Heterogeneous Effects of Renewable Portfolio Standards: The Case of Solar and Wind

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Abstract:

Increasingly, Federal and local governments are recognizing renewable energy as a promising technology for combating climate change and implementing policies to encourage the adoption of renewables. This study analyzes renewable portfolio standards (RPS), a common policy instrument that serves as a subsidy to "clean" renewable energy. Results indicate that mandatory RPS goals result in a 51 MW expansion of solar capacity on average (25% of the average capacity for states in 2014), but the adoption of wind technology appears to be driven by other factors. We also find heterogeneous effects of RPS by the extent to which states are endowed with wind and solar resources. Given these findings, it is important to assess the degree to which continued expansion of solar and wind generating capacity through RPS is desirable from an economic perspective. Stochastic frontier models of utility-scale renewable generation allow us to extrapolate the net present value of new solar and wind projects for 39 US states (39 wind and 28 solar). Expansion of wind capacity is generally found to be economically viable in all states where wind farms are currently in operation, but with current electricity prices 57% of states with solar are projected to generate negative net present values for solar expansion. Furthermore, if we allow electricity prices to include environmental damages the outlook for solar improves, but 29% of the solar states still generate losses under higher social cost of carbon pricing. These findings reiterate the results of other authors suggesting that market-based environmental regulations are the first-best option for addressing climate change.

Keywords: renewable portfolio standard, solar, wind, renewable generation, stochastic frontier

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1. Introduction

In March 2015, President Obama signed executive order 13693 pledging to cut Federal greenhouse gas emissions (GHG) by 40% over the next 10 years. A large portion of the emissions reduction plan includes adoption of renewable energy, and requires that 25% of total federal energy consumption comes from "clean energy" sources by the year 2025 (Exec. Order 13693 2015). Other federal regulations such as the US Clean Air Act provide indirect incentives for increased renewable adoption by increasing the relative costs of fossil-fueled electric generating units (CAA 1970; CAAA 1990). As executive order 13693 highlights, however, these environmental incentives for renewable adoption have generally been viewed as insufficient due to the lack of federal regulations covering GHG emissions. The US Environmental Protection Agencies' (EPA) proposed Clean Power Plan (CPP) is set to partially fill this void beginning in 2017 by requiring all US states to adopt either a rate (e.g. emission standard) or mass (e.g. cap-and-trade) based program to reduce carbon dioxide (CO_2) emissions (U.S. Environmental Protection Agency 2015). After the 2016 US presidential election, the future of the CPP is uncertain with several media sources reporting that President Trump will end the CPP before it becomes operational (Harvey 2016; Rivkin and Grossman 2016).

Given the current uncertainty of the future of US GHG regulations, a prescient research agenda is to determine the likely effect of laws governing CO_2 emissions on the economic viability of renewable electric generating technology. This study attempts to address this gap in the literature by focusing specifically on state renewable portfolio standards (RPS). We do so by i) using state-level data to evaluate the impact of state RPS on solar and wind renewable adoption, ii) using generator-level data to estimate stochastic frontier models for solar and wind generation and evaluate state-level economic viability of renewable technology with current electricity prices and higher prices reflecting the social cost of carbon, and iii) combining our state- and generator-level analyses to examine the extent to which RPS policies encourage wind and solar adoption in states where such technologies are not economically viable.

Most energy experts do not expect renewable generating technology adoption to decline or disappear absent federal GHG regulations due primarily to state and private incentives for renewables (Jaffe 2016; Jurich 2016). State RPS are often viewed as one of the primary incentives for the expansion of renewable generating capacity (see, for example, Berry 2002; Knittel 2002; Wiser 2008; Fischer 2010; Heat 2012; Munoz, Sauma and Hobbs 2013; Tanaka and Chen 2013; Johnson 2014; Wiser, et al. 2016). Currently 29 US states and the District of Columbia have adopted RPS, and over 50% of the renewable capacity expansion from 1998 to 2007 occurred in states with RPS policies (Wiser 2008; Wiser, et al. 2016). Fischer (2010) provides a theoretical overview of the RPS policy instrument, and illustrates that RPS serve as a subsidy to renewable generation and a tax on non-renewables. Specifically, RPS sets a target level for state renewable generation as a percentage of retail electricity sales. Utility compliance with the RPS accruals is typically reconciled using renewable energy credits (RECs), which are a tradable market-based instrument and the primary means for electric utilities in RPS states to demonstrate RPS compliance (Berry 2002). On average utility RPS compliance costs represent 1.2% of electricity rates, and range from -0.2% to 6.5% depending largely on the current renewable target levels established in the state. In addition, most state RPS goals include safety checks on regulatory burden by capping compliance costs at 6% to 9% of electricity rates (Heeter, et al. 2014).

Aside from encouraging potential environmental benefits associated with renewable adoption, RPS may also improve energy efficiency by encouraging distributed generation (e.g.

rooftop solar, and industrial applications) that is under-incentivized in regulated electricity markets without interconnection and net-metering standards (Brown, Scott and Elliott 2003; Heat 2012). Lee (2015) and Shipley, et al. (2008) note that distributed generation has the potential to save 6% to 8% of electricity transmission losses on average. Despite these advantages, RPS should be viewed as a second best policy, as it generally fails to accurately account for benefit heterogeneity between renewable sources (Novan 2015).

Our study focuses on utility-scale investments in solar arrays and wind generation. By focusing on utility generation, we avoid analyzing the disincentives that exist in the absence of interconnection and net-metering for distributed generation. Utility-scale renewable generation captures the majority of renewable electricity generation in the US, but it should be noted that by excluding distributed generation and generation from waste and biofuels, our estimates of the impact of state RPS represent a lower bound on the increases of renewable generation associated with RPS adoption. The expansion of distributed solar generation, for example, is a particularly important emerging area of renewable adoption, and accounted for roughly 39.5% of all solar generation in 2015.[1]

The research presented herein advances the literature in three ways. First, this work contributes to the literature analyzing the heterogeneous impacts of state-level RPS (Yin and Powers 2010; Shrimali and Kniefel 2011; Dong 2012; Munoz, Sauma and Hobbs 2013; Tanaka and Chen 2013). Second, it adds to the literature analyzing the efficiency of electricity generators. The majority of these analyses focus on fossil fuel generators (e.g. Hiebert 2002; Knittel 2002; See and Coelli 2012; Lin and Du 2013; Zhao and Ma 2013; Seifert, Cullmann and von Hirschhausen 2016). Ours is one of only a handful of studies to examine wind power (others include Iglesias,

[1] US information on net generation from renewable sources is available from the US EIA: http://www.eia.gov/electricity/monthly/epm_table_grapher.cfm?t=epmt_1_01_a (last accessed January 2017).

Castellanos and Seijas 2010; Barros and Antunes 2011) and is to our knowledge the first study to apply stochastic frontier analysis to solar arrays. Finally, our work bridges the gap between these two strands of literature to test for potential inefficiencies associated with the siting of RPS-induced solar and wind generating units. Specifically, several authors have noted that state RPS are not the first best policy for reducing GHG emissions (see, for example, Michaels 2007; Bushnell, Peterman and Wolfram 2008; Fischer and Newell 2008; Johnson 2014). By combining our state- and generator-level data and methods, we are able to address some of these concerns by examining not just whether RPS has led to expanded solar and wind capacity in various states, but whether RPS leads to expanded capacity in states where such installations are unlikely to be economically viable.

Our state-level analyses of renewables expansion yields several interesting findings. On average a mandatory RPS goal results in an approximate 51 MW capacity expansion of utility-scale solar arrays. The solar capacity expansions are more likely to occur in states with above average solar resources and below average wind resources, which suggests that RPS are encouraging renewable adoption in geographically preferable locales. This finding may be attributable to the aforementioned tradable RECS mechanism that often allows compliance with RPS using RECS purchased from neighboring RPS states that may be better suited for solar generation. Although state RPS do encourage solar adoption, there is a 5 to 6 year lag between implementation of mandatory RPS goals and capacity expansion. We attribute the lagged RPS effects to tightening RPS standards over time. Finally, the effects of mandatory RPS goals on wind expansion are less certain. An event study suggests that wind capacity expansion occurred well before RPS adoption. This is possibly due to differences in the maturation timing of wind and solar technologies, with the costs of wind power falling to competitive levels before most RPS goals were initiated. Our finding that wind capacity expanded before RPS may help explain the unexpected negative impact of RPS on wind capacity estimated in Shrimali and Kniefel (2011) and the null effect estimated by Hitaj (2013). This finding is consistent with the results presented in Lyon and Yin (2010) that suggests states with higher wind potential may be more likely to adopt an RPS, and suggests that simple cross-sectional analyses of RPS adoption like the ones presented in Wiser (2008) and Wiser, et al. (2016) may be over-attributing expansions in renewable capacity to adoption of state RPS.

Given the fact that mandatory RPS goals do appear to encourage expansions in solar capacity, we next turn our attention to estimating stochastic electricity generating frontiers for solar and wind in order to shed light on the important siting and technology factors for renewable generation. Results from the stochastic frontier analyses yield several important findings. Focusing on our preferred estimates that assume an exponential distribution for the unobserved inefficiency component, the results suggest that solar tracking systems (movable panels) result in a roughly 12.5% increase in the technical efficiency of an array. We do not have estimates of the difference in operating and maintenance costs between fixed tilt and tracking systems, but as those estimates become available (currently only 30% of utility scale arrays have adopted tracking systems) engineers can directly compare the percentage cost difference to our estimated technical efficiency difference to evaluate the economic viability of tracking systems. Panel and turbine degradation rates for solar and wind generation are estimated to be approximately 2.2% and 0.8% of annual generating capabilities, respectively. These results are surprising for two reasons:

1. Degradation rates for wind were expected to be higher due to additional moving components, and the lower degradation rates for wind turbines may be due to better maintenance of wind generators.

2. The annual degradation rates for solar arrays are more than twice the recent estimates provided by Jordan and Kurtz (2013), and the results suggest that field tests of actual degradation rates on operational arrays as suggested in Quintana, et al. (2002) and provided herein are of vital importance for estimating the economic potential of solar.

The parameter estimates from the stochastic frontier models are then used to predict state-by-state electricity generation from a newly constructed typically sized solar array and wind farm. Specifically, the predicted electricity generation estimates are adjusted annually over the 25-year expected equipment life by state electricity prices, inflation rates, interest rates on municipal bonds, and equipment degradation rates in order to calculate the present value of the discounted stream of electricity sales and evaluate the state-specific economic viability of renewables. Expansions in wind capacity are found to be economically efficient in all 39 states in our dataset that have currently adopted some utility-scale wind projects. The case for solar, however, is mixed, and the results indicate that roughly 57% of the states that have currently installed some solar capacity have a negative present value of net benefits for solar using current (inflation adjusted) electricity prices. If we allow for increased electricity prices reflecting environmental regulations that price CO_2 emissions at the social cost of carbon, then the case for solar improves and only 29% of the current solar installation states are estimated to yield negative net benefits for solar.

The remainder of the paper is organized as follows. Section 2 provides an overview of the state and generator-level data used in the analysis. Empirical results are presented in section 3, and section 4 offers a concluding discussion.

2. Data

Data on renewable electricity generation comes from two primary data sources, both of which are from the U.S. Energy Information Administration (EIA). Annual net electricity generation in Megawatt hours (MWh) is collected on EIA form 923, and in 2013 the EIA began collecting data on solar and wind generator characteristics on EIA form 860.[2] Importantly, the EIA datasets contain a unique longitudinal plant id that allows us to match the generator characteristics from EIA-860 to electricity production data from EIA-923.

The key generator characteristic data collected on form 923 includes generator MW capacity, installation month and year, solar tracking technology, wind turbine height, and wind-quality class of the generator. The generator installation date is first used to construct a balanced panel of state-level observations covering all 50 states plus Washington, DC during the 31-year time period 1984-2014 in order to investigate the impact of state RPS on the capacity of utilities' wind and solar installations. The year 1984 was selected for the beginning date of our state-level panel because this date corresponds to the first utility solar installation in the U.S. The state renewable capacity panel is then supplemented with electricity price data from the EIA's State Energy Data System (SEDS) in order to control for the confounding effects of these state characteristics on renewable capacity. In order to examine whether the effect of an RPS on energy capacity varies by the suitability of the energy source, we also collect solar insolation and wind potential data from the National Renewable Energy Laboratory (NREL) and the US Department of Energy's WINDExchange website, respectively. Solar insolation, which is measured in KWh/m^2/day, and wind potential, which is measured in km^2 with a gross capacity factor (GCF) of at least 35%, are both normalized to have mean zero and standard deviation 1 for our analysis.

[2] EIA 860 data is available online at the following: https://www.eia.gov/electricity/data/eia860/ (last accessed November 2016). Survey 923 data on net generation is available at https://www.eia.gov/electricity/data/eia923/ (last accessed November 2016).

Finally, data on state RPS is collected from the North Carolina Clean Energy Technology Center's Database of State Incentives for Renewables & Efficiency (DSIRE).[3]

Panel A of Table 1 provides summary statistics for the state-level data on renewable capacity. Overall, the full sample contains 1,581 state-year observations, and 200 (13%) of those observations are for states with mandatory renewable portfolio goals. The remaining 1,381 (87%) annual state observations are those for which there is no mandatory RPS. Although not reported in Table 1, slightly over half (28) of the states in our dataset have a mandatory RPS goal at some point during the 1984 to 2014 sample, thereby providing a reasonable number of control and treatment states observed before and after RPS adoption in order to identify the effect of RPS using a fixed-effects estimation strategy. The reason that we only observe 200 observations of the states with RPS enforced is due to the fact that mandatory RPS goals were only established during the latter part of the sample from 2002 to 2013.

Focusing on columns 2 and 3 from Table 1 Panel A reveals that states with Mandatory RPS have a significantly larger amount of solar and wind electricity generating capacity in comparison to states with no RPS. Interestingly, however, RPS states have a similar average solar insolation (p value = 0.636) and a lower average wind potential (p value = 0.042) in comparison to non-RPS states. Finally, it is worth noting that states with mandatory RPS face average electricity prices of roughly $116/MWh. These electricity prices are roughly double the average prices faced by non-RPS states (p value < 0.005), and may also contribute to the adoption of renewable technology. Overall, the findings in Table 1 suggest that mandatory RPS may encourage states to expand

[3] SEDS data is available online at the following: http://www.eia.gov/state/seds/, and the DSIRE database is available for download at http://www.dsireusa.org/. The NREL dataset on solar insolation is available at http://www.nrel.gov/gis/data_solar.html and the WINDExchange dataset on wind potential is available at http://apps2.eere.energy.gov/wind/windexchange/windmaps/resource_potential.asp. All four datasets were last accessed November 2016.

renewable generating capacity, and section 3 presents empirical analyses that control for the confounding effects of electricity prices in order to formally test this hypothesis.

Once we establish the impact of mandatory state RPS goals on the expansion of renewable capacity, our second contribution is to use individual-level solar array and wind farm generation data to estimate production frontiers for each of the aforementioned renewable types. Summary statistics for our generator-level analyses are presented in Panels B and C of Table 1 for solar and wind, respectively. The data contain observations for the years 2013 and 2014, as these are the only years for which it is possible to obtain both solar/wind generator characteristics from EIA form 860 and net generation from EIA form 923.

Data on the operating date of each generator is also a key component of the production frontier analysis because it allows us to calculate the age of each solar and wind installation. The constructed age variable reported in Table 1 is measured in months of generator operation, and its inclusion in the frontier analyses allows us to measure average monthly degradation rates of solar and wind generation. The average age of solar arrays in our dataset is slightly over three years and, as column 2 and 3 report, the age of solar arrays installed under mandatory RPS (31 months) is significantly less (p value < 0.005) than those not installed under RPS (70 months). This last feature of the data may simply be an artifact of variable construction, because states did not begin implementing RPS until the 2000s. Specifically, there are 20 states in our dataset with mandatory RPS goals as of 2014 and only 8 states with operable solar arrays and no mandatory RPS in 2014. In addition, roughly 36 of the 138 available observations of arrays installed under a no RPS regime were installed in future RPS states prior to their adoption of mandatory goals.

Roughly 30% of the solar arrays in our dataset have solar tracking systems that adjust the tilt of solar panels throughout the day to track the sun as it moves across the horizon. The remaining majority of solar arrays (70%) are fixed-tilt systems in which solar panels are stationary. The average generating capacity of solar arrays in our dataset is 6.6 MW, and the resulting annual net generation of electricity is roughly 12,644 MWhs. The implied average generation per capacity for the sample is 1,916 MWh/MW, and this number is comparable to the average productivity across RPS and non-RPS arrays equal to 1,966 MWh/MW and 1,680 MWh/MW, respectively (p value =0.145). The solar arrays installed under non-RPS regimes are slightly less productive, but this may simply be due to the fact that they are roughly twice as old as the RPS arrays.

Finally, it is worth noting that the average insolation values as measured at the county level for each solar array in Panel B are higher than the state average insolation values from the state-level data in Panel A even among the states with mandatory RPS goals. This suggests that individual solar arrays are more heavily sited in areas with greater potential for solar production. Similarly, from columns 2 and 3 of Panel B, arrays installed under non-RPS regimes have better insolation on average in comparison to RPS arrays (4.9 vs. 4.7, p value < 0.005), which may explain utilities incentives to install a solar array when there is no mandatory RPS requirement. Of the 1,025 utility solar array observations in our dataset, 887 (87%) were installed under RPS regulatory regimes. This finding is also consistent with the state-level data from panel A suggesting that mandatory RPS are encouraging solar adoption.

Panel C of Table 1 presents an overview of the generator-level data on wind farms available to estimate production frontiers for wind. There are a total of 1,430 utility wind farms available for analysis from 2013 to 2014. Interestingly, 861 (60%) of these observations are of wind farms that were installed without any RPS goals legislated. This feature of the data suggests that mandatory RPS may be a less important factor for wind installation in comparison to solar installation, but it is also worth pointing out that the average generation capacity of wind farms installed in RPS states is nearly twice as large as those installed in non-RPS states at 91 MW versus 58 MW, respectively (p value < 0.005).

Comparing Panel C data on wind farms to Panel B data on solar arrays reveals that the average wind farm is more than 10 times as large as the average solar farm in terms of generating capacity. Specifically, the average wind farm in our data is roughly 71 MW, and the average solar farm is only 7 MW. In addition, wind farms appear to be more efficient on average in comparison to solar arrays, generating 2,884 MWh per MW capacity. Finally, wind farms are older on average in comparison to solar arrays. As mentioned above, the average solar array is roughly 3 years old, and the average wind farm array in Panel C is nearly 7 years old. This finding suggests that wind power became a mature and viable source of electricity generation earlier than solar and is also consistent with the aforementioned fact that the majority of windfarms in our dataset were installed without any RPS requirements.

The average hub height of wind turbines in our dataset is 247 feet, and this measure is slightly greater in RPS turbines (262 feet compared with 238 feet for non-RPS, p value < 0.005). The EIA 860 generator data also includes four wind quality class designations of wind farms defined as follows: high wind quality are those with an average annual wind speed of 10 m/s, medium wind quality indicates turbines with an average annual wind speed of 8.5 m/s, and low and very low wind quality are turbines with average annual wind speeds of 7.5 m/s and 6 m/s, respectively. The majority (62%) of windfarms in our dataset are medium wind quality class farms. Similar to the data on solar insolation from Panel B, windfarms installed under non-RPS regimes tend to have a higher wind quality class, which may help explain the installation of windfarms in non-RPS states. Specifically, roughly 83% of the windfarms in non-RPS states are designated medium to high wind quality, and only 66% of the windfarms in RPS states have medium to high wind quality designations.

The results section that follows presents formal tests for the impact of mandatory RPS goals on renewable adoption, and estimates production frontiers for wind and solar. This frontier analysis is then used to calculate the state-level economic viability of an average wind and solar installation with current electricity prices and projected electricity prices with environmental regulations that price CO_2 emissions at the social cost of carbon.

3. Empirical Results

We conduct three primary analyses to investigate the impact of mandatory state RPS goals on the adoption of renewable energy. First, section 3.A. uses state-level panel data to evaluate the impact of RPS on solar and wind generating capacity. Once the effects of RPS goals are established, section 3.B. uses generator-level windfarm and solar array data to estimate electricity generation production frontiers for solar and wind. Finally, section 3.C. uses the production frontier estimates to forecast state-by-state net electricity generation for an average solar array and windfarm in order to calculate the discounted present value of an average renewable generator over a 25 year lifespan.[4] These present value calculations are then compared to construction costs to evaluate the state-by-state economic viability of renewables with and without adjustments to electricity prices reflecting the social cost of carbon.

3.A. State-level Analysis of Renewable Capacity

Before conducting the primary fixed-effects analysis of the impact of RPS on state renewable generation capacity, a graphical depiction of the treatment effect associated with

[4]The average manufacturing warranty period for a solar panel is 25 years, and wind turbines are estimated to have a lifespan of 20 to 25 years. These estimates are based on NREL expert estimates and are available online at the following: http://www.nrel.gov/analysis/tech_footprint.html (last accessed November, 2016) (see also, Kellogg, et al. 1998; Ailleret 2004; Yang, Lu and Zhou 2007).

mandatory RPS goals is first provided in Figures 1 through 3. The point estimates and confidence intervals plotted in Figures 1 through 3 are estimated using the following event study:

$$Capacity_{e,s,t} = a + \beta * Electricity\,\mathrm{Price}_{\mathrm{s,t}} + \sum_{n=-7}^{7} \partial_n I[RPSY_{s,t} = n] + T_t + S_s + \varepsilon_{s,t}\ , \quad (1)$$

where the installed generator capacity of energy source $e \in \{Wind, Solar\}$ in state *s* and year *t* is a function of average state electricity prices for all consumer types, $Electricity\,\mathrm{Price}_{\mathrm{s,t}}$, and year and state fixed effects T_t and S_s, respectively. In estimating equation (1) the sample is limited to non-RPS states and RPS states within +/- 7 years of implementing the initial mandatory RPS goal. As such, $RPSY_{s,t}$ is equal to the number of years pre or post implementation of the mandatory RPS goal, and $I[RPSY_{s,t} = n]$ is an indicator function equal to one for observations that are n years away from the RPS implementation date. The omitted $RSPY_{s,t}$ indicator variable is one year prior to the initial mandatory RPS goal, and the estimated coefficients plotted in Figures 1-3 can all be interpreted as the relative effects of RPS to the omitted category one year prior to treatment. Finally, $\varepsilon_{s,t}$ is a random error component clustered at the state level to allow for within-state intertemporal correlation.

Figure 1, which presents the event study results for solar capacity, indicates there is no statistically significant difference in installed state solar capacity prior to the implementation of mandatory RPS goals. Interestingly, the results in Figure 1 also indicate that it takes roughly five years following the initial RPS implementation for mandatory RPS goals to have any statistically significant effect on solar capacity.[5] Beginning in year 5 of post RPS implementation, solar capacity increases roughly 19 MW in comparison to the one year pre-treatment category. This

[5]The $RSPY_{s,t}$ indicatory variable for five years post treatment is only statistically significant at the 10% level, but the controls for six and seven years post treatment are both significant at the 5% level as indicated in Figure 1.

steady increase continues in years 6 and 7 where we see a 38 MW and 67 MW increase in capacity, respectively.

In order to investigate a possible explanation for the lag between RPS implementation and increased solar capacity, Figure 2 presents similar event study results using the same specification presented in equation (1), except the size of the mandatory RPS goal is the dependent variable of interest. As Figure 2 illustrates there is a steady increase in RPS stringency over time. On average during the first year of RPS implementation roughly 3.6 percent of state electricity generation is required to be from renewable sources. By years five, six, and seven the required renewable percentages increase to 6.3%, 7.3%, and 7.9%, respectively. These RPS goals can be compared to the actual state renewable mix collected by the US Environmental Protection Agency (EPA) as part of their Emissions & Generation Resource Integrated Database (eGRID).[6] For the most recent round of eGRID data collected in 2012, the median percentage of renewable generation for states with mandatory RPS goals is 7.4%. As a result, the 5-year lag between RPS implementation and impact on solar capacity can largely be attributed to the fact that RPS goals are likely to be non-binding for utilities in the majority of states until approximately six to seven years post adoption.

Finally, Figure 3 presents the event study for wind capacity, and with the exception of the first two years of RPS implementation, the results do not generally find any statistically significant increase in wind capacity post RPS adoption. Even more concerning in Figure 3 is the presence of a statistically significant and increasing pre-treatment trend in wind capacity. This feature of the event study for wind generation is consistent with the generator-level summary statistics on windfarms and solar arrays from Table 1. Recall from Table 1 that the average age of utility-level solar arrays in the US as of 2014 is three years, but average windfarms are nearly eight years old.

[6]eGRID data is available online at the following: https://www.epa.gov/energy/egrid (last accessed November, 2016).

Taken together the results in Figure 3 and average age of respective renewable generators suggests that factors other than mandatory state RPS regulations are driving the increased state wind generation capacity over the 1984 to 2014 time period.

In order to further investigate the impact of state RPS regulations on the expansion of renewable generation capacity, the following fixed effects estimator is utilized:

$$Capacity_{e,s,t} = a + \beta * Electricy\ \mathrm{Price}_{s,t} + \partial * Mandatory\ RPS\ Goal_{s,t} + T_t + S_s + \varepsilon_{s,t}, \qquad (2)$$

where all variables are defined as in equation (1) and an indicator variable is included that is equal to one for all state-year observations with mandatory RPS goals enforced, *Mandatory RPS Goal*$_{s,t}$. As such, the key coefficient of interest is ∂ measuring the impact of RPS goals on state renewable capacity, or the average treatment effect on the treated. Equation (2) is estimated using the full 31 year panel of state renewable capacity from 1984 to 2014.

Results from equation (2) are presented in Column 1 of Table 2. From Panel A of Table 2, state RPS goals are estimated to increase solar capacity by roughly 50.8 MW (95% confidence interval of 2.7 MW to 98.9 MW). To put this number in context, the average installed solar capacity among the 50 US states and DC in 2014 is 204 MW, suggesting that RPS-induced increases to solar capacity are non-trivial. This finding is on par with the event study analysis of solar capacity presented in Figure 1 where there was a delayed uptick in solar capacity beginning five years post RPS enactment that culminated in a 67 MW increase in capacity in year 7.

Column 1 of Table 2 Panel B presents fixed effects estimates of the impact of mandatory RPS goals on state wind capacity. RPS goals are estimated to increase wind capacity by roughly 639 MW on average, but the effect is statistically indistinguishable from zero at any conventional significance level. This finding is not surprising given the fact that the event study in Figure 3 suggests that the major increases in wind capacity in RPS states occurs prior to RPS enactment.

While an average effect is informative, this estimate is likely to mask significant between-state heterogeneity. Specifically, one could conjecture that RPS would increase capacity of a specific renewable energy source in states where the resource is abundant (high-insolation states for solar and high-wind potential states for wind) while having little or no effect in states with low solar/wind resources. Column 2 of Table 2 tests for heterogeneous treatment effects of RPS goals dependent on state-level insolation levels and wind potential. As the insolation and wind potential variables are normalized to have zero mean and standard deviation of 1, we now interpret the coefficient for *Mandatory RPS Goal*$_{s,t}$ as the effect of RPS on capacity for a state with average levels of the resource (e.g., Tennessee and Oregon for solar; Illinois and Arkansas for wind).

As Column 2 of Panel A indicates, RPS goals increase solar capacity by roughly 47 MW for the average-insolation states, though this effect is only marginally significant (p value = 0.056). The interaction of RPS and insolation variables is positive and highly significant, indicating that RPS drives capacity increases for high-insolation states more than their low-insolation counterparts. Indeed, using Wald tests we find that states approximately one standard deviation below mean insolation (e.g., Wisconsin and North Dakota) have no statistically significant effect from RPS while states one standard deviation above mean insolation levels (e.g., Colorado and Oklahoma) have a positive and highly significant effect from RPS.[7] Lastly, the interaction of RPS and wind potential has a negative and significant impact on installed solar capacity. This provides evidence of substitution effects between renewable resources in the face of RPS, and suggests that a one standard deviation reduction in wind potential results in 54 MW (44%) increase in installed solar capacity in states with mandatory RPS goals.

[7] For states one standard deviation below average insolation, the point estimate is -74.233 (p value = 0.140). For states one standard deviation above average insolation, the point estimate is 168.585 (p value = 0.013).

Column 2 of Panel B shows a positive and significant effect of RPS on wind capacity for the average-wind potential state. Additionally, the interaction of RPS and wind potential shows that the effect of RPS is likely heterogeneous. While these results are as one might anticipate, we are somewhat skeptical and hesitant to draw strong conclusions for the effects of RPS on wind capacity. In the case of wind, it is perhaps more likely that these results indicate more correlation than direct cause, as our event study suggests an increasing pretreatment trend in capacity.

Finally, Column 3 of Table 2 tests for heterogeneous treatment effects five or more years post mandatory goal adoption. This decision is based on the observation that RPS standards become more stringent over time as illustrated in the goal event study of Figure 2. For solar, the results suggest that mandatory RPS goals do not have a statistically significant effect on capacity during the first four years of solar adoption. However, for states that have had mandatory RPS goals in place for five or more years, solar capacity is estimated to increase by 260.9 MW and the effect is statistically significant at the 10% level. Alternatively, for wind capacity there is no statistically significant evidence of increased wind adoption due to tightening RPS standards. Specifically, the results from Column 3 of Panel B Table 2 do not find any statistically significant impact of mandatory RPS goals during the first four years of the program or thereafter. Thus, the evidence for RPS impacts are stronger for solar than for wind capacity.

The following subsection turns from statewide capacity data to generator-level wind and solar data. We estimate production frontiers in order to shed light on the technologies affecting wind and solar efficiency, and also estimate the key parameters (net generation and technology degradation) necessary for evaluating the economic viability of the alternative renewable technology.

3.B. Generator-level Production Frontier Estimates for Wind and Solar

Following the generalized models of Aigner, Lovell and Schmidt (1977) and Meeusen and Van den Broeck (1977) we estimate a Cobb-Douglas production frontier for renewable energy net electricity generation of the following form:

$$\ln MWh_{g,s} = a + X_{g,s}\beta + S_s - u_g + v_g \,. \qquad (3)$$

In equation (3) the natural log of megawatt hours of net electricity generation from generator g in state s is a function of a vector of observable explanatory variables, $X_{g,s}$, state fixed effects, S_s, productive inefficiency of the generator, $u_{g,s}$, and a random error component, $v_{g,s}$, that is clustered at the generator level. When estimating the production frontiers for solar generation, generator characteristics include controls for solar tracking technology, county-level insolation, age (in months) of the solar array, and the natural log of the solar array's nameplate generating capacity. For wind generation, generator characteristics include average turbine height of the wind farm, wind quality classification of the wind farm, age of the wind farm, and the natural log of nameplate capacity.

Panel A of Table 3 presents the production frontier estimates for solar arrays using three alternative distributional assumptions for the stochastic inefficiency term, $u_{g,s}$. Column 1 presents results for a baseline OLS specification that does not impose any distributional assumptions on inefficiency. The results indicate that solar tracking systems increase net generation by approximately 12.5% and this effect is statistically significant at the 1% level.[8] Solar insolation has a positive effect on net generation as expected, but the estimated effect is statistically indistinguishable from zero.

[8] Following Halvorsen and Palmquist (1980), the percentage change in net generation for dummy variables is calculated as the exponent of the coefficient point estimate for the dummy variable minus one.

Each additional month of solar operation is estimated to reduce net generation by approximately 0.2%, which we attribute to degradation of the solar panels over time. The implied annual degradation rates are presented in the last row of panel A, and these annual rates suggest that solar arrays lose approximately 2.7% of their generating capabilities annually. One concern with interpreting the coefficient on solar array age as an estimate of panel degradation is that older solar technology may simply be less efficient that more modern panels. In order to investigate this possibility, the sample was further limited to solar arrays constructed post-2000, and although not presented in Table 3, the estimated effect of solar age was robust the exclusion of pre-2000 solar generators. Specifically, in the post-2000 dataset annual degradation rates were actually estimated to be 4.0% (95% confidence interval of 1.8% to 6.2%), and the 95% confidence intervals overlap those presented in the full sample from Table 3. Finally, generating capacity is estimated to result in roughly constant returns to scale, because a 1% increase in nameplate capacity results in a roughly 1.03% (95% confidence interval of 1.00 to 1.05) increase in net solar generation.

The stochastic frontier model presented in equation (3) suggests that in the presence of generator inefficiency, the OLS residuals will be leftward skewed. Column 1 of Table 3 also presents the skewness of the predicted OLS residuals, and the residuals are indeed statistically significantly skewed left.[9] In order to more thoroughly account for the presence of generator inefficiency, columns 2 and 3 of Table 3 present results for stochastic frontier estimates of equation (3) where the inefficiency term is assumed to follow a half-normal and exponential distribution, respectively (see Aigner, Lovell and Schmidt 1977; Meeusen and Van den Broeck 1977; Kumbhakar, Wang and Horncastle 2015 for a thorough review of the alternative distributions). Overall, results from the half-normal and exponential solar frontier models are similar to the

[9] Tests for significance of skewness and kurtosis were conducted using the method proposed by D'agostino, Belanger and D'Agostino Jr (1990).

baseline OLS results presented in Column 1. One noticeable difference, however, is that a one unit increase in county solar insolation is estimated to increase net generation by 10.3% and 9.6% in the half normal and exponential models, respectively, and the effects are statistically significant at the 1% level. Both alternative stochastic frontier models find similar effects of solar tracking systems (11.9% to 12.5% increase in net generation), and both models exhibit constant returns to scale in terms of nameplate capacity.

Interestingly, the average annual solar panel deterioration rates are roughly 0.5 percentage points lower in the half-normal and exponential models in comparison to the OLS results. This finding suggests that the array age may be correlated with idiosyncratic generator inefficiency, but we caution this interpretation by noting that the 95% confidence intervals on the age parameter overlap across all specifications presented in Panel A of Table 3. Finally, Table 3 presents estimates of the average technical efficiency of solar arrays calculated over the data sample for the half-normal and exponential models.[10] The half-normal results suggest that on average solar arrays are 75% efficient while efficiency estimates for the exponential model are slightly higher, suggesting that average solar arrays are roughly 85% efficient.

It should be noted that among the two alternative stochastic frontier models, the exponential model parameter estimates more closely resembles OLS results that do not impose distributional assumptions on the inefficiency term. This finding is driven by the lower (in absolute terms) inefficiency estimates in the exponential model where generators are estimated to be closer to the production frontier (100% efficient) on average. Figure 4 presents this artifact more clearly by plotting the kernel density estimates of the distribution of estimated individual solar generator

[10] Individual generator inefficiency estimates, $u_{g,s,}$ are calculated using the method of Jondrow, et al. (1982), and technical efficiency calculated as $e^{-u_{s,g}}$ is estimated following the method of Battese and Coelli (1988).

technical efficiency. The exponential distribution estimates of technical efficiency are more heavily skewed toward the frontier, and are also more peaked indicating a larger portion of solar generators closely clustered near the frontier.

Panel B of Table 3 presents the generation frontier estimates for windfarms, and the results share some similarities to the solar frontier estimates from Panel A. As with the solar data, OLS generates residuals that are skewed leftward, indicating that a stochastic frontier model is appropriate. Windfarms also exhibit roughly constant returns to scale in generator capacity, and the average technical efficiency estimates follow a similar pattern with average windfarms operating at roughly 75% efficient in the half-normal model, and 82% efficient in the exponential model. Figure 5 plots the kernel density estimates for the wind technical efficiency distribution, and the results are also similar to the density estimates for solar technical efficiency, except the wind distributions do exhibit slightly fatter tails towards less efficiency in comparison to solar. The remaining coefficients are of the expected sign and significance for wind. Specifically a 1 foot increase in turbine height increases net generation by 0.1% to 0.2% and the effect is statistically significant at the 1% level. Lower wind quality classified turbines are generally less efficient than the omitted high wind quality class, and for each additional month of operation wind turbines lose approximately 0.07% to 0.08% of generating ability.

Interestingly, across all models the average annual deterioration rates for wind farms are 0.8% to 1.0%. These deterioration rates are more than 50% lower than the estimated deterioration rates reported for solar arrays in Panel A of Table 3. This result is particularly surprising given the additional moving parts of wind turbines in comparison to fixed-tilt solar arrays, but it may simply reflect better maintenance of windfarms in comparison to solar. Indeed according to the

EIA (2016), the average annual operating and maintenance costs for wind are more than double the operating and maintenance costs for solar at $45.98/kW and $21.33/kW, respectively.

It should also be noted that the stochastic frontier models can accommodate different levels of output efficiency depending on whether the wind farms and arrays were installed under RPS regimes. One concern is that RPS goals may lower the technical efficiency of wind and solar installations. Although not reported in Table 3, we test this hypothesis thoroughly by estimating specifications that included controls for RPS directly in the frontier as well as allowing RPS to be a determinant of the standard deviation of our generator-level technical efficiency variable, $u_{g,s}$. The hypothesis that RPS decreases the efficiency of an array would be supported by a negative coefficient for RPS regarding net generation and a positive coefficient for RPS in the standard deviation of $u_{g,s}$.[11] Overall, we find no evidence that mandatory RPS goals have any statistically significant effect of generator efficiency in any of the half-normal and exponential specifications. This finding holds when considering both the effect on mean net generation and the effect on the standard deviation of technical efficiency, and formal statistical tests of this finding are presented in the last rows of Table 3.

3.C. Present Value of Average Renewable Generation Installations by State

While our lack of evidence supporting the hypothesis that RPS reduces the technical efficiency of installed solar and wind power is perhaps heartening to proponents of RPS policies, technical efficiency is not sufficient to ensure economic efficiency. RPS policies that lead to the establishment of technically efficient but unprofitable installations are potentially problematic.

[11] This effect suggests that arrays built under mandatory RPS goals would have greater variance, meaning more arrays would be further from the production frontier and thus less efficient, compared with the control of no mandatory RPS goal.

With this in mind, we turn to our third research question: Do RPS encourage unprofitable (i.e., negative net present value (NPV)) solar and wind installations?

To answer this question we use the stochastic frontier model from section 3.B to estimate the expected present value of net benefits from a 3 MW solar array and a 30 MW wind farm for each state in our generator-level dataset. These estimates account for state-level variation in renewable resource potential and electricity price.[12] Combining this estimate with our average annual deterioration estimates and using a net discount rate of 2.3%, we estimate a state-specific present value of discounted electricity revenue (net annual maintenance costs) generated by the installation over the 25 year warrantied lifespan of an array.[13]

Panel A of Tables 4 and 5 describe our findings for solar. We generate four different estimates based on assumptions regarding construction costs and electricity prices. Specifically, for cost estimates we use either the EIA's estimates of current construction costs (Column (1) in each table) or the NEMS forecasted future construction and maintenance costs (Column (2) in each table). For electricity prices, we use either current electricity prices (Table 4) or projected electricity prices that include a $41.90 per ton social cost of carbon (SCC, presented in Table 5).[14] The projected SCC electricity prices vary by state and are calculated using the current 2014 electricity prices reported in SEDS adjusted by the state-specific CO_2 emissions factors for electricity generation available in the most current 2012 EPA Emissions and Generation Resource

[12] State electricity prices are available for download from the EIA's State Energy Data System: http://www.eia.gov/state/seds/ (last accessed, Jan. 2017).
[13] The 2.3% net discount rate is based on the lagged five year averages of bond yields for 20 year municipal bonds (4.1%) and the CPI inflation rate for electricity (1.7%), available online at the following: https://fred.stlouisfed.org/series/WSLB20 (last accessed, Jan. 2017), https://www.bls.gov/cpi (last accessed, Jan. 2017).
[14] The $41.90 estimate of the SCC is based on the current median Interagency Working Group on the Social Cost of Carbon estimates and the calculations used in the EPA's Clean Power Plan adjusted for inflation using the CPI to 2014$ (United States Government Interagency Working Group on Social Cost of Carbon 2013; U.S. Environmental Protection Agency 2015).

Database estimates [*SCC Price = Elec. Price ($/MWh) + CO_2 Emissions Rate (Tons/MWh)*SCC($/Ton)*].[15] The values presented in Panel A of each table, in millions of 2016 dollars, represent the present value of revenue net annual maintenance costs (but not accounting for construction costs) from a 3 MW solar array. We compare these numbers to the average construction costs as estimated by EIA and NEMS. Shaded values indicate states whose present value of revenues net maintenance costs exceed construction costs (and thus have a positive NPV) for the given construction cost-electricity price combination.

Several trends are worth noting. First, as one would expect, current construction cost estimates are higher than NEMS forecasted future construction costs for solar. As a result, more states have positive NPV for the array in question when using the NEMS data. Second, including the SCC increases electricity prices, so the average array has a positive NPV for more states when including the SCC than when using current electricity prices. Third, the relative ranking of states changes between Tables 4 and 5. This is because the impact of including the SCC on average electricity prices varies by state based on the current fuel mix of each state. Thus, states with a high-carbon fuel mix see a higher increase in electricity price with SCC pricing included.

There is clear evidence that both state electricity prices and solar insolation impact the economic viability of solar. This is illustrated in Panel B of Tables 4 and 5, which shows a scatter plot of states in our dataset plotted by electricity price and insolation level. States are shaded to indicate the degree of economic viability, with dark shading indicating states that have positive NPV at current and forecasted future construction costs, medium shading indicating states that

[15] The EPA Emissions and Generation Resource Database (eGRID) is available online at the following: https://www.epa.gov/energy/egrid (last accessed Jan. 2017). These estimates are admittedly coarse and implicitly assume the marginal fuel source for each state has the same emissions rate as the average source. Other work has shown that emission rates for the marginal fuel source can vary by time of day as well as the variability of the renewable source being installed (Cullen 2013; Kaffine, McBee and Lieskovsky 2013; Novan 2015). As a result, while our measure results in a constant SCC value having heterogeneous impacts on state electricity prices, it is possible a more nuanced calculation would achieve even greater heterogeneity.

have positive NPV only using forecasted future construction costs, and light shading indicating states that have negative NPV under both cost assumptions. The scatter plots illustrate how states in the third and fourth quartiles for electricity price and insolation tend to be economically viable, while states with cheap electricity and low insolation are not economically viable destinations for solar. The scatters plot also indicate which states currently have RPS in place. While many RPS states (Hawai'i, California, and Connecticut for example) have positive NPV for solar, other RPS states (Oregon, Illinois, and Delaware for example) have clear negative NPV for solar.

We examine the extent to which RPS encourages economically inefficient solar production by identifying whether the policy increases capacity in states with negative NPV for our representative array. If we use the naïve assumption that mandatory RPS goals have a homogeneous impact on installed solar capacity (as indicated in the model from Column (1) of Table 2) and conclude that RPS increases solar capacity in all states, there is strong support that RPS encourage the building of inefficient arrays. Of the 21 states in our generator-level dataset with RPS goals in place, at least 7 and as many as 17 are negative NPV states. However, our model that allows for heterogeneous effects of RPS by resource abundance suggests that RPS impacts on installed capacity are far from uniform. States with high levels of solar potential install more solar, while states with high levels of wind potential install less solar. We next account for this heterogeneity by estimating the net impact of RPS on each state.[16] The results, shown in Table 6, are instructive. We find that RPS increases solar capacity in only 11 of 28 states, specifically states with high levels of solar insolation and/or low wind potential. States with low solar

[16] This is achieved using Wald tests. Specifically, for a state with normalized insolation value X and normalized wind potential Y, We use the model from Table 2, Panel A, Column 2 and test the following hypothesis
H_0: $\beta_{MandatoryRPSGoal} + X^*\beta_{Mandatory^*Insolation} + Y^*\beta_{Mandatory^*Wind} = 0$.

insolation and/or high wind potential do not experience a statistically significant increase in capacity.

When using current electricity prices, illustrated in Panel A of Table 6, we find that RPS is a mixed bag in terms of economic efficiency. Six of the eleven states that we would expect to see[17] an RPS-induced boost in solar are negative NPV states. This is troubling, as it suggests RPS may lead to inefficient allocation of resources, especially if it is expanded to sunny and cheap-energy states in the Southeastern US. Conversely, Panel B of Table 6 provides the same analysis but includes the SCC in electricity prices. While including SCC pricing still results in 8 of 28 states having negative NPV, we now find that seven of these states receive no increase in solar capacity from RPS. Of the eleven states that increase solar capacity as a result of RPS goals, only Oregon is a negative NPV solar state.

4. Discussion and Conclusion

Our analyses reveal several relevant findings, some expected but others less so. First, we find that mandatory RPS goals, on average, increase installed solar capacity. This was expected, though because RPS legislation allows for a variety of renewable sources (wind, hydro, biofuels, etc.) when meeting RPS goals, the result was not a foregone conclusion. We also find that examining the average effect of RPS masks significant heterogeneity among states. Specifically, RPS goals have a greater positive impact on solar capacity in states endowed with larger solar resources and scanter wind resources. While we find some positive impacts of RPS on wind

[17] We say "expect to see" because not all states in Table 6 have RPS. For FL, GA, SC and NM we are projecting that they would see an increase in solar capacity if they implemented RPS, based on their available solar and wind resource.

capacity, this evidence is less robust. As with solar, RPS goals have a heterogeneous effect on installed wind capacity, with states endowed with greater wind resources experiencing larger increases as a result of RPS goals. We also find that the effect of RPS goals on solar capacity is typically delayed; initial goals of 2-5% often do not spur greater solar capacity, as many states already have renewable sources as a small percentage of their electricity generation. Indeed, our analysis suggests that RPS goals tend to increase solar capacity once the goals become binding, meaning they mandate renewable mixes above what is currently being produced in the state.

Our dual findings, that the evidence of RPS increasing capacity is stronger for solar than for wind and that the effect of RPS on solar capacity is delayed, can be at least partially explained by differences in the maturity of these technologies during the study period. From 2005-2015, a time period where the majority of state RPS goals began taking effect, the annual capital costs associated with wind power were relatively constant while annual capital costs for utility-scale solar decreased in excess of 20% (EIA 2016, Figures A-4 and A-12). Similar decreases in the cost of wind turbines occurred earlier, before most RPS goals came into effect.

Turning to our generator-level analysis, we find no impact of RPS goals on the technical efficiency of solar or wind installations. Using a stochastic frontier model, we find no difference in efficiency measures between installations built in state-years with RPS goals and installations built in state-years without goals.

We next estimated the economic efficiency of wind and solar. Using state-level insolation and electricity prices, along with construction and maintenance costs, we calculated the NPV of benefits for a 3 MW solar installation and a 30 MW wind installation with the goal of examining whether RPS leads to an inefficient allocation of resources via increasing renewable capacity in states with negative NPV. We focus primarily on solar, as we find wind to be cost competitive in all 39 states with installed wind capacity in our dataset. Using current electricity prices, we find negative NPV for 57% of the states (16 of 28) in our dataset. This number drops to 29% (8 of 28) if we use electricity prices that include the social cost of carbon. Crucially, RPS goals do not increase solar capacity in all states. Indeed, states with greater solar resources are both more likely to have positive NPV and more likely to respond to RPS goals with greater solar capacity. When using prices that include the social cost of carbon, we find that an RPS goal increases capacity in 11 of the 28 states in our sample. Of these 11 states, only Oregon has negative NPV for solar. Among states that don't see an increase in solar in response to RPS goals, a much larger percentage of states (7 of 17) have negative NPV.

Our findings support economists' traditional view of legislative mandates like RPS: that they tend to be inefficient but this inefficiency is mitigated as the regulation becomes broader and more flexible. RPS policies, while diverse, tend to possess two important similarities that make them flexible. First, they allow a variety of renewable sources to meet the goal.[18] Second, they allow for the purchase and sale of renewable energy credits (RECs) between states. Thus, states with a comparative advantage in renewable energy can specialize and sell any excess RECs to states with poor renewable resource endowments. While these characteristics are not universal (for example, New York's RPS does not allow for interstate REC trading), they are common to the vast majority of state policies and likely reduce inefficient misallocation of resources.

While our findings are instructive, several limitations exist in our data. Our installation-level data (and the state-level panel which was built from it) consist of utility-owned wind and solar installations. This data could be expanded to other utility-owned renewable resource installations (biofuel, for instance), as well as renewable installations that are not utility-owned,

[18] While many RPS laws include solar carve-outs (portions of the goal that must be met with electricity generated from solar), these carve-outs tend to be small relative to the total goal.

for a more comprehensive picture of the impact of RPS. When constructing NPV, while we have state-level electricity prices, our estimates of construction and maintenance costs are at the national level. It may be the case that these costs do not vary much by state or region, but more finely segmented cost data would shed further light on state-level heterogeneity in NPV from solar. While our findings shed light on the heterogeneous impacts of RPS, there are more questions worth asking regarding these increasingly popular state programs. Further research examining the impact of RPS on both capacity and efficiency is warranted.

Table 1. Average State and Generator-level Characteristics

Variable Name (Measurement unit)	Full Sample (Std. Dev.)	Mandatory RPS (Std. Dev.)	No RPS (Std. Dev.)
	Panel A: State-level Panel Data		
Solar Capacity	20.487	123.380	5.585
(MW)	(188.490)	(507.711)	(41.829)
Wind Capacity	258.803	1,212.131	120.740
(MW)	(966.688)	(2,305.033)	(391.091)
Insolation	0	0.036	-0.005
	(1)	(1.187)	(0.970)
Wind Potential	0	-0.127	0.018
	(1)	(0.932)	(1.009)
Electricity Price	77.746	115.864	72.226
($/MWh)	(30.135)	(41.848)	(23.369)
Number of Obs.[a]	1,581	200	1,381
	Panel B: Generator-level Solar Arrays		
MWh	12,643.642	11,762.064	18,310.017
	(27,541.648)	(27,272.171)	(28,674.592)
Solar Tracking	0.302	0.292	0.370
	(0.460)	(0.455)	(0.484)
Capacity	6.645	5.983	10.900
(MW)	(14.092)	(13.369)	(17.535)
Age	36.667	31.407	70.478
(Months)	(42.029)	(17.616)	(99.325)
Insolation	4.712	4.683	4.896
(KWh/m^2/day)	(0.730)	(0.723)	(0.754)
Number of Obs.	1,025	887	138
	Panel C: Generator-level Wind Farms		
MWh	205,300.501	260,219.826	169,006.545
	(225,197.599)	(242,647.704)	(205,101.399)
Height	247.283	261.784	237.701
(Feet)	(45.688)	(32.635)	(50.338)
Capacity	71.175	90.659	58.299
(MW)	(73.615)	(82.811)	(63.705)
Age	82.455	46.425	106.266
(Months)	(72.393)	(25.673)	(82.742)
Very Low Wind	0.070	0.081	0.063
	(0.255)	(0.273)	(0.243)
Low Wind	0.165	0.255	0.106
	(0.371)	(0.436)	(0.308)
Medium Wind	0.617	0.548	0.662
	(0.486)	(0.498)	(0.473)
High Wind	0.148	0.116	0.170
	(0.355)	(0.320)	(0.375)
Number of Obs.	1,430	569	861

[a] This describes the number of observations for all variables except *Insolation*, for which data from Alaska is not available.

Table 2. State-level Estimates of the Impact of Mandatory RPS Goals on Renewable Capacity[a]

Variable Name	**Estimated Coefficients (Std. Errors)**		
	(1)	(2)	(3)
		Panel A: Installed Solar Capacity (MW)	
Mandatory RPS Goal	50.787**	47.176*	3.485
	(24.550)	(24.101)	(12.582)
*Mandatory*Insolation*	---	121.409**	---
	---	(52.800)	---
*Mandatory*Wind Potential*	---	-53.729**	---
	---	(22.559)	---
*Mandatory*6-years post*	---	---	260.944*
	---	---	(144.164)
Observations	1,581	1,550	1,581
R-squared	0.069	0.134	0.121
Number of States	51	50	51
		Panel B: Installed Wind Capacity (MW)	
Mandatory RPS Goal	638.984	761.971***	595.397
	(406.331)	(204.788)	(368.173)
*Mandatory*Insolation*	---	204.181	
	---	(184.291)	
*Mandatory*Wind Potential*	---	1,808.937***	
	---	(268.247)	
*Mandatory*6-years post*	---	---	240.457
	---	---	(447.781)
Observations	1,581	1,550	1,581
R-squared	0.267	0.676	0.269
Number of States	51	50	51

[a]Statistical significance at the 10%, 5%, and 1% level are represented by *, **, and ***, respectively. Although not reported, each model presented also includes a full set of state and year fixed effects and controls for state electricity prices as indicated in equation (2).

Table 3. Stochastic Frontier Estimates for Renewable Energy Efficiency[a]

Variable Name	**Estimated Coefficients (Std. Errors)**		
	(1) OLS	(2) Half Normal	(3) Exponential
	Panel A: Solar Frontier Results		
Solar Tracking	0.118***	0.112***	0.118***
	(0.031)	(0.019)	(0.015)
Insolation	0.071	0.103***	0.096***
	(0.057)	(0.030)	(0.028)
Age	-0.002***	-0.002***	-0.002***
	(0.0003)	(0.0002)	(0.0001)
Ln(Capacity)	1.026***	1.007***	1.024***
	(0.012)	(0.011)	(0.007)
σ_u	---	0.532	0.207
σ_v	---	0.138	0.126
Skewness	-8.3***	---	---
Observations	1,025	1,025	1,025
R-squared	0.879	---	---
Average Technical Efficiency	---	75.0%	84.6%
Average Annual Deterioration	-2.7%	-2.1%	-2.2%
RPS Goal Effects Generation	---	No (p = 0.984)	No (p = 0.716)
RPS Goal Effects σ_u?	---	No (p = 0.348)	No (p = 0.768)
	Panel B: Wind Frontier Results		
Height	0.002***	0.001***	0.001***
	(0.0004)	(0.0002)	(0.0002)
Medium Wind	-0.073	-0.046*	-0.040**
	(0.048)	(0.024)	(0.019)
Low Wind	-0.027	-0.013	0.004
	(0.049)	(0.026)	(0.021)
Very Low Wind	-0.171***	-0.104***	-0.074***
	(0.049)	(0.032)	(0.028)
Age	-0.001***	-0.001***	-0.001***
	(0.0002)	(0.0001)	(0.0001)
Ln(Capacity)	1.051***	1.013***	0.996***
	(0.016)	(0.006)	(0.004)
σ_u	---	0.478	0.231
σ_v	---	0.086	0.100
Skewness	-7.7***	---	---
Observations	1,430	1,430	1,430
R-squared	0.960	---	---
Average Technical Efficiency	---	75.2%	82.3%
Average Annual Deterioration	-0.8%	-1.0%	-0.8%
RPS Goal Effects Generation	---	No (p = 0.414)	No (p = 0.564)
RPS Goal Effects σ_u?	---	No (p = 0.615)	No (p = 0.922)

[a]Statistical significance at the 10%, 5%, and 1% level are represented by *, **, and ***, respectively. Although not reported, each model presented also includes a full set of state fixed effects as indicated in equation (3).

Table 4. Economic Viability of a 3 MW Solar Array with Current Electricity Prices

Panel A: Present Value Calculations under Current and NEMS Forecasted Construction Costs[a]			*Panel B: Scatter Diagram of Economic Viability by State Price and Insolation Quartiles*[b]				
	(1)	**(2)**		**Insolation**			
State (Capacity Share)	**PV Curr. ($Mill.)**	**PV NEMS ($Mill)**	**Current Electricity Price**	*Quartile1*	*Quartile2*	*Quartile3*	*Quartile4*
WA (0.2%)	5.42	4.40	*Quartile1*		WA†		
WI (0.2%)	5.63	4.61			OR†		
TN (0.3%)	5.75	4.73					TX†
OH (1.5%)	5.84	4.82			IN		
IN (1.8%)	6.44	5.43				NC†	
IL (0.3%)	6.52	5.50				TN	
PA (3.0%)	6.62	5.60		IL†			
OR (1.0%)	6.64	5.62	*Quartile2*		MN†		
MN (0.2%)	6.76	5.74				SC	
TX (1.2%)	7.13	6.11					NM
SC (0.2%)	7.33	6.31					NV†
GA (1.3%)	7.36	6.34		OH†			
NC (12.8%)	7.36	6.35				GA	
CO (2.5%)	7.84	6.82				CO†	
FL (1.3%)	7.85	6.83	*Quartile3*				AZ†
DE (0.8%)	8.40	7.38			PA†		
MD (2.5%)	8.93	7.91		WI†			
NJ (15.6%)	9.31	8.29					FL
NM (4.3%)	9.61	8.59				DE†	
RI (0.5%)	9.73	8.71				MD†	
NY (1.2%)	10.11	9.09			NJ†		
NV (1.5%)	10.33	9.31	*Quartile4*	VT			
AZ (6.4%)	10.54	9.53					CA†
MA (9.7%)	11.03	10.01		MA†			
VT (0.7%)	12.12	11.10		RI†			
CT (0.2%)	12.68	11.67			NY†		
CA (28.1%)	14.29	13.27		CT†			
HI (1.0%)	26.53	25.51					HI†

[a]Shaded cells indicate states with positive NPV. Average current costs for a 3 MW solar array are $10.75 million, and NEMS forecasted construction costs are $7.50 million.

[b] Darker shading indicates increased NPV. Specifically, black shading indicates positive NPV of solar installations under current construction costs, dark grey indicates positive NPV of solar using NEMS forecasted construction costs, and light grey states are those where solar has negative NPV. States with mandatory RPS goals are indicated using †.

Table 5. Economic Viability of a 3 MW Solar Array with Social Cost of Carbon Electricity Prices

Panel A: Present Value Calculations under Current and NEMS Forecasted Construction Costs[a]			*Panel B: Scatter Diagram of Economic Viability by State Price and Insolation Quartiles*[b]				
				Insolation			
State (Capacity Share)	**(1) PV Curr. ($Mill.)**	**(2) PV NEMS ($Mill)**	**SCC Electricity Price**	*Quartile1*	*Quartile2*	*Quartile3*	*Quartile4*
WA (0.2%)	5.62	4.60	*Quartile1*		WA†		
OR (1.0%)	7.05	6.04			OR†		
WI (0.2%)	7.15	6.13				SC	
TN (0.3%)	7.16	6.14		IL†			
OH (1.5%)	7.86	6.84				NC†	
IL (0.3%)	7.96	6.94					TX†
PA (3.0%)	8.05	7.03					NV†
MN (0.2%)	8.48	7.46	*Quartile2*			TN	
SC (0.2%)	8.55	7.54			MN†		
GA (1.3%)	9.03	8.01				GA	
NC (12.8%)	9.11	8.09					AZ†
TX (1.2%)	9.12	8.10			PA†		
IN (1.8%)	9.28	8.26			IN		
FL (1.3%)	9.58	8.57					FL
NJ (15.6%)	10.03	9.01	*Quartile3*	OH†			
DE (0.8%)	10.35	9.33					NM
CO (2.5%)	10.56	9.54		WI†			
MD (2.5%)	10.75	9.73				CO†	
NY (1.2%)	10.84	9.83				DE†	
RI (0.5%)	10.93	9.91				MD†	
VT (0.7%)	12.13	11.11		VT			
NV (1.5%)	12.38	11.36	*Quartile4*		NJ†		
MA (9.7%)	12.39	11.37					CA†
AZ (6.4%)	12.84	11.83		MA†			
NM (4.3%)	13.27	12.25		RI†			
CT (0.2%)	13.50	12.49			NY†		
CA (28.1%)	15.42	14.40		CT†			
HI (1.0%)	28.97	27.95					HI†

[a]Shaded cells indicate states with positive NPV. Average current costs for a 3 MW solar array are $10.75 million, and NEMS forecasted construction costs are $7.50 million.

[b] Darker shading indicates increased NPV. Specifically, black shading indicates positive NPV of solar installations under current construction costs, dark grey indicates positive NPV of solar using NEMS forecasted construction costs, and light grey states are those where solar has negative NPV. States with mandatory RPS goals are indicated using †.

Table 6: Comparison of Economic Viability and RPS Effect by State

Panel A: Using Current Electricity Prices		
	Positive NPV	**Negative NPV**
RPS Increases Capacity	**HI**†; **CA**†; AZ†; NV†; NM	CO†; NC†; OR†; FL; GA; SC;
RPS Does Not Increase Capacity	MD†; NJ†; NY†; RI†; **CT**†; **MA**†; **VT**	TX†; DE†; WA†; PA†; MN†; IL†; IN; OH†; WI†; WA†

Panel B: Using Social Cost of Carbon Electricity Prices		
	Positive NPV	**Negative NPV**
RPS Increases Capacity	**HI**†; **CA**†; **AZ†;** SC; **NV†;** **NM**; CO†; NC†; FL; GA;	OR†;
RPS Does Not Increase Capacity	**MD†;** NJ†; NY†; **RI†;** TX†; DE†; **CT**†; **MA**†; **VT;** IN	WA†; PA†; MN†; IL†; OH†; WI†; WA†

† indicates states with mandatory RPS goal in place. Bolded states have positive net benefits using both NEMS future construction costs and EIA current construction costs. Unbolded states have positive net benefits using NEMS future construction costs but not using EIA current construction costs.

Figure 1. Solar Capacity Event Study

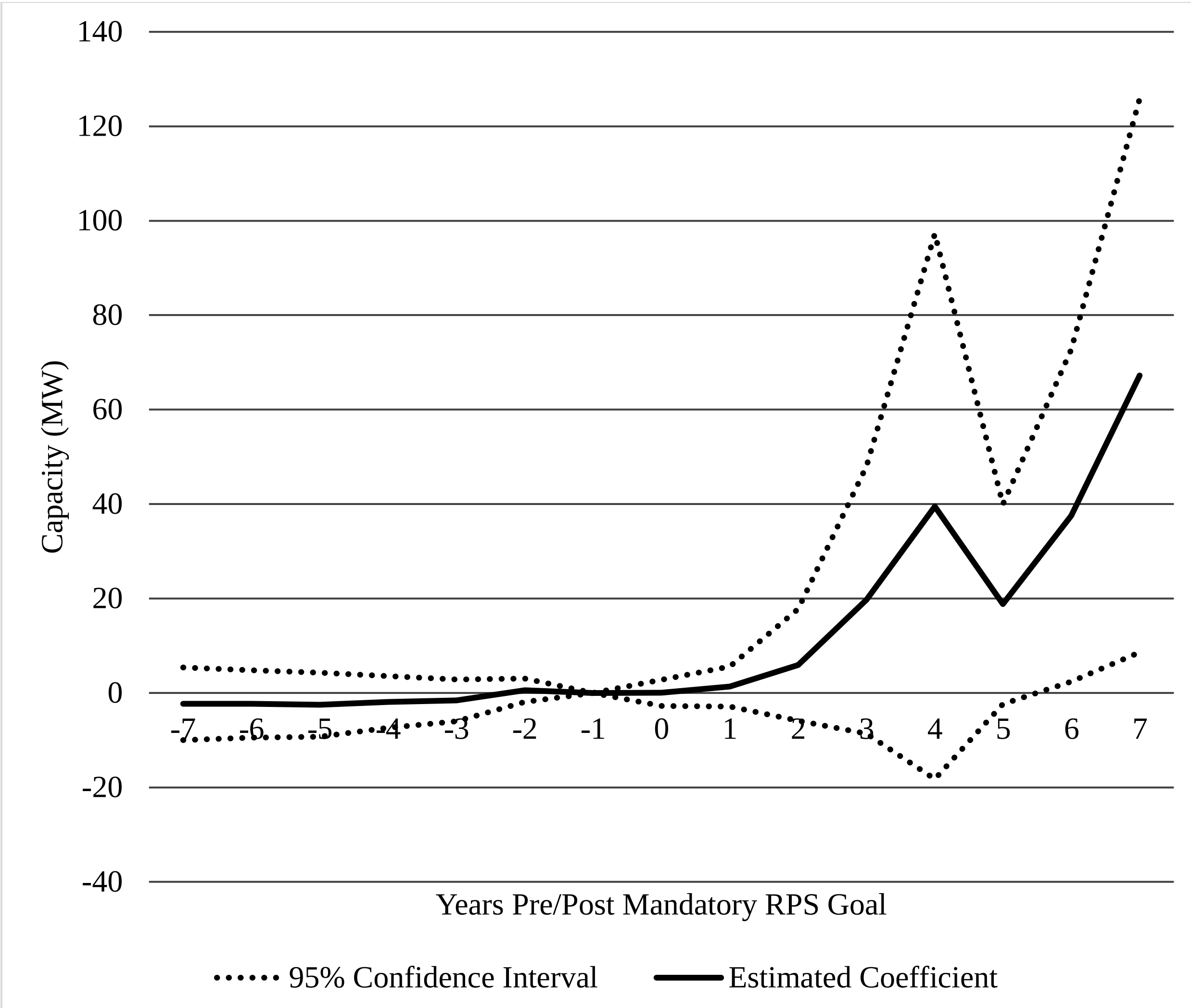


Figure 2. Mandatory Renewable Goals Event Study

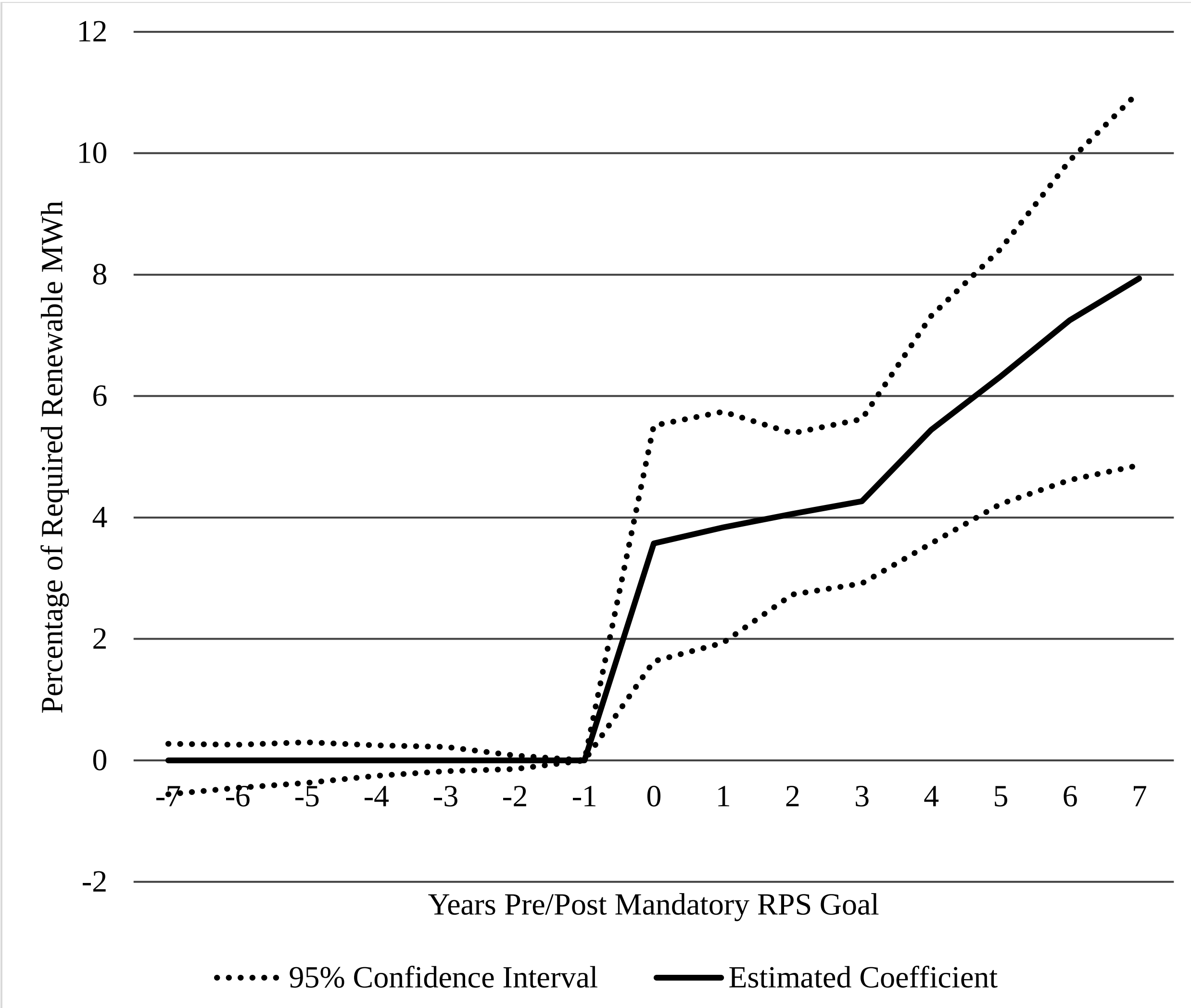


Figure 3. Wind Capacity Event Study

Figure 4. Solar Technical Efficiency Distributions

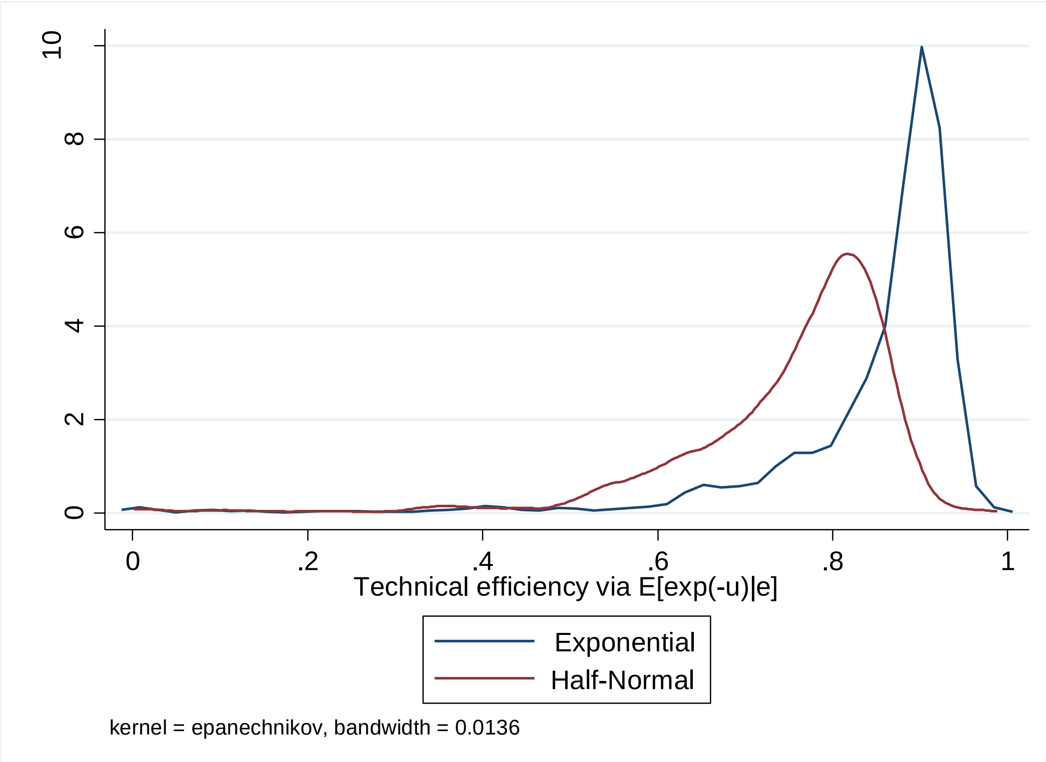
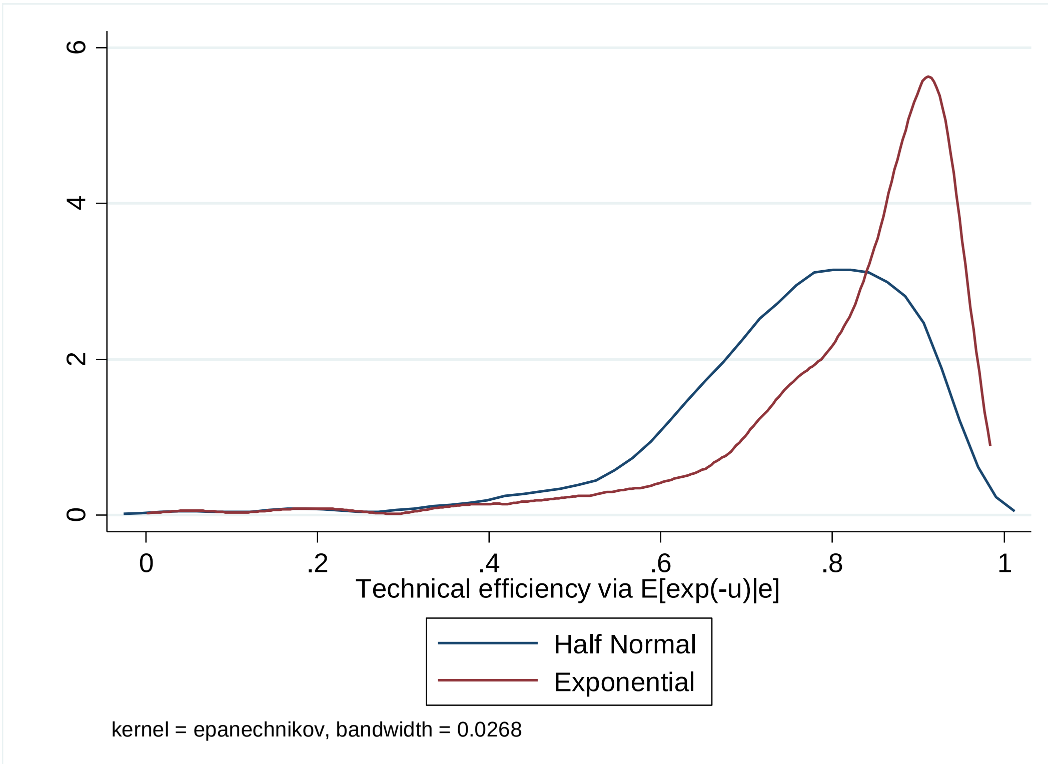


Figure 5. Wind Technical Efficiency Distributions



Appendix

Table A1. Economic Viability of a 30 MW Wind Farm with Current Electricity Prices

Panel A: Present Value Calculations under Current and NEMS Forecasted Construction Costs[a]			*Panel B: Scatter Diagram of Economic Viability by State Price Quartiles and Wind Quality Class*[b]				
	(1)	**(2)**		**Wind Quality Class**			
State (Capacity Share)	**PV Curr. ($Mill)**	**PV NEMS ($Mill)**	**Price**	*Very Low*	*Low*	*Medium*	*High*
NV (0.1%)	83.30	58.94	*Quartile1*		WA†		
TN (0.1%)	85.56	61.21				WV	
WA (2.3%)	86.57	62.21				WY	
UT (0.4%)	87.24	62.88				ID	
AZ (0.5%)	87.65	63.29				IA†	
IN (1.2%)	91.95	67.59				OK	
WV (0.5%)	106.33	81.97				UT	
OR (4.2%)	107.16	82.80				ND	
MO (0.8%)	110.17	85.81				OR†	
ID (4.4%)	111.20	86.84				MT†	
OH (0.8%)	112.87	88.51	*Quartile2*			NE	
IL (3.5%)	118.47	94.12				TX†	
PA (3.4%)	122.69	98.33			SD		
RI (0.3%)	122.83	98.47				IN	
WI (0.4%)	130.76	106.40				MO†	
WY (2.3%)	131.79	107.43				TN	
DE (0.1%)	133.54	109.18				IL†	
NM (1.2%)	135.79	111.43				MN†	
ND (2.7%)	136.25	111.89				NM	
MT (1.4%)	139.56	115.20			NV†		
IA (8.2%)	141.22	116.86	*Quartile3*		OH†		
OK (3.0%)	142.02	117.66				CO†	
TX (12.8%)	145.21	120.85		AZ†			
CO (1.8%)	149.24	124.88				KS	
MI (2.3%)	151.88	127.52				PA†	
MD (0.4%)	155.03	130.68				WI†	
MN(15.4%)	166.30	141.94			MI†		
SD (0.8%)	166.74	142.38				DE†	
ME (1.2%)	167.76	143.40				MD†	
NJ (0.3%)	168.02	143.66				ME†	
NE (1.2%)	170.68	146.33	*Quartile4*			NJ†	
KS (2.5%)	172.72	148.36				VT	
NY (2.5%)	181.16	156.81					CA†

Continued on next page

Table A1. Contd.

Panel A: Present Value Calculations under Current and NEMS Forecasted Construction Costs[a]			*Panel B: Scatter Diagram of Economic Viability by State Price Quartiles and Wind Quality Class*[b]				
	(1)	**(2)**		**Wind Quality Class**			
State (Capacity Share)	**PV Curr. ($Mill)**	**PV NEMS ($Mill)**	**Price**	*Very Low*	*Low*	*Medium*	*High*
VT (0.5%)	183.55	159.19	*Quartile 4*	NH†			
NH (0.4%)	188.13	163.77			MA†		
MA (1.5%)	198.89	174.54					RI†
AK (0.3%)	209.56	185.21				NY†	
CA(12.3%)	214.20	189.84		AK			
HI (1.0%)	670.60	646.24					HI†

[a]Shaded cells indicate states with positive NPV. Average current costs for a 30 MW wind farm are $56.17 million, and NEMS forecasted construction costs are $48.73 million.

[b] Darker shading indicates increased NPV. Specifically, black shading indicates positive NPV of wind installations under current construction costs, dark grey indicates positive NPV of wind using NEMS forecasted construction costs, and light grey states are those where wind has negative NPV. States with mandatory RPS goals are indicated using †.

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