Online Supplemental Appendix for The Dynamic Efficiency of Policy Uncertainty: Evidence from the Wind Industry

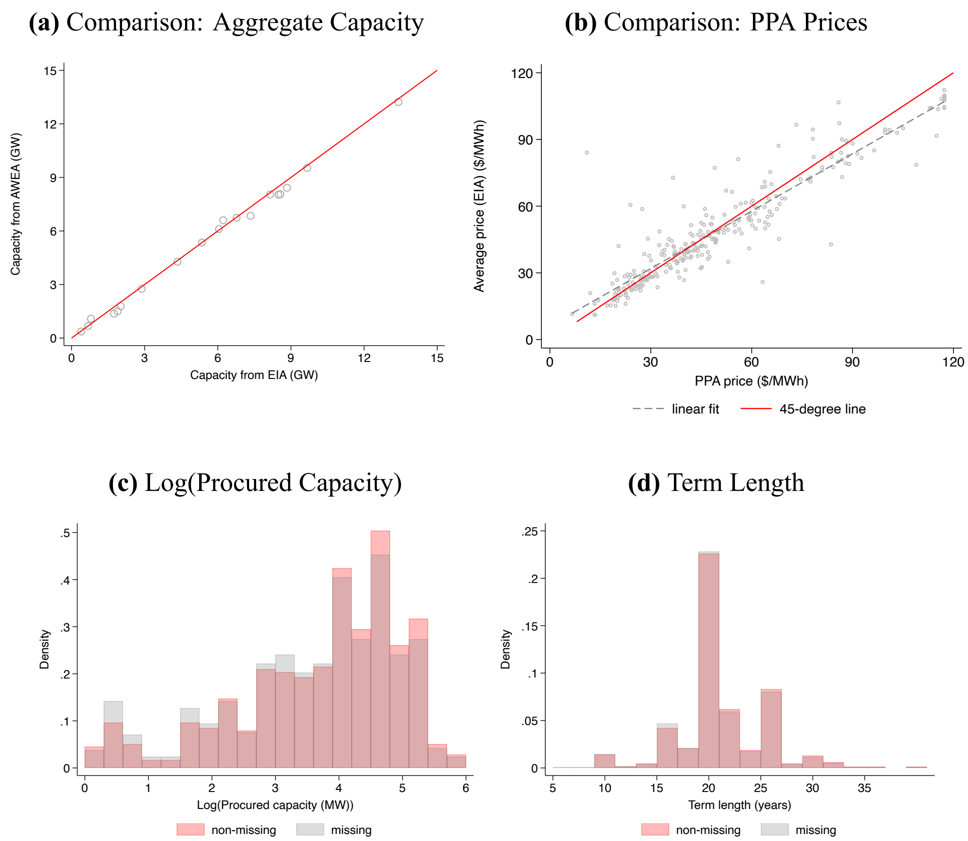
A PPA Data

The main data set I use for the static model is from the AWEA (American Wind Energy Association, now American Clean Power Association), which includes the Power Purchase Agreement (PPA) data in the US wind industry. The wind capacity coverage is complete in the AWEA data, as the aggregate capacity aligns well with that from the EIA data across years (Panel (a) of Appendix Figure OA1).

I keep the PPA data with utilities as the power purchasers from 2001 to 2019. The data is at the contract and purchaser level, and there are in total of 721 observations. However, 13.4% of the observations don't have valid utility names and 4.7% of the observations miss valid wind farm IDs to be matched with the EIA data. Among observations without valid utility names, 20.6% only label the power purchasers as "City," and 12.3% are flagged as "Undisclosed." Among 34 wind farms without valid wind farm IDs, 64.7% has a total capacity of less than 5 MW. Otherwise, the missing pattern appears to be idiosyncratic. Comparing the total capacity and contract lengths between sub-samples with and without missing IDs as shown in Panels (c) and (d) of Appendix Figure OA1, the overall distributions resemble each other, although the contracts with missing IDs seem to have slightly smaller procured capacity.

There are 36.3% contracts missing price information among all the contracts with valid utility names and wind farm IDs. I follow Aldy, Gerarden, and Sweeney (2023) and impute the missing PPA prices from the resale revenues and quantities reported in the EIA Form 923 from 2011 to 2019. By comparing the prices of wind farms whose price information is available both from EIA and AWEA as shown in Panel (b) of Appendix Figure OA1, I find they align well with each other.

Figure OA1: Data Description of the PPA Sample



Notes: This figure presents the results of the data description for the PPA sample. Panels (a) and (b) show the results of the data quality cross-check between AWEA and EIA. Panel (a) plots the annual aggregate new capacity from EIA and AWEA. The red solid line denotes the 45-degree line. Panel (b) plots the PPA prices from EIA and AWEA for each wind farm. The red solid line denotes the linear fit, while the gray dashed line denotes the 45-degree line. I calculate the average price from the EIA 923 using the resale price in 2011-2019 for each wind farm following Aldy, Gerarden, and Sweeney (2023). Panels (c) and (d) show the distributions of the log procured wind capacity and the contract term length for two sub-samples respectively. The "non-missing" group denotes the AWEA sub-sample that matches both utility IDs and wind farm IDs with the EIA, and the "missing" group denotes the AWEA sub-sample with either unmatched utility IDs or unmatched wind farm IDs.

B REC Price Data

I obtain the Renewable Energy Credit (REC) price data between 2006 and 2019 from a financial service platform Marex. I calculate the REC price estimates in a given state and year by taking the average between bids and asks from all active REC markets following

Aldy, Gerarden, and Sweeney (2023). However, only 15 states have available information from Marex and the time coverage also varies across states. I take two steps to impute REC prices for active REC state with missing data. First, for the 15 states covered by Marex, I run the following regression to predict their REC prices in years with missing values.

$$y_{mt} = \beta_m \times t + \xi_m + \epsilon_{mt}.$$

y_{mt} denotes the REC prices in state m and year t. ξ_m is the state fixed effects. I extrapolate the REC prices for those years with missing values from the estimated state-specific time trends β_m.

Second, I extrapolate the REC prices in other active REC states. State-level Renewable Portfolio Standards typically stipulate a minimum share of renewable-sourced electricity out of the total generation for each utility, and utilities need to purchase additional RECs if they fall short of the standards. The demand for the RECs is shifted by the stringency of the Renewable Portfolio Standards as well as the volume of electricity generated by non-renewable sources, while the supply of the RECs comes from new wind capacity addition and the entry of other renewable sources. Appendix Figure OA2 demonstrates that the REC prices are positively correlated with the stipulated ratios in the Renewable Portfolio Standards, as well as the share of electricity generated from fossil fuels and nuclear energy, and they are negatively correlated with the amount of the existing wind capacity.

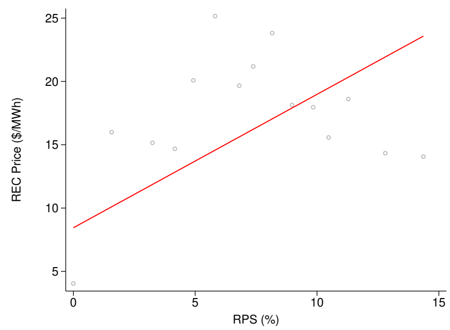
Moreover, the trading of the RECs is fragmented into different markets such that the credits are registered to be traded only in the corresponding tracking systems, as shown in Appendix Table OA1 based on Table 1 in Abito, Flores-Golfin, van Benthem, Vasey, and Velichkov (2022). The tracking system fixed effects could explain around 60% of the REC price variations. Therefore, I estimate the following regression and predict the REC prices for the rest of the active REC states.

$$y_{mt} = \boldsymbol{\beta} \boldsymbol{X_{mt}} + \gamma_{kt} + \epsilon_{mt} \tag{1}$$

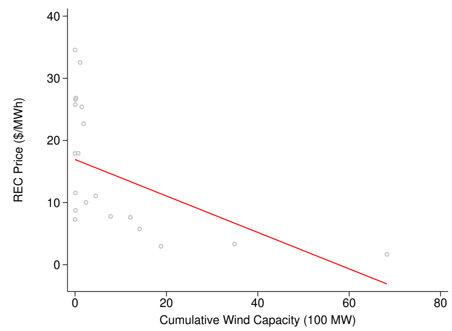
y_{mt} denotes the REC prices in state m and year t. $\boldsymbol{X_{mt}}$ includes the RPS in year t, the cumulative wind capacity in state m and year t, as well as the share of electricity generated out of non-renewable sources. The corresponding tracking system of state m is denoted by k, and γ_{kt} is the tracking-system-by-year fixed effects. Therefore, I extrapolate the REC prices based on both observables and the time trend specific to the tracking system. For states where no price in the corresponding tracking system is available, I impute the REC prices with a national average in that year excluding the New England Power Pool (NEPOOL) because the REC prices in NEPOOL are an order of magnitude higher than the rest of the markets.

Figure OA2: Renewable Energy Credit Prices and Other Market Outcomes

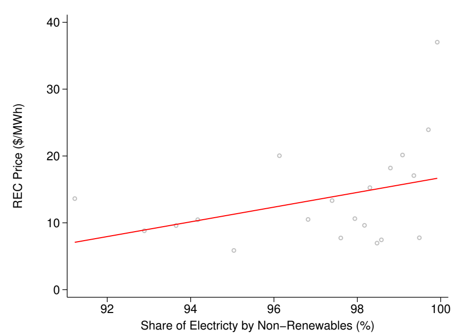
(a) Renewable Portfolio Standards



(b) Cumulative Wind Capacity



(c) Electricity Share by Fossil and Nuclear Power



Notes: This figure shows the relationships between state-level annual Renewable Energy Credit (REC) prices and state ratios of the renewable generation in the Renewable Portfolio Standards (Panel (a)), the amount of the cumulative wind capacity (Panel (b)), and the share of electricity generated by fossil fuels and nuclear energy (Panel (c)). The gray circle denotes the binned scatter plot, while the red solid line is the linear fit.

Table OA1: REC Tracking System and Price Imputation

State	Established year	Tracking system	Imputation
Arizona	2006	None	national average
California	2002	WREGIS	no
Colorado	2004	WREGIS	regression
Connecticut	1998	NEPOOL-GIS	no
Delaware	2005	PJM-GATS	no
Hawaii	2001	None	national average
Illinois	2007	M-RETS, PJM-GATS	no
Indiana	2011	Not designated	national average
Iowa	1983	M-RETS	regression
Kansas	2015	NAR	national average
Maine	1999	NEPOOL-GIS	no
Maryland	2004	PJM-GATS	no
Massachusetts	1997	NEPOOL-GIS	no
Michigan	2008	MIRECS	no
Minnesota	2007	M-RETS	regression
Missouri	2007	NAR	national average
Montana	2005	M-RETS, WREGIS	regression
Nevada	1997	NVTREC, WREGIS	regression
New Hampshire	2007	NEPOOL-GIS	no
New Jersey	1991	PJM-GATS	no
New Mexico	2002	WREGIS	regression
New York	2004	NYGATS	national average
North Carolina	2007	NC-RETS	national average
North Dakota	2007	M-RETS	regression
Ohio	2008	M-RETS, PJM-GATS	no
Oklahoma	2010	None	national average
Oregon	2007	WREGIS	regression
Pennsylvania	2004	PJM-GATS	no
Rhode Island	2004	NEPOOL-GIS	no
South Carolina	2014	None	national average
South Dakota	2008	None	national average
Texas	1999	ERCOT	no
Utah	2008	WREGIS	regression
Vermont	2015	NEPOOL-GIS	regression
Washington	2006	WREGIS	regression
Wisconsin	1998	M-RETS	regression

Notes: This table documents the establishment year as well as the tracking system of the Renewable Energy Credit (REC) market for relevant states based on the Table 1 from Abito, Flores-Golfin, van Benthem, Vasey, and Velichkov (2022). The column "Imputation" documents how I impute missing REC prices in the corresponding states. "Regression" indicates that I impute REC prices following equation (1) with the stipulated ratios in the Renewable Portfolio Standards, the amount of the cumulative wind capacity, and the share of electricity generated from fossil fuels and nuclear energy, as well as time trends specific to the relevant tracking system. "National average" indicates that I impute the REC prices with a national average in that year excluding the NEPOOL when no price in the corresponding tracking system is available. "No" indicates that the data is not missing and no imputation is required.

C Interconnection Queue Data

I access the interconnection queue data from different Regional Transmission Organizations (RTO) and Independent System Operators (ISO), including MISO, CAISO, PJM, ISO-NE, NYISO, and SPP.[1] Since I observe the time when a project entered the queue and withdrew from the queue, I define the former as entry and the latter as exit. I assume that on average wind projects stayed for two years in the queue before obtaining all the approvals and signing the interconnection agreements.[2] Another way to leave the queue is to successfully build a wind farm, which I back out using the EIA data.

I calculate the number of potential entrants for the wind industry for each state as a cumulative number of projects that had entered the queue at least two years ago and had not built a wind farm or withdrawn from the queue. I denote the number of potential entrants in state m and year t as $\text{PotentialEntrants}_{mt}$. The number of projects that entered into the queue, withdrew from the queue and built a new wind farm as Entry_{mt}, Exit_{mt} and NewBuilt_{mt}, respectively. Therefore, $\text{PotentialEntrants}_{mt}$ can be recursively defined as follows.

$$\text{PotentialEntrants}_{mt} = \text{PotentialEntrants}_{mt-1} + \text{Entry}_{mt-2} - \text{Exit}_{mt} - \text{NewBuilt}_{mt-1}.$$

I define $\text{PotentialEntrants}_{m,2002}$ as twice as large as the maximum of NewBuilt_{mt} in the state m, serving as an initial value. I adjust $\text{PotentialEntrants}_{mt}$ to be equal to NewBuilt_{mt} if the former falls below the latter. I describe the time trend for Entry_{mt}, Exit_{mt}, and $\text{PotentialEntrants}_{mt}$ in Appendix Figure OA3. The total number of projects that entered the queue initially increased but fell between 2008 and 2012. After 2012, the trend reversed until 2016. The total number of projects that withdrew from the queue experienced a peak in 2012 and displayed a hump shape. As a consequence of the time trend for entry, exit, and successful new-built which peaked in 2011, the number of total potential entrants is also hump-shaped and peaked in 2010. The entry and withdrawal from the queue are both assumed to be exogenous to my model.

One complication is a lack of interconnection queue data for states that are not part of the ISOs or RTOs. Moreover, I only access ERCOT interconnection queue data between May

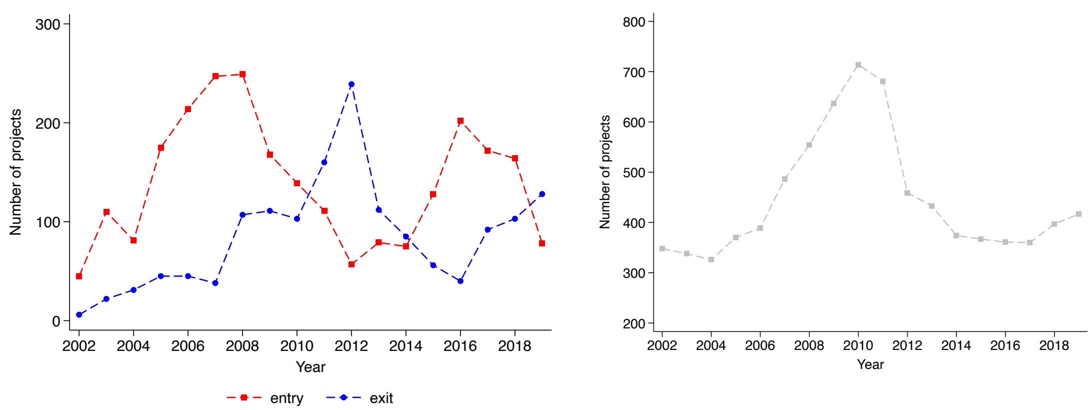
[1] MISO interconnection queue is accessed on Oct 31st, 2022. CAISO interconnection queue is accessed on Oct 31st, 2022. PJM interconnection queue is accessed on Nov 1st, 2022. ISO-NE interconnection queue is accessed on Nov 2nd, 2022. NYISO interconnection queue is accessed on Nov 2nd, 2022. SPP interconnection queue is accessed on Nov 5th, 2022.

[2] Anecdotes suggest that a typical project completed in 2008 spent fewer than two years in the queue for interconnection approval compared to three years in 2015, according to the news. Although the backlog and congestion issues are salient in recent years, two-year waiting time might be a reasonable assumption because it is roughly a median in my sample period (2003-2018).

2014 and July 2018, in which the number of projects that had signed the interconnection agreement could be calculated. As shown in Appendix Figure OA4, the number of newly built wind farms is stable compared to the rest of the US, and the number of potential entrants between 2014 and 2018 was also stable within the range between 40 and 50. Therefore, I assume that the number of potential entrants is constant at 50 across years for ERCOT. For the rest of the states that lack interconnection queue data, I assume that the number of potential entrants in 2002 was twice as large as the maximum number of newly built wind farms annually in that state, which is the same as what I assume for the ISOs and RTOs. For later years, I assume the number of projects that enter the queue or withdraw from the queue follow the aggregate time trend in MISO, CAISO, PJM, ISO-NE, NYISO, and SPP, and the level is adjusted proportionally to the number of potential entrants in 2002.

Figure OA3: Entry, Exit, and Potential Entrants in Queues

(a) Entry and Exit **(b)** Total Potential Entrants

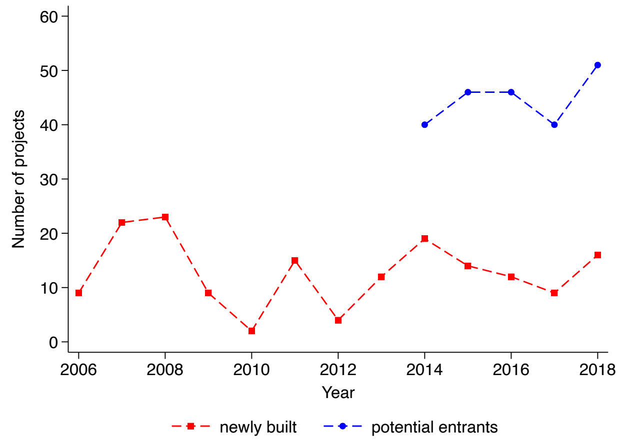


Notes: This figure shows the aggregate time trend for the interconnection queue in MISO, CAISO, PJM, ISO-NE, NYISO, and SPP. "Entry" denotes the number of projects that entered the queue, and "exit" denotes the number of projects that withdrew from the queue. The number of potential entrants for the wind industry for each state is a cumulative number of projects that had entered the queue at least two years ago and had not built a wind farm or withdrawn from the queue.

D Calculation of Social Benefits of Wind Energy

I evaluate the benefits of wind energy following Callaway, Fowlie, and McCormick (2018). I assume wind farms operate for 20 years and calculate total benefits from their twenty-year

Figure OA4: Newly Built Projects and Potential Entrants in ERCOT



Notes: This figure shows the aggregate time trend for the interconnection queue in ERCOT. The number of newly built projects is calculated from the EIA data. The number of potential entrants is directly calculated from the queue data in ERCOT in each July between 2014 and 2018 as the number of projects that had signed the interconnection agreement.

operations. Wind energy substitutes fossil fuels in generating electricity and thus there are three sources of benefits from more wind energy on the grid: reducing carbon emissions, avoiding fossil input costs, and adding capacity values to the system. I estimate the average marginal operating emissions rate (MOER) of coal- or gas-fueled power plants in each state and year, which is defined as the marginal response in the system-wide emissions with respect to the total production change from generators due to more renewable energy, as Callaway, Fowlie, and McCormick (2018) find that regional average MOERs offer a useful means of "calibrating regional policy incentives to compensate for external emissions benefits."

I access the data of total electricity production and carbon emission for each state at the hourly level between January 1, 2004, and December 31, 2018, from the Clean Air Markets Program Data (formerly, Continuous Emissions Monitoring Systems Database). Following Callaway, Fowlie, and McCormick (2018), I first cluster hourly observations according to load profiles and peak loads using a k-means clustering algorithm. The clusters k are generated for each market r, season s, and hour-of-the-day h. I categorize all observations into eight markets according to their ISOs or RTOs, including CAISO, ERCOT, ISO-NE, MISO, PJM, SPP, NYISO, and non-ISO states. I categorize all dates into two seasons: summer/fall

(May to October) and winter/spring (November to April). I generate 12 clusters of observations within each hour of the day, season, and market (such as MISO in summer/fall 10-11 a.m.). The MOER is estimated using the equation below, where E_{mkt} and G_{mkt} represent emissions and electricity generations in each hour t, cluster k, and state m.

$$E_{mkt} = \alpha_{mkhs} + \phi_{mkhs} G_{mkt} + e_{mkt}.$$

ϕ_{mkhs} is the estimated MOER for each state m, season s, hour-of-the-day h, and cluster k. As I calculate the total benefits from twenty-year operations of wind farms, I take an average ϕ_m as the mean MOER for state m. The statistics of the avoided operating costs and capacity values are taken directly from Callaway, Fowlie, and McCormick (2018).

References

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