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ABSTRACT

We examine the effect of in-state and out-of-state renewable energy policies on wind energy patenting. Using a semiparametric fixed-effects Tobit model, we regress patent counts on a series of policy variables within a state and a spatially weighted average for each of these policies implemented in other states. We develop a lower bound for the marginal effects and find important differences across policy types. For renewable portfolio standards, overall demand matters. Policies in other states increase innovation, but own-state policies do not. In contrast, for financial incentives such as tax incentives and subsidy policies, own-state policies induce innovation.

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> In a climate-change speech at Georgetown University, President Obama argued that: "confronting climate change need not threaten economic growth: that investing in windmills, solar panels and other types of clean-energy technology could spur scientific innovation and generate jobs" (New York Times, July 2, 2013).

Over the past three decades, green energy has emerged as an important topic of our social and economic life. It is now more widely accepted that the adoption of renewable energy sources such as wind, solar, geothermal, ocean, biomass, and waste-to-energy can significantly contribute to environmental protection. Also, the diversification resulting from increased shares of renewable energy sources could also lead to greater energy security in the face of uncertainty in fossil fuel markets. During this period various environmental policies, both at the federal level and the state level, have been implemented to encourage the development of renewable energy. As the quote from President Obama illustrates, these policies are often promoted as not only attempts to accelerate the switch from conventional fossil fuels to renewable energy sources, but also as efforts to cultivate innovation in environmentally friendly renewable technologies that will speed up "green growth."

However, in the United States it has been state governments, not the federal government, that have been leaders in policies promoting renewable energy (see Carley 2011). As states race to encourage the growth of renewable energy within their borders, they hope that such policies will promote innovative solutions to position their state as leaders in the renewable energy field. For instance, in his 2013 State of the State Address, New York Governor Andrew Cuomo introduced a series of renewable energy initiatives by stating that "(t)he economy of tomorrow is the clean tech economy. We all know it, it's a foot race—whatever state, whatever region gets there first wins the prize, and we want it to be New York."[1] A state of Texas report on the renewable energy industry proudly notes that "Texas ranked No. 4 in the nation in clean energy-related patents" in 2012, and cites awards made through the Texas Emerging Technology Fund as helping "to create long-term economic benefits to the state through investments in early-stage technology companies, regional innovation centers, and academic research recruitment."[2]

As the Trump Administration moves to roll back climate initiatives proposed under President Obama, the role of states becomes even more important. As of February 2018, fourteen states have pledged reduce greenhouse gases in their states to levels consistent with the Paris Agreement.[3] California pledged to reduce greenhouse gas emissions to 40 percent below 1990 levels by 2030.[4] As a result of the changing political landscape, variation in policies used across states will continue and is likely to increase. Understanding how different state-level policies affect innovation becomes even more important.

Despite the hope that state-level renewable energy policies will promote innovation within state borders and help states become leaders in renewable energy innovation, little is known about the effect of state-level renewable energy policies on innovation. Existing studies focus on national-level policies, providing evidence that national-level renewable energy policies promote innovation (Johnstone *et al*. 2010, Verdolini and Gaelotti, 2011, Nesta *et al*. 2014). Only a few studies consider both foreign and domestic policies, with mixed results. Dechezleprêtre and Glachant (2014) study the effect of both domestic and foreign policies for the promotion of wind innovation. While both promote innovation activity, they find the marginal effect of policies

[1] https://www.governor.ny.gov/press/01092013sostranscript, accessed May 22, 2014.
[2] "The Texas Renewable Energy Industry," http://governor.state.tx.us/files/ecodev/Renewable_Energy.pdf, accessed May 22, 2014.
[3] https://www.usclimatealliance.org/, accessed February 28, 2018.
[4] https://www.arb.ca.gov/cc/pillars/pillars.htm, accessed February 28, 2018.

implemented at home to be 12 times higher. In contrast, Peters *et al*. (2012) find both domestic and foreign demand-pull policies are important for the development of solar PV technology.

However, since the barriers to marketing renewable energy technologies across states may be lower than the barriers for marketing technologies across countries, the lessons from the above papers need not apply to innovation at the state level. Thus, in this paper we examine whether renewable energy policies enacted by a state induce innovation within the state. In addition, we ask whether these policies have spillover effects that facilitate innovation in neighboring states. The relative impact of state renewable energy policies on innovation within state and on innovation of neighboring states has important implications, since the existence of spillover effects may change the relative competitive advantage that states could obtain when competing with firms in neighboring states. If spillover effects do exist, coordinated policies across neighboring states may be more effective for promoting innovation than single-state policies. Finally, we look at the effect of specific policy initiatives on patenting, whereas both the papers by Dechezleprêtre and Glachant (2014) and Peters *et al*. (2012) use aggregate demand for renewable energy as a proxy for policy. This is important, as we find that the effect of policies are not homogeneous.

We use data on wind energy patents granted in the U.S. between 1983 and 2009 to track innovation across states. Using patents allows us to identify the location of invention, using the inventor's address listed on each patent. Because many states have zero patents in a given year, we use fixed-effects Tobit models to regress patent counts on a series of policy variables representing the existence or level of renewable energy policies within a state and a spatially weighted average for each of these policies implemented in other states. Our regressions control for state energy market conditions, socioeconomic conditions, and the renewable energy potential of each state. We find important differences across policy types. For renewable energy rules and mandates such as interconnection policies and renewable portfolio standards it is overall demand that matters. Policies in other states increase innovation, but own-state policies do not. In contrast, for financial incentives such as tax incentives and subsidy policies, locating in the state is typically required to take advantage of the credits. Thus, for these policies, own-state policies induce innovation, and we find some evidence that similar policies in other states have a negative effect on patent applications.

The rest of this paper is structured as follows. We begin by providing background on wind energy production and the relevant policies used to promote wind energy in the U.S. The next section gives a brief overview of the related literature. The third section presents our estimation strategy. Instead of using a Poisson count model for which the zero outcome probability would have to be inflated, making the incorporation of fixed and random effects problematic, we follow the suggestion of Calel and Dechezleprêtre (2016) and use a fixed-effects Tobit model, letting the censoring probability be the probability of a zero outcome. We derive a lower bound for the marginal effect of state-level policies, using analysis by Honoré (2008). The fourth section describes the data used in this study. The fifth section presents the empirical results. The last section concludes and provides some issues for further discussions.

1. Background on Wind Energy in the U.S.

Although the adoption of renewable energy sources has been increasing very rapidly, only recently have their costs fallen enough to be competitive with traditional energy sources under ideal conditions. Thus, during the time frame of our study, wind energy was not viable without government intervention favoring its development. Among non-hydro renewable sources, wind energy has experienced the highest growth, as its costs are closest to being competitive with fossil fuels (Timilsina *et al*. 2013). In 2016, just 5.6 percent of electricity in the United States came from wind energy. While small, this represents 66 percent of all non-hydro renewable electricity production in the U.S. Moreover, wind generation is growing rapidly, having increased 88 percent between 2011 and 2016 (EIA 2017). Variation across stats is also important. Twelve states, primarily in the Southeast, produced almost no wind power during our sample period. Of the 13 states generating the most wind power, most are in the central U.S., which is where wind energy potential is highest (Lopez *et al*. 2012).

To increase the share of renewable sources in the total energy supply, most states have introduced some form of renewable energy policy. By either decreasing the price of renewable energy relative to fossil fuels or increasing the demand for electricity generated from renewable sources, these policy measures improve the relative cost or benefit of renewable electricity generation compared to traditional fossil fuels. Examples of such policies include tax credits, subsidies, tradable renewable energy certificates, renewable energy portfolio standards (RPS), interconnection standards and net metering.[5] Renewable portfolio standards require electricity supply companies to produce a specified proportion of the increased electricity production from renewable energy sources, such as wind, solar, biomass, or geothermal. These may be implemented using renewable energy certificates (REC), which are granted to certified generators for every unit of electricity produced from renewable sources. Earned REC can then be sold to electricity suppliers, who use the certificates to demonstrate that they are in compliance with regulatory obligations. By the end of our sample, 39 states used RPS to promote renewable energy.

Interconnection standards provide clear technical rules such as maximum capacity, connection voltage and connection procedure so that on-site distributed generations can connect

[5] Carley (2011) provides an overview of the various renewable energy policies used in the U.S.

to the electric utility grid conveniently and safely. With net metering, electricity meters record both energy inflows and outflows so that distributed generators can save excess electricity production for future credit. This enables consumer-based small-scale renewable energy facilities such as wind or solar power to interconnect with the grid. By the end of our sample, 43 states had interconnection standards, and 46 states had regulations covering net metering.

2. Related Literature

The existing literature on state-level renewable energy policies examines their impact on renewable technology deployment or renewable energy production. For example, using cross-sectional time-series data from 1997 to 2009, Sarzynski et al. (2012) find that states with either subsidies or a renewable portfolio standard experienced more rapid growth in the capacity of grid-tied PV technology than states without these policies. Using U.S. state-level data from 1998 to 2006, Carley (2009) finds that RPS implementation has not increased the percentage of electricity generated from renewable energy sources relative to the total electricity generation, yet it has increased the total amount of electricity generated from renewable sources. By constructing a new measure for policy stringency that could more accurately characterize the incentives provided by RPS, Yin et al. (2010) find that RPS policy has significantly increased in-state renewable energy development.

While no papers have examined the effect of these policies on innovation at the state level, there is a large literature studying the effect of environmental and energy policies on innovation at the national level. Lanjouw and Mody (1996) use pollution abatement expenditures as a measure of environmental policy stringency in Japan, the U.S. and Germany and find that the environmental patenting activity measured by the number of granted patents is correlated with abatement costs.

Using U.S. environmental technology manufacturing data, Brunnermeier and Cohen (2003) also find that environmentally related patent counts increase as pollution abatement expenditures increase. Examining the role of specific policy instruments, Popp (2003) examines the effects of the 1990 Clean Air Act, which introduced a market for sulfur dioxide (SO_2) permits. Looking at the effects of the 1990 Clean Air Act on SO_2 pollution control patents, he finds that this market oriented environmental regulation did not induce more innovation than the previous command and control regulations, but that innovation occurring after 1990 tended to be more environmentally friendly and more efficient in removing SO_2 emissions. In another study of SO_2 abatement technology, Dekker *et al*. (2012) find that both national policies and international environmental agreements provide incentives for innovation.

Focusing on renewable energy policy innovation, Johnstone, Hascic and Popp (2010) use a panel data set of 25 countries across 26 years to examine the effect of a wide variety of policy tools, including tradable energy certificates, feed-in-tariffs, production quotas and public R&D, on innovations of renewable technology. They find that the effectiveness of each policy tool varies with the relative cost of different renewable technology sources compared to fossil fuels. Quantity-based policies favor development of wind energy, which has the lowest cost among alternative energy technologies and is closest to being competitive with traditional energy sources. In contrast, direct investment incentives are necessary to support innovation in solar and waste-to-energy technologies, which are further from being competitive with traditional energy technologies. Nesta *et al* (2014) observe that renewable energy policies stimulate more innovation in countries with liberalized energy markets. Calel and Dechezleprêtre (2016) find that the European Union Emissions Trading Scheme has led to nearly a one percent increase in that continent's low-carbon patenting.

Most closely related to our paper are studies that consider the relative effects of foreign and domestic environmental or energy regulations. Examining the effect of SO_2 and nitrogen oxide (NO_X) regulations in the U.S., Japan, and Germany, Popp (2006) finds innovation responds to domestic, rather than foreign policy changes across these three countries, each of which are leaders in the pollution control field. In a study of 15 OECD countries, Peters *et al*. (2012) find both domestic and foreign demand-pull policies (such as RPS) are important for the development of solar PV technology, but that technology-push policies such as R&D subsidies only affect domestic innovation. In contrast, Dechezleprêtre and Glachant (2014) compare wind energy patents across OECD countries. While both domestic and foreign demand-pull renewable policies positively affect renewable technology innovation, the marginal effect of policies implemented at home is 12 times higher. Policies such as trade barriers and weak intellectual property rights dampen the influence of foreign policies. However, as the barriers to technology diffusion across states in the U.S. will be lower than the barriers across countries, neighboring state policies may have more influence than do policies in neighboring countries. Thus, we contribute to the existing literature by extending this work to examine the effects of state-level renewable energy policies on innovation both within and outside state borders.

3. Model Specification

To study the role of various renewable energy policies from both within state and out of state on wind energy innovation, we consider two major categories of renewable energy policies: 1) financial incentives such as tax credits and various subsidy policies and 2) renewable energy related regulation rules and mandates such as interconnection standards, net metering and renewable portfolio standards. We include in the models both a series of variables representing the existence or level of a state's own renewable energy policies and a spatially weighted average of each of these variables implemented in other states. We control for other factors that could potentially affect the incentives for wind energy innovation by including variables for energy demand, supply and price, state social, economic and political factors. Detailed definitions and justifications for these variables are provided in the data section. The benchmark reduced-form regression equation is specified as:

$$(1) \qquad Patents_{it} = \beta_0 + (Policy_{it-1})\beta_1 + W_{it}(Policy_{t-1})\beta_2 + (R\&D_{it-1})\beta_3$$
$$+ (ElectricityConsum_{it-1})\beta_4 + (ElectricityPrice_{it-1})\beta_5$$
$$+ (ElectricityConsumGrowth_{it-1})\beta_6 + (PopulationGrowth_{it-1})\beta_7$$
$$+ (PerCapitaIncome_{it-1})\beta_8 + (PoliticalIndex_{it-1})\beta_9 + \varepsilon_{it} \,,$$

where $i = 1, \dots, 48$ represent states and $t = 1983, \dots, 2009$ represents time. The dependent variable is the number of wind technology patent applications for a given state in a given year. Our policy variables include a set of renewable technology policy variables such as a tax incentive index, a subsidy policy index, interconnection rules, net metering rules and renewable portfolio standards. R&D expenditures include all R&D activity within state i to control for the overall level of innovative activity within each state. Electricity consumption, electricity consumption growth and electricity price control for the energy market demand and supply. Population growth and state per capita income may also affect the demand for renewable energy. The political index uses League of Conservation Voters (LCV) Senate and House scores to represent each state's preferences toward pro-environmental legislation.

Our particular interest is in the effect of a state's own policies (β_1) and the effect of those polices implemented elsewhere (β_2). To aggregate policies from other states, we use a spatial weight vector, W_{it}. We use two versions of spatial weight matrices: one dividing log of population by distance, and a second with identical non-zero weights only when states share a common border. Aichele and Gelbermayr (2012), in their study of Kyoto commitments and carbon net trade, use weights that divide population, rather than log population, by distance. But in their case, the most populous country, the United States, is separated from most countries in the sample by large distances, so that the effect of the large U.S. population is mitigated by large distances. This is not the case with California in our data. Using log population rather than population results in lower weights for the most populous states.

$$(2) \qquad W_{ijt} = \frac{\log(Population)_{jt-1}}{Distance_{ij}} \Big/ \sum_{j=1}^{N} \frac{\log(Population)_{jt-1}}{Distance_{ij}} \qquad i, j=1, \ldots, N, i \neq j \;, t=1983, \ldots \;, 2009.$$

W_{ijt} is element j of the spatial weight vector W_{it}, which characterizes the effect of a renewable energy policy implemented in state j on innovation in state i in year t. We normalize the weights for each state-year to sum to one. This matrix places more weight on states that are closer geographically and on those with larger populations (and thus larger potential markets).

The second spatial weight matrix is the contiguity spatial weight matrix created by Anselin (1988):

$$(3) \qquad W_{ijt} = Neighbor_{ij} \Big/ \sum_{j=1}^{N} Neighbor_{ij} \quad ,$$

where

$$Neighbor_{ij}=1 \text{ if state } i \text{ and state } j \text{ are neighbors}$$
$$=0 \text{ otherwise}.$$

In this spatial weight matrix, spillovers occur only between states with common borders.

3.1 Estimation Technique

Our goal is to study the role of various state policies for renewable energy in determining the level of within-state and out-of-state wind-energy innovation. State-wide innovation is measured by the number of patents granted in that state over the course of a year. A standard way of econometrically modeling the determinants of the annual number of patents for a panel of states over time is to assume that the number of patents follows a Poisson distribution that varies by state and year and to estimate by maximum likelihood.

A potential drawback to this approach is the fact that the mean of a Poisson distribution is equal to its variance. Many empirical studies conclude that the sample variance significantly exceeds the sample mean, resulting in over-dispersion. This over-dispersion can be resolved by incorporating controls for state-level unobservables, most commonly with a Gamma-distributed random effect (see Hausman, Hall and Griliches 1984). Alternatively, in a panel setting, one can estimate fixed-effects Poisson models, making use of the fact that the Poisson model is one of the few members of the Generalized Linear Model class for which fixed-effects can be removed in a straightforward manner.

The second potential drawback of the Poisson model is the possibility of an overabundance of zero values in relation to reasonable estimates of the mean. This has led researchers to develop zero-inflated Poisson models in which the probability of a zero value is estimated and may depend on covariates. In principle, there is nothing to prevent incorporation of random effects using Heckman-Singer non-parametric maximum likelihood methods (see Heckman and Singer 1984). Majo and van Soest (2011) develop a two-stage fixed-effects zero-inflated Poisson model and apply it to health-care utilization. A possible drawback of the Majo and van Soest approach is that individuals with a zero in any time period must be dropped in the second stage, which estimates a truncated Poisson model. Otherwise, for large panels where many individuals have positive counts in all time periods, the Majo and van Soest approach is a straightforward method of consistently estimating coefficients on time-varying variables.

In this paper, we use a regression-based approach to modeling the determinants of counts in a panel setting. One of the first studies to consider classical regression to estimate counts is Jorgensen (1961). In a cross-sectional analysis, if it is reasonable to formulate the mean μ_i in the form $x_i'\beta$, ordinary least squares estimates are consistent. A promising way of dealing with the under-estimation of the probability of a zero value is the censored regression or Tobit model (Tobin 1958). These models are now commonplace and STATA, which we use for the estimation, allows users to estimate them with random or fixed effects. The random effects models are completely parametric and assume that both random effects and disturbances are normally distributed. The fixed-effects models are semi-parametric in that they require symmetrically but not necessarily normally distributed errors. Chay and Powell (2001) review fixed-effects models developed by Powell (1984, 1986, 1994), Honoré (1992), Honoré and Powell (1994), and Honoré, Kyriazidou, and Udry (1997). The results that we present are for the Honoré (1992) specification.

Calel and Dechezleprêtre (2016) use firm-level data to find the effect of the European Union Emissions Trading System on technological change. They develop an empirical likelihood treatment effect model with censoring, citing the difficulty of modeling patent development at the firm level. In the present paper, we are seeking the effect of state policies on patent development at the state level, which we are able to model directly in Tobit panel settings.

4. Data

In this study, we use patent count data for the 48 contiguous U.S. states spanning 27 years from 1983 to 2009. We stopped at 2009 because we felt that there is a clear structural break at that point due to the passing of the American Recovery and Reinvestment Tax Act,[6] section 1603 of which offers renewable energy project developers cash payments in lieu of investment tax credits.[7] We use state-level R&D data, electricity consumption, production and price information, state demographic, economic and political factors as control variables. All dollar values are 2009 dollars, adjusted using the Consumer Price Index. Finally, aggregate global wind capacity over this period controls for international trends that increase demand for wind innovation. Details about the source, collection and manipulation of these data are given in this section.

4.1 Dependent Variable

Our dependent variable is the number of patent applications for a specific state in each year. Using patents enables us to identify the location of invention, so that we can track wind innovation across states. While patents are a measure of the output of the innovation process, economists have found that patents provide a good indicator of innovation activity (see Griliches 1990). Moreover, due to the detail available on patent documents, patents are widely used in studies of environmental innovation (see Popp et al. 2010 for a review).

Data on relevant patent information comes from an on-line database provided by Delphion. Detailed descriptive information available includes the patent class, source country, corporate address and application date. We use the International Patent Classification (IPC) to identify wind energy patents granted by the U.S. patent office, searching for patents in IPC class F03D. Using

[6] https://www.treasury.gov/initiatives/recovery/Documents/Status%20overview.pdf accessed November 27, 2018
[7] Applications were due July 31, 2009.

the address of the corporate assignee, we assign each patent to a state. If a patent has inventors from multiple states, the patent is assigned to each of those different states. We use the earliest application date on the patent to identify the year of invention. Year fixed effects will control for any remaining truncation bias due to patents pending for more than four years.[8] Our data include 1,474 patents. As shown in Figure 1, most growth in patent applications occurs during the 2000s. Our counts of patents by state per year include many zeros, as 826 of our 1,296 state-year pairs have zero patents. Nearly 80 percent of all observations have either 0 or 1 patent. The largest number of patent applications for a state in a single year is 32, in South Carolina in 2009. Eight states (California, Connecticut, Florida, New York, Massachusetts, Pennsylvania, South Carolina, and Texas) have more than 50 patent applications in total, on average more than 2 patents every year.

4.2 Policy Variables

With available data from the Database of State Incentives for Renewables and Efficiency (DSIRE), which outlines operational policy instruments across the country and the date of enactment and amendment for each policy instrument by each state, we constructed variables for five different renewable energy policies. Subsidy policies include grants, loans and rebates. We construct the subsidy index by separately counting the existence of loans, grants and rebates, following Caley (2009). Thus, the subsidy index ranges from zero to three, indicating the number of different types of subsidy policies in existence. Similarly, using state corporate, personal, property and sales tax incentives, the tax incentive index ranges from zero to four indicating the number of types of tax incentives in existence for a state in a given year.

[8] We last accessed the patent data in 2014. Any remaining truncation bias is small, as 86% of patents in our sample are granted within four years or less.

We have include three variables for rules, regulations and mandates for renewable energy at the state level described earlier in section 1: interconnection rules, net metering and renewable portfolio standards. We construct dummy variables indicating the existence of the various policies within the state, coded as one if the policy is in effect in a given year. All the data on financial incentives and regulation rules and mandates for renewable energy are extracted from DSIRE.

Table 1 presents summary statistics. The mean value of the tax incentive index is 0.866. Since the tax incentive index characterizes the different kinds of corporate, personal, sales and property taxes present in a state, this means that states have about one out of the four kinds of tax incentives on average across these years. Similarly, a mean value of 0.294 for the subsidy policy index means that states on average have at least one kind of subsidy policy in 29.4 percent of the years. For variables indicating the existence of regulatory rules and mandates, states have a renewable portfolio standard policy in effect in 14.5 percent of the years, interconnection rules in 19.2 percent of years, and net metering policies in 29.2 percent of years.[9]

To study the spillover effect of policies enacted in other states on innovation in that state, we also included a series of spatially weighted averages of policy variables in the regression. If a large proportion of nearby states have adopted some form of renewable energy policy, this will increase the potential market for any wind innovations produced, as well as possibly having "demonstration effects" on renewable technology adoption in the home state. As noted earlier, our weighted outside-state policy variables are created by multiplying each policy variable by one of

[9] In our robustness checks, we include additional policy variables to proxy for the stringency of state policies. We replace the dummy variables with a count variable indicating the number of times a policy has been amended, assuming that amended policies are more stringent and thus more effective in promoting renewable energy adoption and innovation. The variable equals zero if there is no policy in effect, takes a value of one when a policy is first enacted, and adds one to the policy variable each time the policy is amended. Similar cumulative policy variables are used by Yin and Powers (2010) and Menz and Vachon (2006).

the two spatial weight matrices presented in section 3. Table 2 presents summary statistics for the weighted policy variables.[10]

4.3 Control variables

4.3.1 R&D Data

We use total state R&D investment to control for the general scientific capacity of the state. Total funds spent for business R&D performed in each state from 1982 to 2007 come from the Industrial Research and Development Information System (IRDIS) database,[11] which contains data produced by the National Science Foundation's Survey of Industry Research and Development (SIRD) from 1953 to 2007. The R&D data for 2008-2009 come from the Business Research and Development and Innovation Survey (BRDIS).[12] In 2009, the total business spending on R&D activity in the United States was $282 billion, of which $225 billion was funded by companies themselves. Businesses in California lead in R&D investment, accounting for over 23 percent of the nation's business R&D expenditures.

4.3.2 State Electricity Information

We include state electricity consumption, state electricity consumption growth, and electricity price per British Thermal Unit (BTU) to control for potential underling trends in a state's electricity markets. These data are extracted from the EIA's State Energy Data System (SEDS),[13] which contains detailed information on state energy consumption, production and prices by source

[10] Leenders (2002) provides a discussion of how to use a spatial weight matrix to model social influence.
[11] http://www.nsf.gov/statistics/iris/history_data.cfm, accessed February 27, 2018. Note that all control variables are lagged one year, so that we begin with data from 1982.
[12] http://www.nsf.gov/statistics/infbrief/nsf12309/, accessed February 27, 2018.
[13] http://www.eia.gov/beta/state/seds/seds-data-complete.php?sid=US, accessed February 27, 2018.

from 1960 to 2010. State electricity consumption and state electricity consumption growth reflect demand for electricity. When electricity consumption is high and increasing, the state will be under pressure to build more capacity. While this may provide an incentive for renewable energy deployment, which could lead to renewable technology innovation, it may also make costlier energy sources such as wind less attractive. Because wind energy was costlier than conventional sources during the time frame of our sample, we include energy prices in our estimations as wind energy will be more competitive in states that have higher or more volatile conventional electricity prices.

4.3.3 State Social, Economic and Political Factors

We also control for relevant socioeconomic factors. State population and state personal income data are from the Regional Economic Account of the Bureau of Economic Analysis (BEA).[14] We include state population growth because states with high population growth will be under more pressure to construct more capacity for electricity generation, creating a potential market for additional wind energy. Wealthier consumers may have a higher valuation for a clean environment and thus be more likely to prefer energy produced from renewable sources, so that per capita state income may affect demand for wind energy.[15] We use the log of state per capita income adjusted to 2009 U.S. dollars.

Political preferences are also important. Research in political science and public administration provides evidence that a state's institutional framework and other political structures could affect both policy adoption and the outcomes of policy implementation. For

[14] http://www.bea.gov/regional/downloadzip.cfm, accessed February 27, 2018.

[15] Moreover, Sarzynski et al. (2012) suggest that states with higher per capita income may have more consumers that could afford to invest in renewable technology with a high upfront cost. Rodberg and Schachter (1980) find evidence that higher income households are more likely to claim solar income tax credits.

example, Steinmo and Tolbert (1998) find that state political and economic institutions explain state tax policy variation. Ringquist and Clark (2007) argue that state policy efforts could be affected by interparty competition and interest groups. Sapat (2004) claims that the beliefs of political figures and organizational culture could also impact government performance. In this study we use League of Conservation Voters (LCV) voting scores to account for institutional factors that may affect pro-environmental legislation that is important for renewable energy development and renewable technological innovation. The LCV voting scores data are from the National Environmental Scorecard, published yearly by Congress since 1970.[16] A higher LCV score indicates greater support for environmental initiatives.

4.3.4 Global Wind Power Capacity

Finally, to control for the possible underlying trends in the development of the renewable energy industry worldwide, we also include in the estimations a variable for world-wide installed wind-power capacity as an indicator for the development level of wind power technology. This variable is not included in models that include individual year effects, as it is perfectly collinear with the year effects. Data on world-wide installed wind-power capacity and net annual addition are from the International Energy Agency.[17]

5. Empirical Results

Table 3 presents our main results. We present three specifications: models with and without year fixed effects and a model replacing year fixed effects with a time trend and squared time trend. Year effects control for time varying shocks common to all states, such as national policy

[16] http://scorecard.lcv.org/scorecard/archive, accessed February 27, 2018.
[17] http://www.iea.org/, accessed February 27, 2018.

changes or scientific advances that create new opportunities for wind technology. Moreover, because our data uses successful patent applications, which cannot be observed before a patent is reviewed and granted, year effects control for any truncation bias in our data. However, as the weighted policy variables of outside states are highly correlated with individual year effects, we also present models omitting year effects or using time trends in place of year effects to demonstrate robustness of our results. We discuss several robustness checks to our main results in section 5.1.

Our results indicate that the effect of policy on innovation varies by policy type. Most importantly, for renewable energy rules and mandates such as renewable portfolio standards it is overall demand that matters. Across all specifications, the coefficients for own-state renewable energy mandates and rules are small and insignificant. In contrast, the aggregate impact of these policies from other states does matter. Other states' renewable mandates consistently have a large significant impact on patenting, with the one exception being a loss of significance for outside state policies when including both state and year fixed effects due to the collinearity issues discussed above. In contrast, for financial incentives such as tax incentives and subsidy policies, states using tax incentives to promote wind energy see an increase in patenting in their own state. However, outside state financial incentives do not induce innovation within a given state. In fact, the coefficients of variables characterizing other state financial incentives are consistently negative. We find limited evidence of the importance of other rules.

A possible explanation for these two contrasting effects on innovation from renewable energy policies implemented by other states depends on an understanding of the implementation of each policy type. Renewable energy policy regulatory rules and mandates such as interconnection policy, net metering, and RPS implemented in one state make it more convenient to connect to the grid and raise demand for wind energy. Wind turbine suppliers do not need to live in the state with an RPS to take advantage of this increased demand. Moreover, renewable portfolio standards implemented in one state provide incentives for utility companies to purchase electricity produced from renewable sources not only in their own state, but from neighboring states as well. By raising demand for wind energy both within the RPS state and in neighboring states, RPS policies increase innovation across state lines. However, although tax incentives and subsidy policies will make renewable technology more affordable to the general public and ensure a better market prospective for companies developing renewable technology, one has to be a resident of a state where these financial incentives are present to benefit from these tax incentives or subsidy policies. Thus, financial incentives only induce innovation within the state giving the incentive, and targeted financial incentives of neighboring states may even provide a negative competition effect on wind energy innovation.

Table 4 compares the marginal effects for the two policies with consistently significant effects. For the marginal effect of the other-state RPS variable, we change the RPS variable from 0 to 1 for the state (or states) indicated and then re-calculate the weighted other-state RPS policy variable for each state. Greene (1999) shows that the infinitesimal-change marginal effect for covariate x_j in a censored regression model, no matter what the distribution of the disturbance, is

$$\partial E(y|x)/\partial x_j = \beta_j \text{ x Prob}(\ y \text{ uncensored}), \tag{4}$$

where y is the patent count, x is the covariate vector, and β_j is the coefficient of x_j . Honoré (2008) suggests that this formula can be used for infinitesimal-change marginal effects in his semiparametric fixed-effects Tobit model. The trick is to replace the probability in equation (4) by the sample proportion of uncensored observations, which maintains the consistency of the marginal effect. The final step is to recognize that for the discrete changes that we use, the infinitesimal-change marginal effect is a lower bound, since the value of the latent variable can switch due to the discrete change.

We present marginal effect lower bounds for the five states with the most patents, for five other nearby states, and the average and cumulative lower bounds for all 48 states in our sample. We choose the additional five states to provide variation in both population and geographic location. Column (1) shows the marginal effect of adding an additional own-state tax policy. Columns (2)-(5) show the marginal effects of the out-of-state RPS variable for all policies enacted in the year indicated at the top of each column. The states listed above each column are the states enacting a policy in that year. Column (6) shows the net effect of adding an RPS policy in the 17 states that had not enacted such a policy by the end of 2008.[18] This can be thought of as the marginal effect of moving from state-based polies to a national RPS policy. Because the policy variables are lagged one year, the marginal effects represent patent increases in the year after the policy change.

On average, a state adding one additional tax incentive to its policy mix sees an increase of at least 0.95 patents per year, with an effect as large as 2.62 patents per year for California. The average lower bound for the various RPS policies enacted in a given year are smaller in the selected years, ranging from 0.09 in 2003 to 0.60 in 2007. The results also illustrate the importance of geography. For example, the average lower bound of the effect of California on other states after RPS enactment is 0.09, but is as high as 0.28 for nearby Oregon and 0.60 for nearby Nevada.

While the marginal effects of out-of-state RPS policies in a single state are smaller than for own-state taxes, both the last row and column (6) emphasize the impact of total market size. Because all states are affected by external RPS policies, the net effect on all patenting in the U.S.

[18] These 17 states are Alabama, Arizona, Georgia, Idaho, Indiana, Kansas, Kentucky, Louisiana, Michigan, Mississippi, Nebraska, Ohio, Oklahoma, South Carolina, Tennessee, West Virginia and Wyoming.

is much larger. Thus, the bottom row shows the total number of patents induced in all 48 states in our sample. The sum of all marginal effect lower bounds from a new RPS policy is much larger, ranging from 4 to nearly 29 patents in a single year. These are substantial effects. For example, the increase in patents resulting from the policies enacted in 2007 account for 17 percent of all patents in 2008. While this may seem large, note that several large states, such as Illinois and Virginia, enact policies in 2007. Finally, in column (6) we ask what would happen if the 17 states that had not enacted an RPS by the end of our sample did so all at once. The average lower bound for this effect is 1.39 patents per state, which yields a total increase of 56.65 patents.

Overall, our results suggest the promise that enacting renewable energy policies can make a state a leader in wind innovation generally appears unfounded. With the exception of some targeted tax incentives, it is overall policy support (and thus overall demand) for wind energy, not demand within the state that matters. This result differs from the cross-country work of Decheztleprêtre and Glachant (2014) and Peters *et al.* (2014), who look at cross-country renewable energy patenting and find that domestic regulations are important. It also differs from cross-country work on innovation for other environmental technologies, such as Popp (2006), that finds domestic environmental policies to be important. Looking across countries, Dechezleprêtre and Glachant (2014) find evidence that trade barriers diminish the influence of foreign environmental policy on local innovation. Such barriers are not an issue across states. Indeed, one of the states with the most wind patent activity, South Carolina, generates little energy from wind and has no renewable energy mandate. It does, however, have financial incentives for wind energy. For state officials looking to promote renewable energy industry within their states, other factors such as lower taxes may be more important than enacting environmental regulation within the state.

All estimated control variable coefficients are insignificant. Only two variables attain t-statistics greater than 1.5. These are electricity price and global wind capacity. States with higher energy prices are expected to do more wind innovation, as higher electricity prices make wind energy more competitive with other energy sources. The electricity price variable is significant at the 5 percent level, but only in the model with year effects. The best result for global wind capacity is in the model with time trends. Other control variables have substantially less explanatory power.

5.1 Robustness checks

Our main finding is that own-state policies have a much smaller impact on wind-patenting activity than policy initiatives in other states. Our model lags both local and other state policies by one year. One potential concern may be that the timing of the innovative response differs across states. States with an existing wind industry may see rapid increases in patenting in response to new policy initiatives. In contrast, if states without an existing wind industry enact policies to encourage the development of such an industry, it may take time for the industry to develop. Thus, the effect of local policies may have a longer lag than out-of-state state policies. In Table 5 we consider different combinations of lags for in-state and out-of-state policies, allowing up to a three year lagged effect for each. Nonetheless, our main results remain – own-state policies, except the tax incentives, have no effect, even after three years. Moreover, the effect of out-of-state policies gradually disappears, becoming insignificant after three years. This is consistent with other studies finding that innovation responds quickly to policy incentives (e.g. Popp 2006).

We might also be concerned that local policies are endogenous. While there is evidence of policy endogeneity in the effectiveness of renewable energy policy (e.g. Delmas and Montes-Sancho 2011), it need not be the case that endogeneity exists in the case of renewable energy innovation. In the case of renewable energy generation, policies focus on wind energy generated within the state. These wind farms are typically owned by local electric utilities or by independent power producers. However, the wind turbine equipment they purchase for generation need not be produced locally. Turbine producers are mostly large global companies, such as U.S.-based General Electric, Gamesa from Spain or Siemens from Germany. In 2010, nearly one-half of wind turbine capacity installed in the U.S. used General Electric turbines, with Siemens and Gamesa accounting for another 27 percent (Wiser and Bolinger 2013). Since most wind turbines come from a few large global producers, the location of these producers should be exogenous, and thus not influence policy to promote renewable energy generation in a given state.

Endogeneity leads to two potential biases. One is that firms in states with a strong wind industry lobby for regulations to support the industry. This would lead to a positive bias in our coefficients. However, since our main result is that own-state policies have little effect, such bias does not seem to be an issue. Another possible bias is that states with unfavorable conditions for a wind industry enact regulations to support the development of wind energy. Here, we would see a negative bias on own state coefficients. Thus, to confirm our result of no effect for own-state policies, we want to ensure that such negative bias is not an issue.

Unfortunately, given the discrete nature of our policy variables and the many policy types that states use, finding valid instruments for each of our five own-state policies is difficult, if not impossible. Instead, we run the following falsification test, regressing current patents on future own-state policies. If states lacking wind capacity are enacting policies to spur the development of wind technology, we would find a negative effect of future own-state policy on patenting. As shown in Table A1 of the appendix, this is not the case. Future own-state policies also have an insignificant effect. Thus, any potential bias here has little if any effect on our main conclusions.

Appendix Table A2 considers whether our results are sensitive to the weighting matrix used for outside state policies. While the magnitudes of our coefficients differ due to the different weights used, the pattern of results for in-state and out-of-state policies remains essentially the same. Appendix Table A3 considers alternative policy measures. To proxy for the stringency of state policies, we replace the dummy variables with a count variable indicating the number of times a policy has been amended. Under the assumption that amended policies would be more stringent and thus more effective in promoting renewable energy adoption and innovation, the variable equals zero if no policy in effect, takes a value of one when a policy is first enacted, and increases by one each time the policy is amended. Similar cumulative policy variables are used by Yin and Powers (2010) and Menz and Vachon (2006). In addition, we adjust our dummy variables for the RPS, omitting states whose RPS appears non-binding. In the first alternative, we code RPS policy as 0 if the RPS standard is met with 100 percent compliance in the first year of implementation and remains at 100 percent afterwards. In our second alternative, the variable takes value 0 if states with RPS have a target less than 5 percent in 2009. As Appendix Table A3 shows, our main results are generally unchanged when using these alternative policy variables. The one exception is that the coefficient on out-of-state RPS standards becomes insignificant when not including states whose RPS target is less than 5 percent.

6. Conclusion

In this study, we examine the effect of state renewable energy policies on patenting activity in individual states. Our results show that other states' renewable portfolio standard mandates have the largest impact on innovation. Own state policies generally have no effect on innovation, with the exception of a small effect from own state tax incentives. These results are robust to alternative model specifications.

Given that the barriers to technology transfer across state lines are small, these results indicate that it is overall demand within the U.S, rather than in one particular state, that drives innovation. This surprising result suggests that enacting policies to promote renewable energy is not necessary to become a leader in the development of renewable energy technology. Given the political popularity of efforts to promote green jobs, our finding that patenting activity does not coincide with state-level regulations suggests that the factors influencing the development of wind innovation across states is worthy of further study. Are the trends in patenting across states with low wind energy a result of state-level industrial policies designed to increase manufacturing jobs within the state? We leave this question for future research.

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Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Log R&D Investments (Millions 2009 USD)	7.137	1.795	1.189	11.12
Electricity Consumption (Billion BTU)	11.84	0.992	9.450	13.99
Electricity Consumption Growth (%)	2.273	3.652	-21.49	41.44
Electricity Price (2009 USD per BTU)	3.339	0.299	2.705	4.098
Population Growth (%)	1.002	1.036	-5.986	7.325
Log Per Capita Income (2009 USD)	10.37	0.191	9.814	10.97
Log Global Wind Capacity (Megawatts)	8.645	1.843	4.500	11.70
LCV Senate Score	0.478	0.298	0	1
LCV House Score	0.468	0.250	0	1
Tax Incentive Index	0.866	1.074	0	4
Subsidy Policy Index	0.294	0.545	0	3
Interconnection Existence	0.168	0.374	0	1
Net Metering Existence	0.292	0.455	0	1
Renewable Portfolio Standard Existence	0.145	0.352	0	1
Interconnection Cumulative	0.233	0.588	0	5
Net Metering Cumulative	0.361	0.628	0	3
Renewable Portfolio Standard Cumulative	0.215	0.585	0	4

Note: Units are in parenthesis. All dollar values in 2009 USD.

Table 2: Summary Statistics of Neighboring States' Average Policy

	Variable	Mean	Std. Dev.	Min	Max
Contiguity Weighting	Tax Incentive	0.908	0.729	0	3.667
	Subsidy Policy	0.294	0.314	0	2
	Interconnection Dummy Variable	0.209	0.306	0	1
	Net Metering Dummy Variable	0.336	0.352	0	1
	Renewable Portfolio Standard Dummy Variable	0.168	0.274	0	1
	Interconnection Cumulative	0.306	0.545	0	5
	Net Metering Cumulative	0.436	0.542	0	3
	Renewable Portfolio Standard Cumulative	0.261	0.466	0	2.667
Log(Population)/ Distance Weighting	Tax Incentive	0.964	0.548	0.330	2.597
	Subsidy Policy	0.328	0.258	0	1.416
	Interconnection Dummy Variable	0.199	0.251	0	0.952
	Net Metering Dummy Variable	0.321	0.271	0.009	0.963
	Renewable Portfolio Standard Dummy Variable	0.171	0.221	0	0.896
	Interconnection Cumulative	0.287	0.405	0	1.915
	Net Metering Cumulative	0.407	0.398	0.009	1.643
	Renewable Portfolio Standard Cumulative	0.263	0.380	0	1.971

Table 3: Semiparametric Fixed-Effects Tobit Results
(standard errors in parentheses)

	No Year Effects	Year Effects	Trend
Neighbor Tax Incentive	1.079	0.409	0.259
	(3.411)	(8.194)	(5.533)
Neighbor Subsidy Policy	-2.336	-10.70	-4.179
	(5.990)	(10.70)	(7.208)
Neighbor Interconnection	0.339	-6.133	4.723
	(6.391)	(12.96)	(6.295)
Neighbor Net Metering	3.145	3.498	0.954
	(3.845)	(7.090)	(4.379)
Neighbor RPS	10.45	14.54	11.02
	(4.414)	(11.86)	(5.914)
Tax Incentive Index	2.763	2.462	2.617
	(1.337)	(1.183)	(1.259)
Subsidy Policy Index	0.857	0.831	0.854
	(0.962)	(0.803)	(0.940)
Interconnection	0.703	0.551	0.641
	(1.326)	(1.427)	(1.217)
Net Metering	0.0291	-0.208	0.0825
	(1.748)	(1.320)	(1.561)
RPS	-0.428	-0.156	-0.419
	(1.350)	(1.217)	(1.305)
Log Inflation Adjusted R&D	-0.0692	0.176	0.0528
	(1.182)	(1.025)	(1.038)
Log Electricity Consumption	2.143	0.357	0.402
	(6.261)	(6.351)	(6.648)
Electricity Consumption Growth	-0.142	-0.146	-0.0986
	(0.0721)	(0.0676)	(0.0693)
Log Electricity Price	4.702	6.530	6.702
	(3.728)	(3.803)	(4.311)
Population Growth	0.0789	-0.0143	0.0479
	(0.443)	(0.484)	(0.470)
Log Per Capita Income	-4.877	-4.418	-6.909
	(8.599)	(10.71)	(9.240)
Log Global Wind Capacity	0.0568		-0.897
	(0.395)		(0.573)
LCV Senate Score	-0.232	0.0457	-0.473
	(1.320)	(1.459)	(1.367)
LCV House Score	0.730	-0.420	0.490
	(2.177)	(2.199)	(2.030)
trend			0.533
			(0.580)
$trend^2$			-0.001
			(0.025)
N	1296	1296	1296

Table 4: Semiparametric Fixed-Effects Tobit Marginal Effect Lower Bounds

	(1)	(2)	(3)	(4)	(5)	(6)
Year of Policy:	2008	1999	2003	2004	2007	2008
	Own State Tax Policy	ME, OR, NJ, & TX	CA	MD, NM, NY, & RI	IL, MN, NH, NC, ND, VA, & WA	17 States RPS
California	2.62	0.87	N/A	0.48	1.23	2.21
New York	2.04	1.42	0.11	0.97	1.55	2.68
South Carolina	0.58	0.16	0.03	0.16	0.48	1.05
Texas	2.13	0.32	0.21	0.56	1.11	3.70
Massachusetts	1.84	1.21	0.08	2.64	1.76	1.85
Pennsylvania	1.55	0.89	0.08	1.39	1.25	2.52
Connecticut	1.55	1.03	0.07	1.77	1.13	1.63
Florida	1.45	0.35	0.08	0.29	0.63	2.09
Oregon	1.45	0.13	0.28	0.19	1.20	1.17
Nevada	1.16	0.37	0.60	0.21	0.54	1.01
Mean	0.95	0.35	0.09	0.37	0.60	1.39
Sum	45.56	16.98	4.21	17.99	28.99	56.65

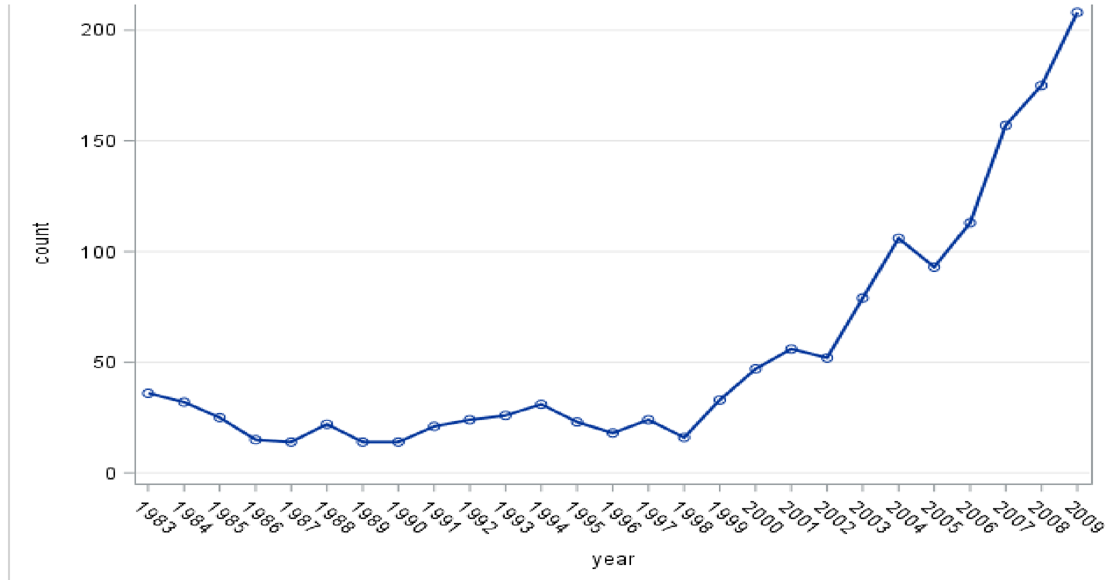
NOTES:
The table shows the marginal effects of various policy initiatives for the five states with the most wind patents (in bold), along with other selected states. Because the policy variables are lagged one year, the marginal effects represent patent increases in the year after the policy change. The probability of censoring for the fixed-effect results is the sample proportion of censored cases for the given state across all sample years.

Column 1 shows the own-state marginal effect of adding an additional tax policy in 2008. Columns 2-5 show the marginal effect of the other state RPS variable for all policies enacted in the year indicated at the top of each column. The states listed above each column are the states enacting a policy in a given year. Column 6 shows the net effect of adding an RPS policy in 2008 in the 17 states that had not enacted such a policy by the end of our sample. This shows what would have happened had the U.S. moved to a national policy in 2008.

Table 5: Sensitivity to Policy Lag Structure (standard errors in parentheses)

In State Policy Lags	1	1	1	2	2	2	3	3	3
Out of State Policy Lags	1	2	3	1	2	3	1	2	3
Neighbor Tax Incentive	0.259	3.532	-5.529	1.108	1.954	-5.650	1.714	3.291	-4.877
	(5.533)	(7.471)	(6.215)	(5.215)	(6.580)	(5.447)	(5.349)	(7.200)	(5.606)
Neighbor Subsidy Policy	-4.179	-11.29	-7.135	-4.523	-8.817	-7.748	-5.110	-11.25	-8.507
	(7.208)	(8.552)	(9.102)	(6.523)	(7.759)	(8.308)	(6.271)	(8.499)	(9.223)
Neighbor Interconnection	4.723	-5.924	3.750	-2.122	-8.537	1.387	1.067	-9.608	-2.192
	(6.295)	(6.061)	(6.263)	(5.145)	(5.927)	(5.940)	(4.824)	(7.264)	(6.838)
Neighbor Net Metering	0.954	6.187	1.458	4.574	8.796	3.048	2.971	9.123	1.903
	(4.379)	(3.897)	(5.291)	(5.632)	(4.319)	(5.637)	(5.560)	(5.193)	(5.805)
Neighbor RPS	11.02	17.66	11.36	14.40	18.32	13.17	14.80	21.12	17.95
	(5.914)	(7.551)	(10.83)	(6.396)	(8.099)	(9.843)	(5.484)	(8.171)	(10.43)
Tax Incentive Index	2.617	2.588	2.705	3.931	3.520	3.805	3.235	2.971	3.132
	(1.259)	(1.192)	(1.349)	(1.488)	(1.307)	(1.514)	(1.707)	(1.461)	(1.622)
Subsidy Policy Index	0.854	0.408	0.870	0.638	0.551	0.722	-0.166	-0.211	-0.004
	(0.940)	(0.787)	(0.918)	(0.822)	(0.730)	(0.752)	(1.007)	(0.911)	(0.894)
Interconnection	0.641	0.660	0.657	1.183	1.069	0.709	0.941	1.363	0.785
	(1.217)	(1.178)	(1.117)	(1.304)	(1.365)	(1.299)	(2.497)	(2.460)	(2.329)
Net Metering	0.0825	-0.778	-0.148	-1.746	-2.171	-1.514	-0.926	-1.999	-1.186
	(1.561)	(1.266)	(1.323)	(1.137)	(1.185)	(1.247)	(1.419)	(1.357)	(1.328)
RPS	-0.419	-0.029	-0.249	0.0079	0.052	-0.096	0.248	0.713	0.757
	(1.305)	(1.228)	(1.252)	(1.250)	(0.985)	(0.998)	(1.643)	(1.599)	(1.467)

Figure 1
Total Number of New Patents in the 48 States
By Year of Application (1983-2009)



Data Source: Authors' calculation, using data from Delphion

Appendix: Robustness Checks

Table A1: Semiparametric Fixed-Effects Tobit Results with Lead Own-State Policy Variables (standard errors in parentheses)

	No Year Effects	Year Effects	Trend
Neighbor Tax Incentive	-0.381 (3.285)	-2.632 (7.885)	-0.125 (5.677)
Neighbor Subsidy Policy	-1.425 (6.083)	-10.39 (11.26)	-3.389 (7.531)
Neighbor Interconnection	8.460 (6.526)	1.129 (13.96)	12.66 (6.776)
Neighbor Net Metering	1.130 (4.509)	3.897 (6.725)	0.313 (5.689)
Neighbor RPS	5.975 (4.700)	10.37 (10.12)	7.809 (5.196)
Tax Incentive Index(t+1)	1.086 (0.744)	1.157 (0.870)	1.024 (0.798)
Subsidy Policy Index(t+1)	1.340 (1.073)	0.840 (0.895)	1.166 (1.105)
Interconnection(t+1)	1.894 (1.305)	2.088 (1.408)	2.080 (1.410)
Net Metering(t+1)	1.169 (1.391)	-0.145 (1.288)	0.630 (1.558)
RPS(t+1)	-0.836 (1.633)	-0.448 (1.365)	-0.749 (1.481)
Log Inflation Adjusted R&D	-0.155 (1.272)	0.286 (1.026)	0.0173 (1.140)
Log Electricity Consumption	3.338 (7.194)	1.100 (7.530)	1.068 (8.002)
Electricity Consumption Growth	-0.145 (0.072)	-0.143 (0.070)	-0.103 (0.077)
Log Electricity Price	6.288 (3.488)	7.168 (3.119)	8.085 (3.552)
Population Growth	-0.0175 (0.532)	-0.216 (0.541)	-0.0607 (0.553)
Log Per Capita Income	-6.837 (10.15)	-5.671 (11.75)	-9.228 (10.85)
Log Global Wind Capacity	-0.303 (1.460)		-1.015 (0.617)
LCV Senate Score	1.077 (2.511)	-0.115 (1.541)	-0.505 (1.477)
LCV House Score	0.126 (0.512)	-0.336 (2.355)	0.637 (2.108)
Trend			0.742 (0.688)
$trend^2$			-0.0148 (0.0287)
N	1296	1296	1296

Table A2: Semiparametric Fixed-Effects Tobit Results with Contiguity Weighting (standard errors in parentheses)		
	No Year Effects	Year Effects
Neighbor Tax Incentive	0.827	-0.253
	(1.181)	(1.944)
Neighbor Subsidy Policy	-1.219	-2.362
	(2.144)	(2.691)
Neighbor Interconnection	3.913	1.348
	(2.795)	(4.976)
Neighbor Net Metering	0.775	0.233
	(1.483)	(2.057)
Neighbor RPS	4.710	5.094
	(3.000)	(3.701)
Tax Incentive Index	2.578	1.994
	(1.274)	(1.102)
Subsidy Policy Index	0.846	0.864
	(0.787)	(0.838)
Interconnection	0.913	0.711
	(1.186)	(1.420)
Net Metering	-0.247	-0.0671
	(1.250)	(1.140)
RPS	0.0231	-0.0932
	(1.212)	(1.122)
Log Inflation Adjusted R&D	-0.116	0.134
	(1.221)	(1.191)
Electricity Consumption	3.236	0.564
	(6.610)	(6.075)
Electricity Consumption Growth	-0.148	-0.138
	(0.0739)	(0.0647)
Electricity Price	5.955	6.464
	(4.740)	(3.581)
Population Growth	-0.0822	-0.182
	(0.509)	(0.510)
Log Per Capita Income	-0.0962	0.911
	(8.505)	(8.959)
Log Global Wind Capacity	-0.917	
	(1.305)	
LCV Senate Score	-0.0033	-0.321
	(2.089)	(1.420)
LCV House Score	-0.0109	-0.453
	(0.434)	(2.214)
N	1296	1296

Table A3: Semiparametric Fixed-Effects Tobit Results with Alternative Policy Variables (standard errors in parentheses)

	Cumulative Policy	RPS Alternative 1	RPS Alternative 2
Neighbor Tax Incentive	0.700	0.885	0.362
	(6.078)	(5.075)	(5.962)
Neighbor Subsidy Policy	-3.118	-3.885	-0.855
	(5.516)	(6.297)	(6.715)
Neighbor Interconnection	-6.719	3.836	4.247
	(8.953)	(6.399)	(6.370)
Neighbor Net Metering	9.383	0.433	1.757
	(6.288)	(4.425)	(4.241)
Neighbor RPS	9.454	14.44	1.074
	(5.252)	(6.842)	(9.872)
Tax Incentive Index	2.445	2.687	2.816
	(1.206)	(1.242)	(1.268)
Subsidy Policy Index	0.620	0.696	0.890
	(0.859)	(0.912)	(0.968)
Interconnection	-0.368	0.687	0.125
	(1.036)	(1.226)	(1.249)
Net Metering	-0.974	-0.196	0.376
	(1.121)	(1.541)	(1.610)
RPS	-0.297	1.548	0.353
	(0.957)	(1.590)	(1.209)
Log Inflation Adjusted R&D	-0.225	0.0962	-0.0260
	(0.768)	(0.992)	(1.090)
Log Electricity Consumption	1.258	-0.609	-0.958
	(6.557)	(6.250)	(6.635)
Electricity Consumption	-0.112	-0.096	-0.081
Growth	(0.062)	(0.068)	(0.062)
Log Electricity Price	6.277	5.065	8.068
	(4.015)	(4.158)	(4.526)
Population Growth	0.0738	0.135	-0.0093
	(0.446)	(0.453)	(0.479)
Log Per Capita Income	-5.880	-9.782	-3.864
	(8.601)	(8.281)	(8.775)
Log Global Wind Capacity	-0.602	-0.720	-0.850
	(0.472)	(0.530)	(0.594)
LCV Senate Score	-0.783	-0.791	-0.422
	(1.402)	(1.374)	(1.428)
LCV House Score	0.416	0.0842	1.309
	(1.712)	(1.918)	(1.895)
trend	0.278	0.586	0.336
	(0.387)	(0.508)	(0.597)
$trend^2$	-0.002	-0.009	0.004
	(0.017)	(0.022)	(0.026)
N	1296	1296	1296