. Some states implement RPS requisites to all its utilities while other states to only its investor-owned utilities (IOUs). Besides, ensuring compliance can be a daunting procedure. In some states, enforcement for RPS policies materializes in terms of financial penalties like alternative compliance payments. In other states, it comes in terms of procurement of renewable energy credits for the utilities by a state central agency. All well considered, there are many aspects of RPS mandates that have contributed to the adoption of renewable energy technology within electricity firms. We measure RPS as the target set by percentage.

Legislature. PURPA and the Energy Policy Act of 1992 represent the main federal energy legislations in the United States. In the past decades, they have opened the wholesale electricity market to competition from independent power producers (IPPs). But, by and large, electricity generation is mostly regulated at the state level. Electricity firms' investments decisions are usually sensitive to prospective instability in regulatory mandates. Most firms would align their investment strategies under a platform that swiftly acclimatizes them to regulatory change. In some cases, firms' decisions strategies will cause regulatory policies to be less effective. Since new investments are the cornerstone of technology progress in electricity markets, this article argues that changes in policy mandates in states could dampen firms’ reactions to those policies. State governments have a substantial amount of authority over electricity restructuring in their jurisdictions. In particular, state regulatory authorities over electricity markets have been quite conspicuous in state constitutional provisions and anti-trust laws.

The challenge for state legislatures has been and still is their capacity to reflect the political preferences of their constituents. Referring to challenges facing policy makers in state legislatures, Brennan (2003) remarks that “The goal is not to impose a right policy (e.g. promoting efficiency) through a rhetorical back door, but to set up rules that would best reflect constituent views.” In a broader context, the views of the constituents create the agency problem. Brennan (2003) posits that when interests are aggregated across larger groups of families, regional communities or ethnic groups, it is often the case that ethical claims may override individual interests. For example, ethical claims held by those other than individuals – animal rights or ecosystems – apart from the values persons place upon them. While these may not appear to play a significant role in electricity restructuring decisions, they have been found to be included in policy debates. Thus, the influence of special interests also plays a strong role at the local level. For example, Brennan (2003) highlights how very few of the constituents are likely to participate in state Public Utility Commission (PUC) hearings on whether a utility's proposed rate change is reasonable or justifiable. Ultimately, the question of how much state legislators affect environmental regulations remains and should stay relevant. We measure legislature as a dichotomous 0–1 variable with 1 representing Republican and 0, otherwise.

Renewable Electricity Production Tax Credit. The Renewable Electricity Production Tax Credit is often referred to as PTC and was originally enacted in 1992. According to IRS (2017), the Federal Renewable Electricity Production Tax Credit “is an inflation-adjusted per-kilowatt-hour (kWh) tax credit for electricity generated by qualified energy resources and sold by the taxpayer to an unrelated person during the taxable year.” Practically, PTCs are federal performance-based incentives. As indicated by Cox (2016), they are “credits for onsite use of renewable energy for large-scale renewable energy that is fed into the grid.” Cox (2016) further observes that “In relation to renewable energy, corporate investment tax credits are based on initial cost of renewable energy systems, while production tax credits are based on actual energy produced. Therefore, production tax credits can be more effective in incentivizing maximization of energy production over the long term.” The primary goal of PTCs is to advance the development of renewable energy technologies. Electricity firms building wind farms have greatly benefited from PTCs. The PTCs have kept wind energy attractive as incentives for firms to build wind farms thus contributing to the development of the wind turbine technology. This explains why, under the platform of financial incentives, this study defends that intra-firm learning is reinforced. We measure the production tax credit variable in actual dollar amounts.

Qualified Energy Conservation Bonds. Better known as QECB, a Qualified Energy Conservation Bond is not a grant but a taxable bond. OEERE (2017) defines QECB as “a bond that enables qualified state, tribal, and local government issuers to borrow money at attractive rates to fund energy conservation projects.” The main objective of QECBs is to decrease energy consumption in public buildings. Since they are taxable bonds, electricity investors have to pay federal taxes on interests received from QECBs. There are two options that make QECBs particularly attractive. The first is that investors can structure their

QECBs as bonds on which they can receive federal tax credits instead of interest payments tax credit bonds. The second option is that "investors can directly receive cash rebates from the U.S. Department of the Treasury to subsidize their net interest payments." For electricity firms, QECBs are enticing in that profits derived from these bonds can be used to capitalize expenditures on firms' innovation projects. OEERE (2017) points that QECBs are great incentives for "implementing green community programs including loans, grants, or other repayment mechanisms such as efficient street lighting replacements and loan programs for residential energy efficiency improvements." In deciding on picking firms that are eligible for QECBs, special consideration is bestowed on firms with projects that demonstrate feasibility and readiness and expand economic opportunities (Hunton and Williams, 2010). Hence, notwithstanding that QECBs are employed to promote renewable energy-related research, they contribute to the transfer and acquisition of knowledge only within the firms. We measure the bond variable in the actual dollar amounts.

Federal Appliance Standards. The Federal Appliance Standards (FAS) set minimum standards of energy efficiency for several appliances. Most of these data account for 90 percent of residential energy use, 60 percent of commercial, and 29 percent of industrial usage (NRDC, 2014). The products covered by FAS range from refrigerators, central AC and HP, gas furnaces, to dishwashers and washing machines. Commercial and industrial equipment like electric motors and distribution transformers are also covered. FAS was established by the U.S. Congress in the Federal Energy Policy and Conservation Act (EPCA) of 1975, and have been subsequently amended by succeeding energy legislation, including the Energy Policy Act of 2005 and the Energy Independence and Security Act of 2007 (DOE, 2017). FAS foster the development of efficiency standards that will culminate into the best energy savings. Since customers are often motivated by costs, by choosing energy savings products, they can achieve costs saving and efficiency at the same time. But, in some cases, appliances with energy-efficient capability are not as cheap. However, if the electricity price is lower, the customer can still be motivated to opt for an energy efficient appliance. This analysis predicts that FAS by themselves may not have a strong an effect as expected. Yet, the analysis still holds that some other financial incentives would only favor learning within the electricity firm. Ideally, it would be more effective to let electricity firms themselves find ways to boost the development of energy efficient technologies while their supply portfolios are reliable and efficient (Deluque et al., 2018). This would catalyze innovation into cheaper energy options. We measure the FAS variable as a count.

3.5. Model

According to Darr et al. (1995), the cumulative output produced is a proxy variable for knowledge acquired through production. Hence, decreasing unit cost can be viewed as a function of organizational knowledge. In this context, the electricity firm's acquired learning is due to technological change. This concept is used to capture the electricity firms' rate of technological learning in specific technologies. The same framework allows us to determine whether the evolution of learning in a given technology is spatial-dependent. The spatial-dependency may explain the uncertainties created by policy instruments given their influence on adoption decisions. Finally, using the formulated framework, the influence of learning on technology adoption decisions is examined.

The electricity industry's specific knowledge in a given technology is captured by aggregating firms' outputs in MW in that technology through time. The impact of state-level policy prescriptions such as RPS on the learning elasticity for a given technology is explored. According to Ishii (2006), electricity firms share the properties of franchises. This share-out is explained by the fact that electricity firms operate across their regulated domains. They behave in the same manner in other states where they own independent power plants. Thus, the learning elasticity for a specific firm, the subsidiary, may be accounted for by aggregating the cumulative output across all states where that firm has a production plant. This approach produces the intra-firm learning elasticity. For inter-firm knowledge estimation, the cumulative output across all firms is aggregated. $Q_{k,i,s,t}$ represents the firm-specific knowledge in a given technology in a given state. It is evaluated using least squares regression along with equations (3.1), (3.2) and (3.3), (3.4), (3.5), and (3.6), seven models probe whether learning has occurred and its associated effects are evaluated. The matrix equation of the multivariate regression analysis is given by

$$\log\left(\frac{\zeta_{k,i,s,t}}{q_{k,i,s,t}}\right) = \beta_0 + \sum_{m=1}^{M} \beta_m \log\overrightarrow{Q} \tag{3.7}$$

The left hand side of (3.7) is the dependent variable. It represents the cost per unit of electricity output by technology, state, and firm. The right hand side is the summation of the appropriate variables in (3.3)–(3.6). Accordingly, the basic model with appropriate lagging is given by

$$\log\left(\frac{\zeta_{k,i,s,t+1}}{q_{k,i,s,t+1}}\right) = \beta_0 + \beta_1\log(Q_{k,i,s,t}) + \beta_2\log(FQ_{k,i,t}) + \beta_3\log(FTQ_{k,t}) + \beta_4\log(CTQ_t) + \beta_M\theta_{k,i,s,t} + \xi_{k,i,s,t} \tag{3.8}$$

4. Results

Table A1 displays the means, standard deviations, and correlations for the coal, gas, solar, and wind technologies, respectively. For the solar technology, there is a positive correlation between energy bonds with the proxy for inter-firm learning ($r = 0.03$). Production tax credits positively correlate with the proxy for inter-firm learning ($r = 0.07$) for the wind technology. However, energy bonds negatively correlate with the proxy for technology progress for the coal technology ($r = -0.03$). At the same time, RPS mandates positively correlate with the proxy for technology progress for the solar technology ($r = 0.08$) but negatively with that for the wind technology ($r = -0.06$). Another remark is that production tax credits positively correlate with the proxy for firm-specific knowledge ($r = 0.64$) for the wind technology. While assessing these results on correlations, the analysis does not by any means deduces causality from correlation. Given the large values of the means and standard deviations, a residual analysis is carried out. It is discussed later in the study.

The objective QECBs (Qualified Energy Conservation Bonds) is the reason for the positive correlation between energy bonds and inter-firm learning for solar technologies. These bonds allow local government or other bond issuers to borrow money at very competitive rates to fund energy conservation projects. Since solar technologies are very viable to such projects, collaboration among project participants across different firms is enhanced. The same analysis can be made to explain the positive correlation between the firm specific learning and production tax credits for the wind technology.

However, the ecological effects of electricity generation from coal has dampened the demand for coal technology. Given that the coal industry does not benefit from energy conservation bonds, It highlights the negative correlation between energy bonds and technology progress for the coal technology. The correlations between RPS mandates and technology progress for the solar and wind technologies are respectively positive and negative. A possible justification has to do with widespread benefits that electricity generators using solar technology have received from RPS mandates compared to those received by electricity generators using wind technology. The widespread prevalence of solar renewable energy certificates (SRECS) further supports the result.

Table 2
Econometric analysis results – solar technology.

SOLAR	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1)	−0.1394	−0.1288	−0.1291	−0.1303	−0.0995	−0.1045	−0.1045
(p-Values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intra-Firm Learning (β_2)	−0.0394	−0.0294	−0.0295	−0.0301	−0.0317	−0.0316	−0.0315
(p-Values)	(0.0123)	(0.0615)	(0.0605)	(0.0555)	(0.0436)	(0.0435)	(0.0445)
Inter-Firm Learning (β_3)	1.9000	1.9206	1.9195	1.8632	1.8651	1.8720	1.8734
(p-Values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Technology Progress (β_4)	−1.2515	−1.2852	−1.2856	−1.2633	−1.2724	−1.2763	−1.2778
(p-Values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
RPS Target Percentage (β_5)		1.3785	1.3157	1.3512	1.2521	−0.0140	0.0190
(p-Values)		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9742)	(0.9655)
Republican State Legislature (β_6)			−0.0499	−0.0804	−0.1234	−0.3122	−0.3146
(p-Values)			(0.7249)	(0.5741)	(0.3892)	(0.0384)	(0.037)
Democratic Governor (β_7)				−0.1454	−0.1619	−0.1659	−0.1663
(p-Values)				(0.1075)	(0.0732)	(0.0656)	(0.0652)
Production Tax Credit (β_8)					−0.0002	−0.0002	−0.0002
(p-Values)					(0.0006)	(0.0006)	(0.0005)
Qualified Energy Bonds (β_9)						0.0000	0.0000
(p-Values)						(0.0001)	(0.0001)
Federal Appliance Standards (β_{10})							0.0054
(p-Values)							(0.6777)
R-Square (R^2)	0.0371	0.0483	0.0483	0.0491	0.0527	0.0575	0.0575

4.1. Cost effect

The cost effect provides two outcomes. First, as the existing technology improves because of the acquisition of new knowledge, the technology cost reduces supporting Hypothesis 1. An example is the development of off-grid solar panels. Fu et al. (2017) show the effects created by the enhancement of the photovoltaic technology that includes declining equipment costs as well as operating and maintenance costs. Second, given the impact of policies on the development and adoption of renewable technologies, the cost reductions have been significant. For instance, producers of electricity from wind have benefited from production tax credits and they have also been exempted from paying sales taxes. These combine to decrease operational costs (Morris et al., 2016).

4.2. Hypothesis test

In Tables 2–5, the first three coefficients assess firm-specific learning, intra-firm learning and inter-firm learning, respectively. The fourth coefficient evaluates the degree of innovation in the electricity sector. In this case, innovation is progress measured in terms of knowledge gained without specific emphasis on technology portfolios. The last three coefficients on these Tables estimate the impact of policy mandates and financial incentives.

All coefficients are estimated in seven main models. The first model is basic and represented by Equation (3.8). The second model accounts for RPS mandates. The third and fourth model inspect the impacts of states legislatures and governorships, respectively. The fifth model examines the effects of renewable electricity production tax credits. The

Table 3
Econometric analysis results – wind technology.

WIND	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1)	−0.2333	−0.2306	−0.2381	−0.2378	−0.2125	−0.2327	−0.2327
(p-Values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Intra-Firm Learning (β_2)	0.0054	0.0053	0.0034	0.0037	0.0030	0.0043	0.0043
(p-Values)	(0.5558)	(0.5639)	(0.7382)	(0.7136)	(0.764)	(0.6672)	(0.6673)
Inter-Firm Learning (β_3)	−1.2220	−1.2127	−1.3288	−1.3098	−1.2645	−1.2094	−1.2094
(p-Values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Technology Progress (β_4)	0.7520	0.7445	0.8378	0.8250	0.7968	0.7429	0.7429
(p-Values)	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0003)	(0.0003)
RPS Target Percentage (β_5)		0.2160	0.3392	0.3390	0.4137	−1.5804	−1.5791
(p-Values)		(0.2025)	(0.1259)	(0.1261)	(0.0622)	(0.0000)	(0.0000)
Republican State Legislature (β_6)			0.0792	0.0979	0.1215	−0.0900	−0.0899
(p-Values)			(0.3945)	(0.2984)	(0.197)	(0.3443)	(0.3472)
Democratic Governor (β_7)				0.0863	0.0949	−0.0210	−0.0209
(p-Values)				(0.2137)	(0.1712)	(0.7627)	(0.7655)
Production Tax Credit (β_8)					−0.0000	−0.0001	−0.0001
(p-Values)					(0.0000)	(0.0083)	(0.0083)
Qualified Energy Bonds (β_9)						0.0000	0.0000
(p-Values)						(0.0000)	(0.0000)
Federal Appliance Standards (β_{10})							0.0001
(p-Values)							(0.9886)
R-Square (R^2)	0.0854	0.0856	0.0932	0.0933	0.0958	0.106	0.106

Table 4
Econometric analysis results – coal technology.

COAL							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1)	−0.0838	−0.0825	−0.0700	−0.0703	−0.0583	−0.0555	−0.0573
(p-Values)	(0.0004)	(0.0006)	(0.0006)	(0.0006)	(0.0053)	(0.0083)	(0.0074)
Intra-Firm Learning (β_2)	0.0786	0.0772	0.0625	0.0628	0.0555	0.0524	0.0544
(p-Values)	(0.0016)	(0.0026)	(0.0037)	(0.0036)	(0.0105)	(0.0163)	(0.0144)
Inter-Firm Learning (β_3)	−0.1177	−0.1172	−0.1042	−0.1035	−0.1058	−0.1066	−0.1079
(p-Values)	(0.3209)	(0.3239)	(0.2948)	(0.299)	(0.2852)	(0.2813)	(0.2765)
Technology Progress (β_4)	0.1578	0.1579	0.1531	0.1522	0.1573	0.1599	0.1603
(p-Values)	(0.0878)	(0.0882)	(0.0483)	(0.0505)	(0.0421)	(0.0387)	(0.0385)
RPS Target Percentage (β_5)		0.0173	−0.3690	−0.3634	−0.3343	−0.1969	−0.2450
(p-Values)		(0.8208)	(0.0000)	(0.0000)	(0.0000)	(0.1427)	(0.1435)
Republican State Legislature (β_6)			−0.4101	−0.4103	−0.4153	−0.4162	−0.4174
(p-Values)			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Democratic Governor (β_7)				−0.0044	−0.0070	0.0101	0.0115
(p-Values)				(0.8429)	(0.7546)	(0.6967)	(0.6613)
Production Tax Credit (β_8)					−0.0000	−0.0000	−0.0000
(p-Values)					(0.0326)	(0.0328)	(0.0355)
Qualified Energy Bonds (β_9)						−0.0000	−0.0000
(p-Values)						(0.2059)	(0.1941)
Federal Appliance Standards (β_{10})							−0.0026
(p-Values)							(0.6294)
R-Square (R^2)	0.461	0.461	0.624	0.624	0.63	0.633	0.633

qualified energy conservation bonds are investigated in the sixth model while the effects of the federal appliance standards are analyzed in the seventh model.

Hypothesis 1 is tested in Table 2 (3rd and 4th row). The results for Hypothesis 2 are shown in Table 3 (3rd and 5th row) and Table 2 (3rd and 5th row). Hypothesis 3 is tested in Table 3 (4th and 10th row). Finally, Hypothesis 4 is tested in the 6th, 7th, and 8th row of Table 2, Table 3, Table 4, and Table 5. The results are discussed in detail below.

Hypothesis 1 predicts that intra-firm knowledge acquisition increases as technology improves in solar technology. β_1 represents the coefficient for firm-specific learning. The results for the solar technology are displayed in Table 2.

Under the foundational model (Model 1), β_1 is noticeably negative (99% confidence interval). This simply shows that improvements to existing technology are brought about by the acquisition of new knowledge, culminating into declining costs. In all models, knowledge acquisition occurs through cumulative installed electricity. β_2 stands for the coefficient for intra-firm learning. The negative sign of β_2 indicates that intra-firm knowledge acquisition defines the reduction in the unit cost of electricity production. Furthermore, as β_1 becomes significantly more negative (model 5 to model 6), β_2 increases (95% confidence interval). The same finding is verified from model 5 to model 7. Thus, Hypothesis 1 is justified all the more as empirical research shows that successful enhancements to current technology are accompanied by declining costs (Morris et al., 2016). The ensuing observation is that electricity firms in the solar technology tend to reinforce learning within themselves. Consequently, collaborations with other firms investing in solar technology dampen. However, Wilman et al. (2003)

Table 5
Econometric analysis results – gas technology.

GAS							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Firm Specific Learning (β_1)	0.0042	0.0045	0.0045	0.0046	0.0041	0.0041	0.0040
(p-Values)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0006)	(0.0006)	(0.0008)
Intra-Firm Learning (β_2)	−0.0007	−0.0008	−0.0007	−0.0007	−0.0007	−0.0007	−0.0008
(p-Values)	(0.4628)	(0.4516)	(0.473)	(0.4713)	(0.4743)	(0.4746)	(0.4417)
Inter-Firm Learning (β_3)	−6.5461	−6.3964	−6.5884	−6.7593	−6.7703	−6.7729	−6.4979
(p-Values)	(0.1743)	(0.1844)	(0.1714)	(0.1606)	(0.1599)	(0.1598)	(0.1774)
Technology Progress (β_4)	5.6617	5.5410	5.6987	5.8376	5.8465	5.8486	5.6274
(p-Values)	(0.1453)	(0.1541)	(0.1426)	(0.1332)	(0.1326)	(0.1325)	(0.1477)
RPS Target Percentage (β_5)		0.0292	0.0580	0.0611	0.0613	0.0621	0.0774
(p-Values)		(0.0987)	(0.0035)	(0.0022)	(0.0021)	(0.0099)	(0.0017)
Republican State Legislature (β_6)			0.0244	0.0266	0.0266	0.0267	0.0303
(p-Values)			(0.0014)	(0.0006)	(0.0006)	(0.0008)	(0.0002)
Democratic Governor (β_7)				0.0106	0.0106	0.0106	0.0107
(p-Values)				(0.0886)	(0.0885)	(0.0895)	(0.0853)
Production Tax Credit (β_8)					0.0000	0.0000	0.0000
(p-Values)					(0.4661)	(0.4657)	(0.5427)
Qualified Energy Bonds (β_9)						−0.0000	0.0000
(p-Values)						(0.9567)	(0.3217)
Federal Appliance Standards (β_{10})							0.0023
(p-Values)							(0.0034)
R-Square (R^2)	0.224	0.224	0.225	0.225	0.225	0.225	0.226

point out that, ideally, cooperation among firms should eventually allow them to successfully mitigate challenges related to technological improvement. Comparably, Colombo et al. (2011) report how "firms can improve their innovative performance by taking advantage of knowledge residing in networks of external stakeholders." By concentrating all their efforts into internal knowledge acquisition, electricity firms or utilities that generate electricity from solar are least likely to collaborate with other firms.

The relevance of financial incentives for clean technologies is assessed by Hypothesis 2. It infers that more financial incentives for clean technologies enhance clean technologies through inter-firm learning captured by β_3. From Table 2 (Solar technology), β_3 increases while β_1 becomes more significantly negative from model 5 (production tax credits) to model 6 (qualified energy bonds). Model 5 (production tax credits) to model 7 (federal appliance standards) elicits the same result. These findings reasonably support the argument that more financial incentives for solar technology are likely to strengthen technological improvement under the framework of inter-firm learning. From Table 3 (Wind technology), β_3 increases from model 5 (production tax credits) to model 6 (qualified energy bonds) and to model 7 (federal appliance standards).

Concomitantly, β_1 gets more significantly negative from model 5 (production tax credits) to model 6 (qualified energy bonds) and to model 7 (federal appliance standards). These results demonstrate that, to a measurable extent, for the wind technology, greater financial incentives are proportional to the level of technological progress when knowledge is shared across firms. Consequently, Hypothesis 2 is corroborated.

Hypothesis 3 supports that production tax credits benefit knowledge acquisition within firms in wind technologies. In Table 3 (Wind technology), β_2, the coefficient for intra-firm learning, gets larger from model 5 to model 6 (statistically not significant). Noteworthy is that β_8 (production tax credits) also increases from model 5 to model 6, warranting Hypothesis 4. Notably, through production tax credits, wind technology is exempted from sales taxes, thus decreasing operational costs.

The stringency of policy mandates is investigated in Hypothesis 4. It posits that stringent policy mandates tend to create a diverse effect in the progress on technological change across technologies. Technological progress (β_4) is maximized with firms' investments in knowledge acquisition. β_6 measures the impact of clean energy policies ratified by Republican state legislatures across all states. From Table 4 (Coal technology), as RPS mandates (β_5) are strengthened, technological progress (β_4) decreases (model 3 to model 4).

But, under the same circumstances, the impact of Republican state legislatures (β_6) is less acute. In Table 2 (Solar technology), as RPS mandates (β_5) get more exacting, technological progress (β_4) increases (model 3 to model 4). However, from Table 2 (Solar technology), as RPS mandates (β_5) get more stringent (model 5 to model 2), technological progress (β_4) decreases. However, β_4 remains in Table 3 (Wind technology) as RPS mandates become pronounced (model 6 to model 7). The resulting diversity subsequently corroborates Hypothesis 4. Similarly, in Table 5 (Gas technology), RPS mandates (β_5) increase from model 4 to model 5 although β_6 is unchanged.

The ensuing effects create ambivalence among firms as to whether their investments in learning acquisition will pay off or not. Therefore, in face of RPS stringency, the response of β_4 is versatile. Our Hypothesis 4 is supported. Kuhhen (2015) and Akkemik (2009) have also uncovered asymmetries associated with progress in technological learning acquisition. However, contexts in which electricity firms seek to adapt to RPS mandates are crucial in achieving technological progress. A forceful consequence is the resulting general state of uncertainty. The latter is generated by the complexity of measuring the real effects of policy mandates on learning dynamics. Among other things, Fabrizio (2013) indicates that histories of policy adoptions and reversals increase uncertainties and hazards in electricity markets. In such an environment, learning investments are likely to be depressed, which ultimately affect the capacities of electricity firms to develop disruptive technologies.

This study also inspects the effects of knowledge transfer within firms (intra-firm learning) and across firms (inter-firm learning) on cost per unit of electricity produced. For the solar technology (Table 2, 4th row), the intra-firm learning coefficient (β_2) is negative while it is positive for the wind technology (Table 3, 4th row). This means that knowledge collaboration within electricity firms has contributed more to the reduction in unit capital and operating costs of electricity production for the solar technology than for the wind technology. This finding suggests that, for the solar technology, knowledge transfer within firms explains the decreases in the unit cost of electricity production. Thus, more intra-firm knowledge acquisition occurs in solar technology than in wind technology. Although revealing, this result is not as unexpected. An example of study is the investigation by McDowell (2015) of the impact of knowledge acquired through installation and generation on the productivity of solar and wind projects. The author finds evidence of "substantial within-project learning" and "within owner learning" for the solar technology.

In contrast, the analysis uncovers a negative coefficient for inter-firm learning (β_3) for the wind technology (Table 3, 5th row). But the same coefficient is positive for the solar technology (Table 2, 5th row). Besides, (β_3) is more significantly negative for the wind technology than for the solar technology. This result shows that the adoption of wind technology due to inter-firm learning leads to more reduction in the unit cost of electricity produced than the adoption of solar technology does. Therefore, knowledge acquisition via inter-firm learning accounts more for cost-effective electricity production for the wind technology than for the solar technology. It is notable to point out that Nemet (2011) has also found existence of inter-firm knowledge spillovers for the wind technology.

4.2.1. Implications of high p-values

For the gas technology, β_2 and β_3 the coefficients for intra-firm and inter-firm learning, respectively, are characterized by high p-values. This implies that intra-firm and inter-firm knowledge acquisitions do not significantly account for the decrease in the unit capital and operating cost of electricity production for the gas technology. The same implication is valid for inter-firm learning for the coal technology and intra-firm learning for the wind technology. Equally, high p-values for β_4 with respect to the coal technology indicate that technology progress for the coal technology is not statistically significant for the period covered in the analysis.

4.3. Learning rates

Learning rates for the coal, gas, solar, and wind technologies are computed using formula (4.1) from Rubin et al. (2015a,b). In (4.1), 2^{β_1} is the technology progress ratio where β_1 is the coefficient for firm-specific learning. All results are illustrated in Fig. 2.

$$LR = 1 - 2^{\beta_1} \tag{12}$$

As shown by Rubin et al. (2015a,b), the learning rate represents "the fractional reduction" in capital cost "for each doubling of cumulative" production of electricity. Our study finds that RPS mandates, more than some financial incentives such as production tax credits, have a positive effect on the learning rates of solar and wind technologies. This is shown in Fig. 2. This finding is not surprising since the market penetration for solar technology was not significant during the period covered in our analysis. Notably, Morris et al. (2016) state that with relevant policies, renewable technologies such as solar can achieve higher learning rates. They further point to possible decreases in technology cost that such policies could bring about. Furthermore, Barbose (2016) observes that solar technology was the largest source for meeting the RPS mandates in recent years. The study points to the creation of

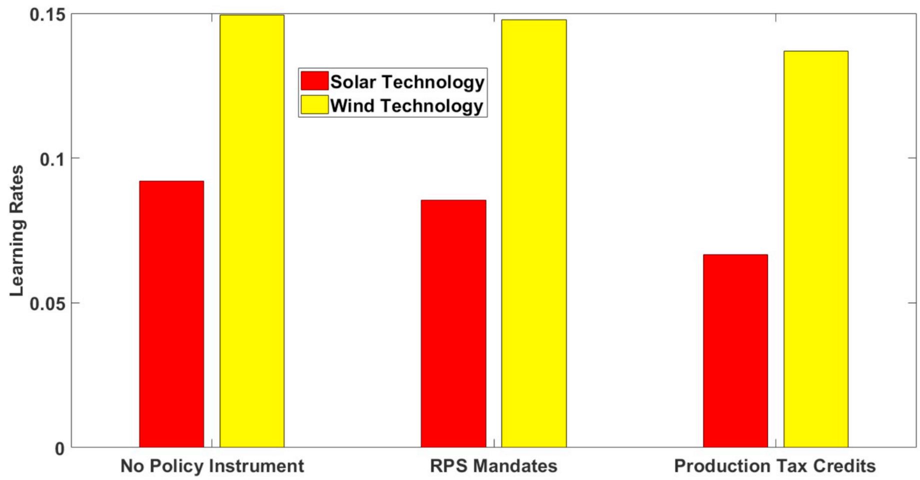

Fig. 2. Learning rates.

successful “residential solar program funded through RPS” as being the main reason behind this attainment. However, as shown in Fig. 2, compared to wind, much is yet to be accomplished to improve the learning rate in solar technology. Therefore, policy instruments could successfully be wielded to accelerate the pace of learning in these technologies.

Also, as demonstrated by Fig. 2, the learning rate of the wind technology is higher than the learning rate of the solar technology. This result, on first check, appears contrary to an earlier study that finds the mean learning rate for solar to be at least twice that for wind Rubin et al. (2015b). First, Rubin et al. (2015b) only provides values based on model estimates and not empirical data. Second, our result is to be viewed from the lens of the implications of policy instruments in the estimation of learning rates from actual electricity capacity data by technology.

Interestingly, Rubin et al. (2015a,b) make similar observations after undertaking a worldwide meta-analysis of the literature on learning rates for electric power plants. While focusing on learning by researching, they find a higher learning rate for onshore wind systems (16.5%) than for PV systems (12%). These particularly high learning rates are not as surprising as wind and solar technologies constitute some of the fastest growing renewable energy technologies.

4.4. Residual analysis

The examination of the residuals of the coal technology, for example, shows evidence of normal distribution. This is shown[1] by the “Normal probability plot” of residuals in Fig. 3.

The “Histogram of residuals” displays symmetric residuals, which confirms a reasonable fit to normally distributed residuals. From the “Plot of residuals vs fitted values”, there are few unusual points in comparison with points that lie together. Hence, the variation around the estimated regression line is constant. This is confirmation of an acceptable level of homoscedasticity. The “Plot of residuals vs lagged residuals” exhibits no specific pattern in the residuals. This validates independence amongst the residuals. Accordingly, there is no plausible evidence of autocorrelation. This is confirmed by the Durbin-Watson test. For a confidence level of $\alpha = 0.05$, the p-value, 0.4114, of the residuals in the coal technology is less than the Durbin-Watson t statistic ($1.9381 \approx 2$).

The initial analysis of the residuals of the gas technology does not uncover normality. For remedy, a new regression matrix of explanatory variables is created by shifting the time base backwards by the number of observations that did not display normality. Consequently, the original number of plant-year observations is truncated from 24,368 to 9368. This procedure also rectifies the serial correlation. Using the Durbin-Watson test, a t-statistic closer to 2 than the original Durbin-Watson t-statistic is found. This reduces autocorrelation since the closer to 2 the Durbin-Watson t-statistic is, the less autocorrelation. The same procedure is used for the solar and wind technologies. The only difference in this case is that fewer observations are not lost compared to the gas technology.

A broad analysis of the coefficients of determination, R-Square, shows heterogeneity among the models across the technologies. For the coal technology, the average coefficient of determination is 0.6. This indicates a non-negligible degree of variability between the response and explanatory variables. The gas technology exhibits an average R-square of 0.2. For the solar and wind technologies, the average coefficient of determination stands at 0.1. Insofar as R-square is non-trivial, the regression coefficients correlate to the mean change in the response of a unit of electricity produced.

5. Conclusion

The endeavor of this study is centered on the heterogeneous effects of knowledge acquisition within the U.S. electricity industry. The aim of this article is to deduce a framework in which policy along with technological knowledge acquisition become the main driving forces behind energy technological innovation. Notably, Griliches (1960) has hypothesized and demonstrated that technological change reinforces the economies of scales. This finding catalyzed the work of Mansfield (1968) on the adoption of new technology across firms in the manufacturing and transport sectors. Specifically, the author found that “larger firms tend to adopt innovations sooner than do their smaller counterparts.” Building on this work, this article extends the theory of technological adoption to U.S. electricity firms. It posits that intra-firm knowledge acquisition is proportional to technological improvement in solar technology. This study also postulates that more financial incentives for clean technologies generate more technological improvement in clean technologies under inter-firm learning. Further, we hypothesize that more stringent policy mandates lead to more variation in the progress of technological change across different technologies.

Applying the learning curve model, this study has developed several regression models that have been applied to a longitudinal analysis of 5573 U.S. electricity plants belonging to 1542 U.S. electricity firms between 1998 and 2010. The analysis has uncovered heterogeneities in

[1] Illustrations of the residuals of other technologies are available and can be provided upon request.

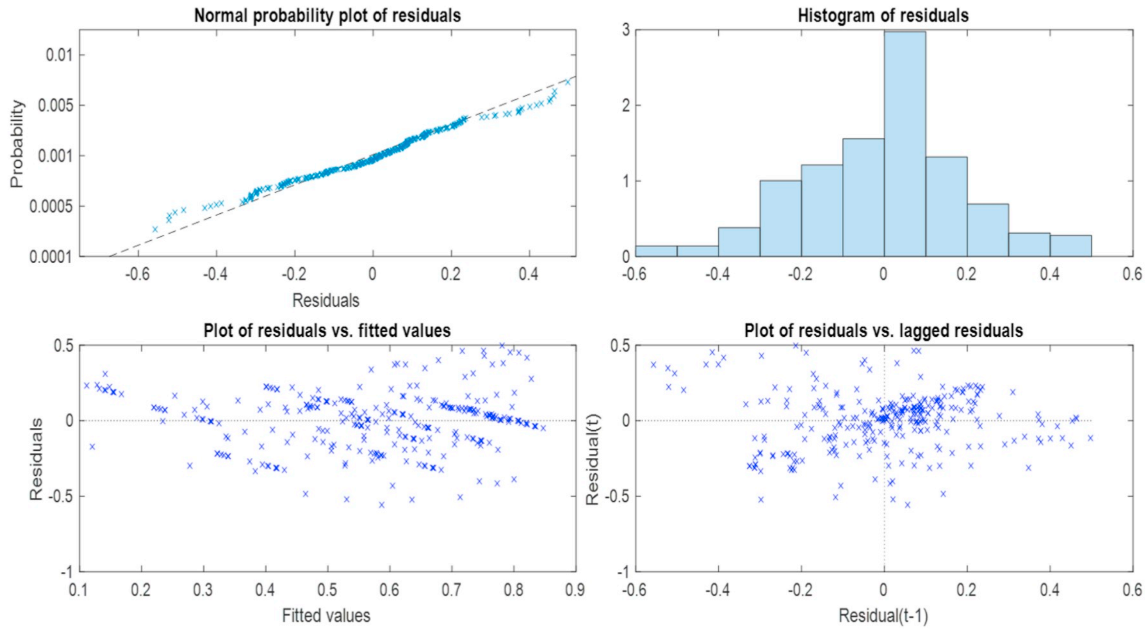

Fig. 3. Residual analysis – coal technology.

learning dynamics within and across electricity firms in the U.S. Particularly, this paper brings to light the positive relationship between the acquisition of new knowledge through intra-firm learning in electricity firms and the enhancement of the existing solar technology. This work also uncovers a beneficial association between financial incentives for clean technologies and improvement in clean technologies under inter-firm learning. Furthermore, the analysis brings to light the importance of production tax credits in improving knowledge acquisition within electricity firms for the wind technology. Finally, this paper unwinds the differences related to complying with policy instruments. It specifically notices that, as electricity firms seek ways to comply with policy instruments, the progress of the electricity sector in terms of knowledge acquisition is diverse. The study gauges the strains created by policy instruments due to their susceptibility to induce diversity in technologies improvement and development. Thus, it reveals the possible turmoil generated by policy instruments in depressing learning investments to develop disruptive new technologies. This work is enlightening in that it draws out the importance of knowledge collaboration across firms in developing new technologies. Moreover, this study shows that knowledge spillovers across firms prevail more for wind technology than for solar technology. The study subsequently derives a higher learning rate for the wind technology than for the solar technology irrespective of the intervention or non-intervention of policy instruments. A key takeaway is the possibility for firms investing in wind technologies to gain from the knowledge generated by the experience and investment of other wind technology firms.

The policy implications can be clustered into four main aspects. First, policy mandates and financial incentives should continue to be promoted because they contribute to technological improvement. Second, local governments should have more control and power in managing financial incentives such as production tax credits for better effects on technological innovation in developing new renewable energies. Third, federal regulators should seek more effective strategies to incentivize electricity firms to collaborate in order to foster the development of disruptive technologies while still effectively responding to policy mandates. Fourth, given the economic benefits of pollution emissions reductions, much is yet to be done policy-wise.

This study, while uncovering learning heterogeneities in U.S. electricity firms, offers a valuable exposition of the dynamics of knowledge acquisition. The outcome of this paper is not to say that the sole driver of technological cost declines is due to learning. Instead, we are postulating the underlying characteristics of the different tenets or scopes of learning on the cost reduction experienced across different technologies conditioned on the *a priori* assumption that innovation and cost decline are inextricable. Other preliminary studies such as Christensen and Greene (1976) indicate that "technical change unrelated to economies of scales deserves the primary attribution for declines in the cost of production." Our argument is that if that was true between 1955 and 1970, it may not necessarily be so today. Nonetheless, our study finds that financial incentives are good motivators when it comes to implementing renewable energy technologies. However, as discussed in Cox (2016), a key challenge facing policy makers is to align each financial incentive with each state's or city's circumstances. This is rather intricate yet necessary for better efficiency and risk management. An unintentional consequence of policy mandates are the risks created by the adopt-repeal or the push-pull effects that could discourage firms from investing in new renewable technologies. Hence, designing incentives or models that would bring about strategies that are immune to uncertainties in policies are needed.

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Appendix

Table A1
Measure Characteristics and Correlations

Coal Technology

		Mean	SD	Min	Max	1	2	3	4	5	6	7	8	9	10
1	Cumulative electricity output over years	144.67	299.68	0.01	2000.00	1.00									
2	Cumulative of 1 over states	630.60	1360.34	0.01	7712.08	0.82	1.00								
3	Cumulative of 2 over firms	$6.38\cdot10^{4}$	$5.86\cdot10^{4}$	574.13	$1.82\cdot10^{5}$	0.21	0.32	1.00							
4	Cumulative of 3 over technologies	$4.60\cdot10^{8}$	$5.03\cdot10^{8}$	$9.74\cdot10^{5}$	$1.54\cdot10^{9}$	0.20	0.32	0.99	1.00						
5	Renewable portfolio standard	0.40	0.15	0.00	0.50	0.14	0.17	−0.03	−0.03	1.00					
6	Republicans in legislature	0.10	0.30	0.00	1.00	−0.12	−0.10	0.02	0.02	−0.50	1.00				
7	Democratic Governors	0.58	0.49	0.00	1.00	−0.01	−0.05	−0.37	−0.38	0.43	−0.24	1.00			
8	Production tax credits	3038.09	6293.37	0.21	$4.20\cdot10^{4}$	1.00	0.82	0.21	0.20	0.14	−0.12	−0.01	1.00		
9	Energy bonds	$6.59\cdot10^{7}$	$1.58\cdot10^{8}$	$1.37\cdot10^{7}$	$3.81\cdot10^{8}$	0.12	0.18	−0.04	−0.03	0.87	−0.44	0.60	0.12	1.00	
10	Appliance standards	5.05	3.39	2.00	16.00	−0.09	−0.14	0.02	0.02	−0.84	0.38	−0.32	−0.09	−0.74	1.00

Gas Technology

		Mean	SD	Min	Max	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	Cumulative electricity output over years	413.85	1147.62	0.00	$1.68\cdot10^{4}$	1.00									
2	Cumulative of 1 over states	3575.40	$1.40\cdot10^{4}$	0.01	$3.05\cdot10^{5}$	0.03	1.00								
3	Cumulative of 2 over firms	$1.7\cdot10^{7}$	$1.65\cdot10^{7}$	$1.11\cdot10^{5}$	$5.11\cdot10^{7}$	0.14	0.19	1.00							
4	Cumulative of 3 over technologies	$4.49\cdot10^{8}$	$4.96\cdot10^{8}$	$9.74\cdot10^{5}$	$1.54\cdot10^{9}$	0.14	0.18	1.00	1.00						
5	Renewable portfolio standard	0.19	0.17	0.00	0.55	−0.10	0.01	0.00	0.00	1.00					
6	Republicans in legislature	0.36	0.48	0.00	1.00	0.02	−0.03	−0.13	−0.14	−0.46	1.00				
7	Democratic Governors	0.45	0.50	0.00	1.00	−0.02	−0.01	−0.06	−0.06	0.03	−0.17	1.00			
8	Production tax credits	8690.88	$2.41\cdot10^{4}$	0.04	$3.53\cdot10^{5}$	1.00	0.03	0.14	0.14	−0.10	0.02	−0.02	1.00		
9	Energy bonds	$5.26\cdot10^{7}$	$1.08\cdot10^{8}$	$5.53\cdot10^{6}$	$3.81\cdot10^{8}$	−0.01	0.01	0.01	0.01	0.51	−0.12	0.04	−0.01	1.00	
10	Appliance standards	10.50	4.56	2.00	16.00	0.08	0.00	0.01	0.01	−0.39	0.11	−0.10	0.08	−0.50	1.00

Solar Technology

		Mean	SD	Min	Max	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	Cumulative electricity output over years	9.31	48.40	0.00	1107.50	1.00									
2	Cumulative of 1 over states	54.11	319.36	0.00	5670.00	0.10	1.00								
3	Cumulative of 2 over firms	$7.99\cdot10^{4}$	$4.46\cdot10^{4}$	1591.16	$1.42\cdot10^{5}$	−0.02	0.02	1.00							
4	Cumulative of 3 over technologies	$7.42\cdot10^{8}$	$5.46\cdot10^{8}$	$9.74\cdot10^{5}$	$1.54\cdot10^{9}$	−0.01	0.01	0.98	1.00						
5	Renewable portfolio standard	0.33	0.19	0.00	0.55	−0.12	−0.06	0.09	0.08	1.00					
6	Republicans in legislature	0.18	0.39	0.00	1.00	0.00	0.00	−0.15	−0.14	−0.62	1.00				
7	Democratic Governors	0.50	0.50	0.00	1.00	−0.06	0.00	−0.33	−0.33	0.17	−0.18	1.00			
8	Production tax credits	195.60	1016.39	0.02	$2.33\cdot10^{4}$	1.00	0.10	−0.02	−0.01	−0.12	0.00	−0.06	1.00		
9	Energy bonds	$2.11\cdot10^{8}$	$1.56\cdot10^{8}$	$6.45\cdot10^{6}$	$3.81\cdot10^{8}$	−0.09	−0.04	0.03	0.02	0.74	−0.29	0.11	−0.09	1.00	
10	Appliance standards	6.86	4.60	2.00	16.00	0.11	0.02	0.00	0.01	−0.63	0.33	−0.11	0.11	−0.68	1.00

Wind Technology

		Mean	SD	Min	Max	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	Cumulative electricity output over years	111.84	387.13	0.00	$1.02\cdot10^{4}$	1.00									
2	Cumulative of 1 over states	480.88	2862.21	0.00	$1.57\cdot10^{5}$	0.00	1.00								
3	Cumulative of 2 over firms	$1.45\cdot10^{6}$	$1.36\cdot10^{6}$	$1.40\cdot10^{4}$	$4.09\cdot10^{6}$	0.19	0.12	1.00							
4	Cumulative of 3 over technologies	$4.96\cdot10^{8}$	$5.16\cdot10^{8}$	$9.74\cdot10^{5}$	$1.54\cdot10^{9}$	0.18	0.12	0.99	1.00						
5	Renewable portfolio standard	0.27	0.19	0.00	0.55	−0.06	−0.01	−0.06	−0.06	1.00					
6	Republicans in legislature	0.26	0.44	0.00	1.00	0.04	0.00	−0.11	−0.10	−0.55	1.00				
7	Democratic Governors	0.49	0.50	0.00	1.00	−0.02	−0.02	−0.12	−0.12	0.14	−0.18	1.00			
8	Production tax credits	136.21	644.29	0.00	$2.46\cdot10^{4}$	0.64	−0.01	0.07	0.07	−0.06	0.04	−0.02	1.00		
9	Energy bonds	$1.48\cdot10^{8}$	$1.43\cdot10^{8}$	$5.53\cdot10^{6}$	$3.81\cdot10^{8}$	0.01	−0.01	−0.07	−0.06	0.65	−0.25	0.20	0.00	1.00	
10	Appliance standards	8.90	5.06	2.00	16.00	0.00	0.02	0.05	0.05	−0.58	0.22	−0.21	0.02	−0.61	1.00

Table A2
Summary of Technology Costs

TYPE	SOURCE
Conventional Fossil-Based Technologies	Energy Information Administration (EIA)
Electricity Price by Technology Type	State Energy Data System (SEDS)
Renewable Electricity Cost	Environmental Protection Agency (EPA)
Wind and Solar (Electricity)	Climate Protection Partnerships Division (EPA)
Wind	U.S. Wind Power Installation, Cost, and Performance
Solar	Lawrence Berkeley National Laboratory (LBNL)
Financial Incentives	Database of State Incentives for Renewable Energy

Table A3
Descriptive Analysis of Cost Data ($/kW), all states by technology

	Mean	Std Dev	Min	Max	Range
Coal	1.59	0.43	1.11	2.32	1.21
Gas	5.61	2.02	2.57	9.11	6.54
Solar	8591.45	1717.26	5941.60	11,140.00	5198.40
Wind	1660.58	302.57	1253.78	2158.30	904.52

Table A4
Descriptive Analysis of Cost Data ($/kW), by year and technology

Mean					Standard Deviation				
	Coal	Gas	Solar	Wind		Coal	Gas	Solar	Wind
1998	1.19	2.59	11,140.00	1593.00	1998	0.43	0.66	0.00	0.00
1999	1.17	4.18	10,000.00	1603.00	1999	0.41	1.07	0.00	0.00
2000	1.21	4.55	10,519.40	1265.88	2000	0.47	1.66	74.95	48.65
2001	1.26	3.54	9775.40	1466.76	2001	0.49	0.73	108.89	29.98
2002	1.32	5.36	8936.80	1336.74	2002	0.55	1.20	118.79	19.37
2003	1.38	5.95	8517.60	1563.04	2003	0.57	1.24	483.64	268.63
2004	1.52	8.30	7993.20	1600.48	2004	0.67	1.79	526.44	230.72
2005	1.66	6.93	7940.00	1630.18	2005	0.70	1.39	843.83	217.91
2006	1.77	6.91	7858.40	1647.72	2006	0.73	1.42	848.75	193.51
2007	2.07	8.99	5977.60	1921.20	2007	0.89	1.91	2652.30	87.65
2008	2.21	4.83	6439.00	2144.00	2008	0.97	1.15	2695.07	0.00
2009	2.28	5.16	8000.00	2155.00	2009	0.98	0.93	0.00	0.00

Range					Max				
	Coal	Gas	Solar	Wind		Coal	Gas	Solar	Wind
1998	2.11	3.72	0.00	0.00	1998	2.11	3.72	11,140.00	1593.00
1999	1.87	5.81	0.00	0.00	1999	1.87	5.81	10,000.00	1603.00
2000	2.27	9.28	530.00	344.00	2000	2.27	9.28	10,530.00	1603.00
2001	1.99	4.74	770.00	212.00	2001	1.99	4.74	10,530.00	1471.00
2002	2.96	7.48	840.00	137.00	2002	2.96	7.48	9760.00	1471.00
2003	2.66	7.67	3700.00	952.50	2003	2.66	7.67	9300.00	2182.50
2004	3.08	10.27	3700.00	751.51	2004	3.08	10.27	9300.00	2182.50
2005	2.78	10.12	5800.00	751.51	2005	2.78	10.12	9100.00	2182.50
2006	2.94	9.10	5500.00	635.17	2006	2.94	9.10	8800.00	2066.16
2007	3.71	11.81	7300.00	315.95	2007	3.71	11.81	8300.00	2066.16
2008	4.01	7.71	7090.00	0.00	2008	4.01	7.71	8090.00	2144.00
2009	4.16	7.12	0.00	0.00	2009	4.16	7.12	8000.00	2155.00

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