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Effects of government incentives on wind innovation in the United States

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Abstract

In the United States, as elsewhere, state and federal governments have considered or implemented a range of policies to create more sustainable energy generation systems in response to concerns over climate change, security of fuel supply, and environmental impacts. These policies include both regulatory instruments such as renewable portfolio standards (RPSs) and market incentives such as tax credits. While these policies are primarily geared towards increasing renewable generation capacity, they can indirectly affect innovation in associated technologies through a ‘demand-pull’ dynamic. Other policies, such as public research and development (R&D) funding, directly incentivize innovation through ‘technology-push’ means. In this letter, we examine these effects on innovation in the United States wind energy industry. We estimate a set of econometric models relating a set of US federal and state policies to patenting activity in wind technologies over the period 1974–2009. We find that RPS policies have had significant positive effects on wind innovation, whereas tax-based incentives have not been particularly effective. We also find evidence that the effects of RPS incentives differ between states. Finally, we find that public R&D funding can be a significant driver of wind innovation, though its effect in the US has been modest.

Keywords: innovation policy, wind power, production tax credit, renewable portfolio standard, R&D, renewable energy

 Online supplementary data available from stacks.iop.org/ERL/8/044032/mmedia

1. Background: policy and innovation in wind energy

The history of wind energy technology in the United States shows, anecdotally, the significant effects government policy can have on the wind industry. An almost blind push towards centralized power systems by the Rural Electrification Administration (REA) curtailed the small-scale wind generator market in the 1940s, while a national ‘obsession with nuclear power’ effectively postponed utility-

scale wind power development until the mid-1970s (Richter 1996). US wind energy policy has gone through several distinct stages. In 1978, the Public Utilities Regulatory Policies Act (PURPA) was the watershed event that made the modern wind industry possible by forcing electric utilities to purchase electricity from renewable generation facilities at an ‘avoided cost rate’—the rate they would have to pay for electricity from substitute sources. High energy price forecasts led to these rates being locked in at 7–10 cents kWh⁻¹ for 10 years in California (Musgrove 2010). Coupled with federal and state Investment Tax Credits (ITCs), these guaranteed prices made wind plants attractive investments. The late 1970s and early 1980s were also characterized by increased public R&D funding geared towards developing large, utility-scale turbines for



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commercial production. Following the post-ITC crash of the California wind boom and the failure of federal funding to produce a commercially viable large turbine, the 1990s saw a lull in wind developments, though a federal production tax credit (PTC) was instituted during this time. In the 2000s, states have taken the lead in supporting wind power, largely through the adoption of renewable portfolio standards (RPSs), mandates that a certain portion of electricity sales be met from renewable sources.

The goal of this study is to assess quantitatively the impact of this policy history on innovation in the wind industry. While the renewable energy policy effectiveness can be assessed with respect to the primary aim of increasing renewable *electricity generation* or *capacity* (e.g., Shrimali and Kniefel 2011), this analysis falls into a separate but related literature on technological *innovation*. Innovation is defined as technological change responsible for growth in productivity not attributable to increases in capital or labour³. Improving technology yields greater returns to tangible economic inputs in addition to opening new frontiers to output. In the wind industry, innovation in virtually every component of the turbine has recently allowed construction of plants with sizes unsuccessfully attempted in the 1970s, lowered the cost of wind power, and made it possible to build turbines in areas with lower-quality wind resources (Wiser and Bolinger 2013).

We use yearly patent counts as a measure of innovation. Patent data are an appealing proxy for technological change due to their availability, richness, seeming objectivity, defined relationship to ‘inventiveness,’ and correlation with R&D (Griliches 1998). We acknowledge, however, that patent data are an imperfect measure: *invention* is not necessarily *innovation*, the latter including the crucial step of successful commercialization; not all innovations are patented; and not all patents are of equal value⁴. Nonetheless, it is a common and useful approach in the innovation literature. Fairly recent studies of policy and innovation in renewable energy generation include work by Johnstone *et al* (2009), Nemet (2009), and Taylor (2008), while Lee *et al* (2011) and Taylor *et al* (2005) use a similar approach to look at innovation in automotive and power plant emissions control technology, respectively.

Policy incentives for innovation can be categorized by incentive type and innovation dynamics. First, policies can use either financial incentives or regulation (market-based versus command-and-control policies, or ‘carrots’ versus ‘sticks’). Second, policies can be based on ‘demand-pull’ or ‘technology-push’ theories of innovation. The former ‘implement(s) measures that increase the private payoff to successful innovation,’ such as a tax structure that favours renewable technology; the latter ‘reduces the private cost of producing innovation,’ as in public research funding (Nemet 2009). Taylor (2008) argues that this dichotomy is not always straightforward and suggests categorizing policies based on whether they are aimed at ‘upstream’ technology

investment, ‘downstream’ market development, or ‘interface improvement’ between innovators and end-users. In this letter, we broadly categorize policies as aimed at either *technology development* (e.g., government-funded R&D) or *market development* (e.g., tax incentives for deployment).

Time series of policy variables are commonly related to patent counts to analyse policy effects on innovation. Using data from the European Patent Office (EPO), Johnstone *et al* (2009) test six policy types for effects on innovation, finding that, in the wind sector, only government-supported R&D, renewable energy credits, and renewable quotas have strong positive significance. Nemet (2009) assessed the effect of policy drivers in California from 1975 to 1991 on innovation as measured by patents filed at the United States Patent and Trademark Office (USPTO). He finds that, while demand-side policies did increase deployment of wind generation, this increase did not foster innovation, and that R&D lags, rather than leads, patenting activity. He suggests that demand-side policy structures led to an increase in output from existing Danish wind technology rather than innovation and that uncertainty around policy longevity made the lag from innovation to payoff unacceptable. Other studies do not paint quite so bleak a picture of R&D effects. Both Ruegg and Thomas (2009) and Margolis and Kammen (1999) show innovation effects resulting from DOE-funded projects in the renewable energy sector, while the National Research Council (2001) found that federal Department of Energy (DOE) R&D programs delivered relevant technology innovations in energy efficiency and fossil fuels.

Several papers that examine effects of other environmental regulations can also provide insight. In a paper examining automotive emission control technology, Lee *et al* (2011) find that, when stringent enough, command-and-control regulations can promote technology development. Taylor *et al* (2005) examine the effects of such policies on sulfur-dioxide mitigating technology for power plants. In contrast to Nemet (2009), they find market-development policies to be effective at promoting innovation—in fact, more so than directed public R&D funding. Like Nemet, they conclude that the significant innovations to their particular case studies occurred before the relevant market-based policies went into effect; however, they attribute this patent lead to anticipatory effects, whereas Nemet finds such anticipation not credible with respect to the California wind boom.

2. Methodology and data

Like many of the papers discussed above, we construct a regression model to estimate the effects of US policies on wind innovation, as measured by patent counts.

2.1. Patent data

Braun *et al* (2011) note the importance of accurate patent identification in studies of innovation. Patent searches must exclude inappropriate patents and include relevant ones, and those relying solely on patent class will necessarily miss on both counts, since relevant patents are mostly concentrated

³ Innovation is a key component of total factor productivity, the A term in the Cobb–Douglas production function $Y = AK^\alpha L^\beta$.

⁴ For further discussion of patents as an innovation proxy, see Griliches (1998) and OECD (2009).

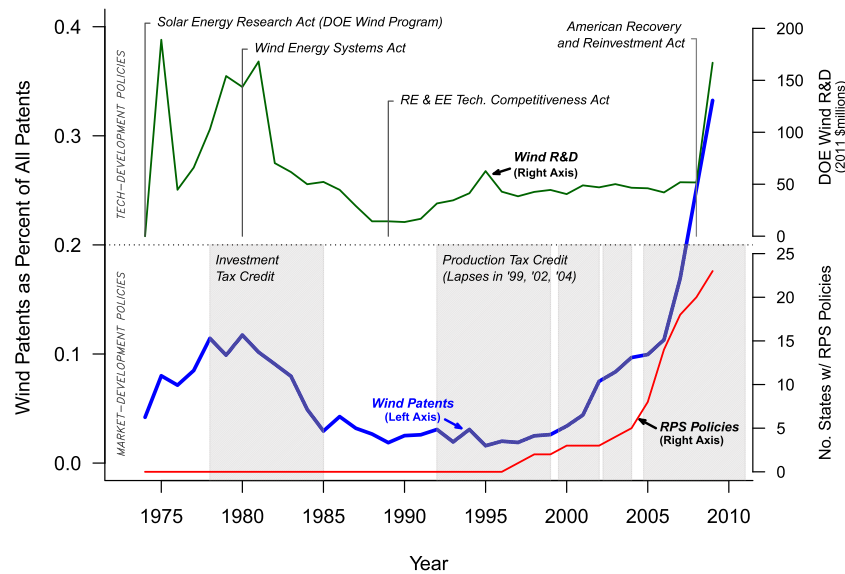


Figure 1. Wind patenting trend and major policy activity, 1974–2009. The bold curve shows the proportion of ultimately granted wind-related patents applied for in each year as a *percentage* of all patents (left axis; 0.1 = 0.1%). The upper half shows major technology-development policies and the annual level of funding for the DOE wind program (right axis). The lower half shows major market-development policies and the increasing trend of RPS adoption at the state level (right axis). Figure produced by authors using data from the USPTO for patent counts, DOE for federal wind R&D, and DSIRE (North Carolina Solar Center 2012, EERE 2009, Ruegg and Thomas 2009), and the Library of Congress (thomas.loc.gov) for other policies.

in one or two patent classes but can also be spread thinly across a distribution of related classes. At the same time, keyword searches can be somewhat arbitrary whereas patents are assigned to classes based on the expertise of the examiner. In order to mitigate the weaknesses and leverage the strengths of each method, we use a hybrid search approach consisting of both class- and keyword-based searches.

Patent data for this study were extracted from the USPTO online database⁵, which provides comprehensive patent data⁶ in HTML format for patent applications dating from 1976 to the present. We supplement the patents in the two most relevant USPTO classes, *wind-related fluid current motors* (290/55) and *electrical control of wind-related fluid current motors* (290/44), with a keyword search of patent titles and abstracts using the same search string as Nemet (2009), which returns patents referencing *wind power*, *wind turbines*, and *windmills* as well as mentions of *wind* and *electricity* with *rotors*, *blades*, or *generation*⁷. This search strategy returned approximately 4000 wind patent grants with application dates between 1974 and 2013⁸.

⁵ <http://patft.uspto.gov/>.

⁶ Fields of interest for this study include application and grant dates; inventor and assignee names and addresses; and title and abstract text.

⁷ The keyword-based portion of the actual search string is: ('wind power' OR (wind AND turbine) OR windmill) OR (wind AND (rotor OR blade\$ OR generat\$) AND electric\$). Dollar signs are wildcards; e.g., electric\$ will pick up *electricity* and *electrical*. We limit the search to utility patents.

⁸ As of September, 2013. Because many patents applied for in later years have not yet been granted, we limit this study to patents applied for in 2009 or earlier. This lag from application to grant averages 2.5 years for the set of wind patents; approximately 80% of patents are granted by the 3-year mark. Our results are robust to several different truncation treatments (available in the supplemental materials available at stacks.iop.org/ERL/8/044032/mmedia).

Figure 1 shows the annual level of wind patenting activity juxtaposed with major policy trends. We observe that wind patenting appears to track the level of federal R&D funding until the mid-1990s, after which it may be increasingly driven by the adoption of market-oriented policies like the PTC and RPSs. We control for other factors to determine if these apparent relationships are significant.

Much of the wind patenting activity in the USPTO database originates in the United States (figure 2). Figure 2 also shows an increasing proportion of foreign inventors patenting wind technology in the US over time. The increase in foreign patenting is both more volatile and more pronounced in the wind technology sector than that observed across the set of all patents⁹.

2.2. Policy data

An overview of major applicable policies was shown in figure 1. Modelling these policies as continuous variables rather than discrete dummies, where possible, is important to comparing policy effects. While the Federal and California ITCs present from 1978 to 1985 can be modelled easily as the percentage amount of the credit, the PTC and the state-level RPS policies are more involved. Johnstone *et al* (2010) note that 'incentives for innovation arise out of the underlying policy attributes and not the broad policy type *per se*.' That is, the implementation details can strongly determine the effects of the policy. For instance, the American Wind Energy Association (AWEA) has long claimed that the volatility of the PTC has hindered development of the US wind

⁹ More information is available in the supplemental materials (available at stacks.iop.org/ERL/8/044032/mmedia).

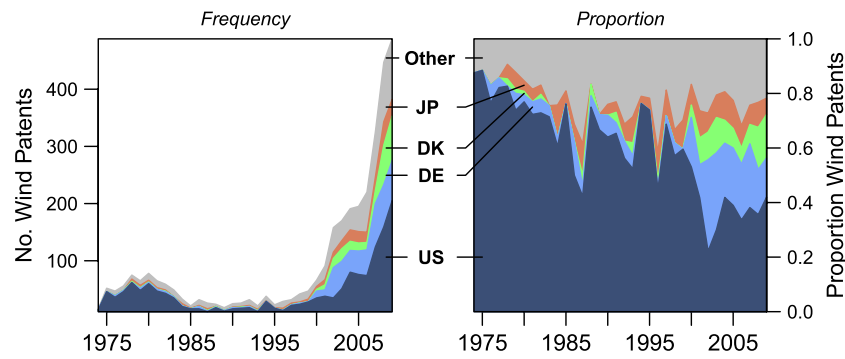


Figure 2. Domestic versus foreign wind patents in USPTO database, 1974–2009, by residence of first inventor. The same data are represented as a cumulative count (left) and proportionally (right).

industry (AWEA 2012). We attempt to model this volatility by tracking the imminence of the PTC’s in-service deadline, or the date by which a facility must be operating to receive the credit. The PTC is represented as the average number of months in any given year until its current legislated expiration date. Shorter horizons, caused by pending expiration of the credit with uncertainty about its renewal, should lessen its incentive effect.

State RPS policies vary widely, and more aggressive or stringent policies should provide greater incentives to lower the costs of wind energy through innovation. We model the aggregate national RPS target as well as the separate RPS policies of four of the seven top wind-producing states: California, Texas, Iowa, and Minnesota. The remaining three states—Oregon, Washington, and Illinois—implemented RPSs too late to be included in the time series. In order to compare various RPSs on an equal basis, we convert each to an annual renewable generation target using policy data from DSIRE (North Carolina Solar Center 2012) and state electricity load data from EIA (2012b)¹⁰. In terms of renewable energy generation, California’s target is by far the largest, despite being the last of the four to implement an RPS. Texas’ and Minnesota’s mandates range from 5 to 10% of California’s. Iowa’s RPS target is much smaller (around 0.5% of the California target), though it was the first state in the US to create such a standard.

2.3. Other data

Beyond the policy measures, we include several additional variables to control for other factors in the environment that might explain changes in the level of wind patenting. We use electricity price and consumption data, which are weighted averages and totals across sectors, respectively, from EIA (2012a). As an alternative to electricity consumption, we capture the macroeconomic environment by including GDP,

¹⁰ DSIRE provides data on percentage targets as well as the portion of state electricity load to which the target applies. We include only the portion of each RPS mandate for which new wind is eligible (excluding, for instance, existing generation and solar carve-outs). In general, wind is an eligible technology for most RPS tiers. Most RPSs identify the renewable target in terms of a percentage of retail sales. For the few states where targets are stated as MW installed capacity, we assumed a wind capacity factor of 0.33.

also from EIA (2012a). Finally, we include the overall level of patenting activity (from the USPTO)—as a proxy for the favourability of the innovation climate.

3. Model specification and results

The general specification of the econometric model used is a negative binomial regression:

$$E[\text{windpats}_t | \text{policies}_t, \text{controls}_t] = \exp \{ \beta_1 (\text{policies}_t) + \beta_2 (\text{controls}_t) + \epsilon_t \} \quad (1)$$

where *policies* and *controls* are vectors of policy and control variables as described above. That is, the yearly level of wind patenting is explained by a vector of policy variables and a vector of control variables. In general, the policy variables are the PTC horizon, the combined federal and California ITCs, and the four RPSs discussed above. Control variables in the initial model are the same as those used by Johnstone *et al* (2009): electricity price and consumption, and overall level of patenting. However, we ran several specifications different from this model, with alternative variable representations (e.g., using GDP instead of electricity consumption) and combinations to check for robustness.

Table 1 shows results from several different model specifications¹¹. Models 1 and 2 differ in how they represent RPS policies; the *state* model (1) includes individual RPS targets for each of the four states considered, while the *aggregate* model (2) sums the targets for all states with an RPS obligation. We lead patenting 2 years with respect to the RPS targets under the assumption that innovators respond in advance to quotas on the horizon¹². Model 1 attempts to look at differences in inter-state effectiveness, while Model 2 sacrifices this detail to use a representative

¹¹ Since this is a negative binomial specification, the effect of a unit change in each variable is interpreted as a percentage change in wind patenting. So, for example, a \$1 million increase in DOE R&D funding is associated with a 0.4% increase in wind patenting, which yields one additional patent every five years at a historical median of 50 wind patents/year. Thus, an R&D budget of \$50 million/year yields an additional 10 patents/year. However, due to the limitations of the model discussed below, we caution against making such specific claims based on the coefficient values.

¹² A sensitivity analysis showed a two-year lead to generally have the most significant effect at the individual state level.

Table 1. Regression results, 1974–2009. (Note: Standard errors in parentheses.)

	(1) State	(2) Aggregate	(3) US-state	(4) US-aggregate
DOE R&D (\$millions)	0.003 94 ^a (0.001 04)	0.003 53 ^b (0.001 09)	0.004 48 ^a (0.001 23)	0.004 45 ^a (0.001 35)
PTC horizon (Months)	0.000 168 (0.002 57)	−0.000 540 (0.002 48)	−0.000 610 (0.003 19)	−0.001 35 (0.003 14)
ITC-Fed + CA (%-pts)	0.006 40 (0.005 00)	0.006 38 (0.005 11)	0.011 5 (0.006 08)	0.010 4 (0.006 41)
RPS-CA2 (Annual TWh)	0.023 1 ^a (0.004 10)		0.011 5 ^c (0.005 33)	
RPS-TX2 (Annual TWh)	0.121 ^c (0.055 8)		0.242 ^a (0.072 4)	
RPS-IA2 (Annual TWh)	0.283 (1.337)		0.654 (1.660)	
RPS-MN2 (Annual TWh)	0.152 ^c (0.069 3)		0.028 8 (0.088 7)	
RPS-Tot2 (Annual TWh)		0.023 9 ^a (0.001 95)		0.020 1 ^a (0.002 45)
All patents (Thousands)	0.013 6 ^b (0.004 44)	0.017 0 ^a (0.003 69)	0.010 1 (0.005 52)	0.008 53 (0.004 79)
Elect. Price (cents kWh ^{−1})	0.059 1 (0.090 3)	0.079 9 (0.092 3)	−0.089 7 (0.110)	−0.072 4 (0.116)
Elec. Cons. (Annual TWh)	−0.000 974 ^b (0.000 300)	−0.001 12 ^a (0.000 295)	−0.000 967 ^b (0.000 370)	−0.000 819 ^c (0.000 378)
<i>N</i>	36	36	36	36
<i>Log-likelihood</i>	−143.0	−144.6	−129.2	−132.0
χ^2	113.0	109.7	81.44	75.81
$p > \chi^2$	0.00	0.00	0.00	0.00

^a ($p < 0.001$).

^b ($p < 0.01$).

^c ($p < 0.05$).

national-level metric¹³. We observe that the California, Texas, and Minnesota RPSs were significant drivers of innovation in the first model, and the second model echoes that finding at the national level. Federal R&D and the overall level of patenting activity also had significant, positive effects as expected. Electricity consumption was also significant, but surprisingly its sign is negative¹⁴. We would expect higher electricity consumption to drive innovation. However, the effect is very small in magnitude: a 1 TWh increase in consumption is associated with a 0.1% decrease in wind patenting.

Recognizing that foreign inventors contribute an increasing proportion of wind patents to the data set (see figure 2), we attempt to isolate the impact of the foreign patenting trend. Models 3 and 4 are the same as Models 1 and 2, except they use only wind patents originating in the United States as the response. We see that R&D funding and RPS policies remain significant at the national level, but in the

state-level model the Texas RPS has increased in magnitude and significance, while the coefficients on California and Minnesota have decreased in both (the latter dropping out altogether). This difference could mean that the RPS policies in these states are driving patenting by foreign, rather than US, inventors. This hypothesis is reinforced by the fact that overall level of patenting activity is no longer significant, indicating that the proportional increase in patenting is coming mainly from abroad.

These models assume that the impact of R&D on patenting is immediate. If R&D is allowed to lead patenting even one year, its effect becomes insignificant in all of these model specifications. While counterintuitive, this finding is consistent with other work on innovation. Griliches (1998) makes the case that while patents are highly correlated with R&D, the lag between R&D input and patenting output is small, due to the fact that patents are applied for early on in the research process and that most R&D finances the D rather than the R. Other econometric models of patenting also do not lag R&D.

Figure 1 shows a stark dichotomy in policy implementation over time. From 1974 to about 1990, US wind policy was characterized by investment tax credits and higher R&D funding. Subsequent to 1990, policy shifted to incorporate less R&D, a production tax credit, and implementation of state-level RPS obligations. When running the same models on only post-1990 data, the same findings as in table 1 hold, with the difference that R&D funding is no longer significant.

¹³The individual RPS variables exhibit high correlation. Large correlations are an indicator of possible partial multicollinearity in the regression, which increases the variance of the errors. Correlation among RPS variables means that it may not be possible to differentiate the effects among the individual states modelled with a high degree of confidence, in which case aggregate measures of RPS policy may be more appropriate. In general, the state-level RPS variables are sensitive to the lead (see footnote 15). In models aggregating RPS targets, the effect was robust across a range of leads tested.

¹⁴This result persisted for GDP as an alternate control and also when electricity price—a related and potentially confounding factor—was removed from the model.

Econometric model results are of course dependent upon model specification. While the form of an econometric model should be based on the theory of the phenomenon it is designed to represent, it can be useful to run alternative models as a sensitivity analysis to determine the robustness of the results. In this letter, we have constructed an econometric model based on the theory that both market-focused and technology-focused policies affect innovation in the wind industry. Key assumptions in this model are that absolute patent counts are a reasonable proxy for innovation; that our model includes the relevant explanatory variables; that the policy attributes, such as stringency, matter; and that innovators ‘look ahead’ at coming policy mandates, which directs our representation of the RPS and PTC policies. We refer to the innovation literature for the first two assumptions, while a series of models testing alternative policy representations and policy lags showed our findings of significance for RPS policies and R&D to be robust¹⁵.

4. Conclusions

4.1. Policy implications

While the results of these models should be interpreted cautiously (see discussion of limitations below), they do suggest that RPSs have more effectively spawned innovation in the US than tax credits and, surprisingly, R&D. We theorize that RPSs function as ‘technology forcing’ regulations because they require producers to meet their obligations within the existing market environment (Komor 2004). This market pressure drives electricity suppliers to focus on lower production costs, which in turn drives innovation. ITCs are at the other end of the spectrum, incentivizing only the construction of capacity without regard to quality. Between these two extremes lie PTCs, which incentivize production but without a direct focus on lowering costs by providing some guaranteed price support. According to our models, the PTC has not been associated with increased innovation. However, the relatively small number of observations may not make this null finding conclusive.

Government R&D is—in effect—direct funding for innovation and would thus be expected to have a significant positive impact. Our analysis provides only muted support for this theory, and, in fact, wind patenting generally *leads*, rather than lags, R&D. The contention in Griliches (1998) that R&D is weighted towards development seems to have been true of the DOE wind program, which funded several large demonstration projects for utility-scale turbines. Perhaps an existing body of innovation was a necessary prerequisite for this R&D program, rather than a result of it.

¹⁵ A major uncertainty is the magnitude of the lags (when firms are reactive to policies) or leads (when firms are proactive with respect to coming policies). We ran alternative specifications with differing lags for the ITC, RPS (assuming firms react to the establishment of an RPS), and electricity price signals and with differing leads on the RPS targets (assuming, alternatively, that firms respond to renewable generation targets on the horizon). (Results for these alternative specifications are available in the supplemental materials (available at stacks.iop.org/ERL/8/044032/mmedia).

Findings at the individual state policy level are less robust and warrant further study. In particular, the effectiveness of state-level RPS obligations in promoting innovation is sensitive to both the time frame of the study and the lead the variable is given. A sensitivity analysis of RPS leads indicates that California’s policy has a greater and more significant effect 2–3 years in advance of policy implementation, while Texas’ policy has a greater and more significant effect only 0–1 years out. This difference might reflect differing policy dynamics between these states: more deliberation or policy planning in California and a more rapid implementation process in Texas.

4.2. Limitations

The conclusions discussed above are conjectures based on the model formulations analysed in this study, but these models suffer from important limitations.

4.2.1. Single-country focus. This analysis intentionally focused only on the United States, with the goal of seeing if its policy-innovation dynamics mirror what has been found elsewhere. However, constraining the model to a single country gives our model less confidence than a cross-country study due to the small number of observations. Regarding the possibility that the increasing number of foreign inventors applying for IP protection in the US (figure 2) are responding instead to incentives in their own countries, the fact that, until recently, the US constituted the world’s largest market for both electricity and wind power makes it likely that US policies are at least partial drivers¹⁶.

Because our findings are supported both by the historical narrative of wind technology development and by other studies in this area, we feel justified in drawing general conclusions based on the signs and general magnitudes of the regression coefficients. However, we caution strongly against making inferences based on their specific values.

4.2.2. High-value patents. Nemet (2009) uses patent citations to determine the value of individual patents. This adds complexity to the model and requires normalization, because more recent patents have not yet had the opportunity to receive citations. Rather than using citation analysis, Johnstone *et al* (2009) use a patent set from the European Patent Office (EPO) database under the theory that submission to the EPO rather than to one’s home-country patent office represents a minimum threshold of value, since doing so is more expensive. Filing for a US patent is not inexpensive, and we might view the USPTO as a similar quality threshold. We should do so with some scepticism, however; fees are not exorbitant, and historically two of every three applications are ultimately granted (Griliches 1998). Using a ‘quality filter’ on the wind patent set, perhaps using citation or renewal rates, would increase confidence

¹⁶ An alternative model that included Feed-in Tariffs (FITs) from the largest foreign sources of innovation showed that these policies had no significant effect.

in our findings. However, given the high level of recent wind patenting activity and the fact that measures of patent quality generally take time to manifest themselves, we have necessarily left patent quality analysis outside the scope of this study.

4.2.3. RPS heterogeneity. RPS policies are nuanced, and the models used here gloss over many of those nuances. We have compared RPS policies on a common basis by converting them to obligated renewable generation. However, a myriad of other policy attributes could make them more or less effective, including penalties, reporting and verification procedures, and eligible technologies.

4.2.4. Other factors. We have used the policy variables that have been the ‘headlines’ of US support for wind energy: R&D, the ITC and PTC, and RPSs. These are the most likely candidates for innovation drivers. It is possible, however, that other policy types—such as green labelling, green power options, and procurement regulations—may be important¹⁷. Additional policies could be modelled, although addition of a large number of policy variables risks over-specifying the model.

4.2.5. Innovation versus deployment. Our conclusions speak solely to the effect of policies on *innovation*, which is generally a secondary goal. The primary goal of these policies is to increase renewable energy generation. Policies that may be effective at driving innovation may not be optimal for increasing generation. While innovation is likely to be necessary for the large gains in renewable generation desired by policy proponents, policy decisions should not be undertaken without also understanding effects on deployment.

Despite these limitations, the finding that RPSs have been more effective than other US policies appears robust. From a policy perspective, we suggest that focusing on the establishment of RPSs with aggressive targets and meaningful penalties while continuing a basic level of public R&D funding will have a greater impact on innovation than continuing the PTC. More work, however, needs to be done with respect to analysing RPS policy design to determine which attributes matter, both for supporting innovation as well as deployment.

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¹⁷ Comprehensive lists of energy policy types can be found in the IPCC report on climate change (Edenhofer et al 2011, chapter 11) and in the DSIRE database (North Carolina Solar Center 2012).

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